Daniel Alexandre Martins Guerreiro

“Semantic inhibitory model of creative cognition”

Faculdade de Ciência Humanas e Sociais

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Trabalho efetuado sob a orientação do Professor:
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Declaração de Autoria do Trabalho

Declaro ser o autor deste trabalho, que é original e inédito. Autores e trabalhos consultados estão devidamente citados no texto e constam na listagem de referências incluídas.

Assinatura

(Daniel Alexandre Martins Guerreiro)

Resumo

A criatividade é uma das capacidades mais importantes e fundamentais da mente humana. A possibilidade de gerar novas ideias, mais abstratas e complexas, a partir de conceitos previamente aprendidos permitiu o desenvolvimento da humanidade como a conhecemos. No entanto, apesar da sua importância indiscutível, o campo de investigação sobre a criatividade continua a ser um dos mais teoricamente fragmentados e subdesenvolvidos dentro das Ciências Cognitivas.

Essa fragmentação pode ser atribuída a três fatores: 1) a falta de uma definição capaz de abranger a diversidade de manifestações da criatividade; o termo é aplicado para definir um leque alargado de conceitos, tais como processos, características de personalidade e fatores ambientais que dão origem a produtos criativos, o que dificulta o emergir de uma teoria geral da criatividade; 2) práticas metodológicas fortemente dependentes do pensamento divergente para medir a criatividade; o conceito de pensamento divergente é insuficiente pare medir criatividade pois o pensamento divergente pode não ser criativo e, ao inverso, o pensamento convergente pode dar origem a resultados criativos; por outro lado, sendo o pensamento divergente um processo compósito, dependente de vários outros processos distribuídos, não pode servir como base para a compreensão do processo criativo; 3) a falta de definir um mecanismo cognitivo claro que possa explicar os aspetos transitórios e involuntários da criatividade; ao contrário de outras capacidades cognitivas, como a compreensão e produção linguística, a criatividade nem sempre é acedida voluntariamente, sendo as ideias criativas habitualmente descritas como surgindo espontaneamente.

Todos esses problemas decorrem em grade parte da falta de um modelo conciso de como a criatividade é gerada. Por isso, propomos um novo modelo que define a criatividade como fenómeno emergente, produzido pela interação de dois mecanismos cognitivos bem compreendidos: a “difusão de ativações” (*spreading activation)* e o controlo inibitório. A difusão de ativações diz respeito às ativações que ocorrem aquando da ativação de um conceito na memória semântica, que, por sua vez, se difunde através da rede de conceitos associados, proporcionando informação contextual. É através desta difusão que se torna possível formar novas associações entre conceitos distantes, formando ideias originais. O controlo inibitório é um mecanismo

exercido pelo córtex pré-frontal responsável da redução do alcance destas ativações. Esta inibição é necessária ao funcionamento cognitivo quotidiano, pois uma ativação extensa da rede de associações semânticas sempre que se ativasse um conceito na memória seria altamente ineficiente em termos gestão de recursos cognitivos. Assim, o controlo inibitório permite excluir os conceitos mais remotos da difusão desencadeada perante a ativação de determinado conceito, garantindo que apenas os conceitos mais próximos e pertinentes recebam a ativação.

Este modelo possibilita a resolução dos principais problemas apontados na área da investigação da criatividade. Em primeiro lugar, apesar de se basear em dois processos simples, a complexa interação entre eles permite uma caracterização dinâmica e altamente flexível da criatividade, permitindo distinguir três tipos de criatividade, dependendo do nível em que cada um dos processos está mais envolvido: a) “criatividade analítica”, caracterizada por alto nível de envolvimento de processos inibitórios e um muito baixo envolvimento de difusão de ativações. Neste tipo de criatividade, ao invés de usar a difusão de ativações, possíveis associações são testadas sequencialmente, de forma a encontra uma solução válida; este tipo de processo é bastante ineficiente na geração de novas ideias; b) “criatividade associativa”, caracterizada por um alto nível difusão e baixo nível de inibição. Neste tipo de criatividade, na ausência de controlo executivo, as ativações estendem-se para além dos seus níveis normais aumentando o potencial para alcançarem conceitos distantes e, assim, formar associações originais; contudo, sem o auxílio do sistema de controlo que guie o processo, estas ativações podem tornar-se aleatórias e, como tal, também ineficientes; c) “criatividade inspiracional”, caracterizada pelo envolvimento ótimo de ambos os processos. Este tipo de criatividade dá-se quando um estímulo com um nível intermédio de originalidade é processado; o processamento desse estímulo original exige associar conceitos na memoria semântica, pelo que os mecanismos inibitórios têm de relaxar o seu impacto na difusão de ativações, mas mantendo outras áreas analíticas (como a memória de trabalho) a funcionar para guiarem o processo de interpretação. Assim, o processamento de estímulos criativos induz (“inspira”) um estado mental propenso à geração de ideias criativas.

Com base neste modelo, delineámos um paradigma experimental para induzir criatividade recorrendo a frases metafóricas originais. Os participantes foram separados em dois grupos: no grupo experimental, era necessário selecionar entre duas frases (frase com sentido metafórico versus frase sem sentido) qual a que tinha significado; no grupo de controlo, os participantes

tinham de fazer a mesma tarefa, mas agora era apresentada uma frase com sentido literal contraposta a uma frase sem sentido. Espera-se que a interpretação das frases metafóricas originais induza o estado mental associado à criatividade inspiracional, não observado no grupo de controlo.

Os efeitos desta manipulação ativadora dos mecanismos de criatividade inoperacional foram medidos recorrendo a uma "tarefa de usos alternativos" aplicada aos dois grupos antes e depois da manipulação experimental. Para avaliar se a manipulação experimental afetava a rede semântica, recorreu-se a representações em rede da produção numa tarefa de fluência semântica ("nomes de animais durante um minuto") realizada antes e depois da manipulação experimental.

Os resultados mostraram um aumento da conectividade e flexibilidade na representação do domínio semântico "animais", bem como uma maior pontuação na tarefa de usos alternativos no grupo experimental. Aparentemente, a interpretação de metáforas, ao requerer a desinibição da difusão semântica, permitiu uma maior fluência das ativações da rede semântica dos participantes do grupo experimental quando realizaram posteriormente as tarefas de fluência verbal e de usos alternativos. Pelo contrário, no grupo de controlo, a interpretação de frases literais não requereu essa desinibição da ativação, pelo que o desempenho ulterior na tarefa de usos alternativos não revelou maior criatividade e a produção na tarefa de fluência verbal não revelou alteração significativa na conectividade da rede semântica.

Estes resultados suportam a hipótese de que o processo criativo é regulado por processos inibitórios *top-down*, que podem ser influenciados passivamente pelo tipo de informação que está a ser processada. Corroborámos também a adequação da metodologia das redes para o estudo da criatividade em contexto experimental.

Palavras-chave: Criatividade, Pensamento divergente, Ativação, Controlo inibitório, Memória semântica, Análise de redes

Abstract

Creativity is one of the most important and fundamental abilities of the human mind, the ability to generate new and more abstract and complex ideas out of previously learned concepts is what allowed the development of humanity as we know it. However, despite this undisputed importance the field of creativity research remains one of the most underdeveloped, and theoretical fragmented fields within cognitive sciences.

This fragmentation can be attributed to 3 factors: 1) the lack of a well-articulated definition able to encompass the diversity of creativity manifestations. 2) methodological practices heavily reliant on the use of divergent thinking to measure creativity. 3) the lack of a clear cognitive mechanism able to account for the transient and non-volitional aspects of creativity.

All these problem steam from a lack of concise model as such we propose a new model that defines creativity an emergent phenomenon, produced out of the interaction of 2 cognitive mechanism: spreading activation and inhibitory control. We then present and test hypothesis based on this model. For this an experimental paradigm using novel metaphoric, nonsensical and literal sentences was employed, where individuals had to interpret and judge what sentence made more sense. The effects of this interpretation were measured using both an Alternative uses task and a Network Science approach to examine group-based semantic memory graphs. Networks were constructed from a semantic fluency task.

The results showed an increase in the connectivity and flexibility in semantic memory and a larger score in the Alternative uses task associated with the interpretation of metaphors. These findings support the hypothesis that the creative process is regulated by top-down inhibitory processes and that these mechanisms can by passively influenced by the type of information being processed. Finally, we also corroborate the network science methodology applied to an experimental paradigm as a valid approach to the study of creativity.

Keywords: Creativity, Divergent thinking, Spreading activation, Inhibitory control, Semantic memory, Network analysis

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1. Introduction

1.1. Theoretical and Methodological Gaps in Creativity Research

Creativity is one of the most fundamental concepts used to define human nature (Dietrich,2019a, 2019c). Some researchers have argued that creativity, the ability to generate new, more abstract, and complex concepts from previously learned ones, constitutes humankind's ultimate resource (Batey, 2008b). Furthermore, there is an undeniably important practical dimension associated with creativity: understanding its mechanisms and to comprehend how to influence it would give us the means to elevate the human scientific, technological, artistic domains (Batey, 2008a; Dietrich, 2019c; Runco, 2004).

Despite creativity's undisputed importance, psychological research regarding creativity remains an academically stagnated, heavily fragmented and theoretically incoherent field (Batey, 2008a; Dietrich, 2007a, 2019b, 2019d). These problems can be attributed to several factors.

One of the primary challenges in creativity research is the lack of definitional consensus, namely regarding its specific aspects and characteristics (Parkhurst, 1999; Runco, 2004). The term "creativity" does not refer to a specific psychological attribute or process that directly leads to creative outcomes. Instead, it serves as an umbrella term encompassing a variety of phenomena like personality traits, cognitive processes or environmental factors that result in a creative outcome. While this broad definition is useful for artists, scientists, and laypeople alike (Wehner et al., 1991), by allowing for connections across different domains, it dilutes the meaning of creativity and diminishes its significance (Batey, 2008b). To address this, a concrete model of cognitive processing is needed to unify these diverse concepts under a cohesive vision of what creativity truly is (Dietrich, 2019d). Accounting for this diversity is essential, it is uniformly agreed upon that creativity is a complex and multifaceted construct that can present itself in very diverse ways (Abraham, 2016; Dietrich, 2004; Smith et al., 1995). For this reason, it is also universally agreed that creativity must be subdivided into different types if it is to be made tractable, especially for research in cognitive neuroscience. However, serious and solid theoretical work on developing suitable subtypes is lacking (Dietrich, 2019b).

These challenges are further compounded by the common reliance on divergent thinking as a measure of creativity, often in combination with neuroimaging techniques (Dietrich, 2019d, 2019b). The inadequacy of divergent thinking as a creativity metric stems from two main issues. First, it lacks discriminatory power: both divergent and convergent thinking can generate creative ideas, and divergent thinking can also lead to non-creative productions. Second, divergent thinking is not a single, clearly defined process—it involves a wide range of separate and distributed mental processes, including working memory, cognitive control, semantic memory, perceptual processing, and executive attention (Dietrich, 2019d). Currently, little is understood about how these processes converge to form divergent thinking (Dietrich, 2015), a problem widely acknowledged in the field (Abraham, 2013; Sawyer, 2011; "The Creative Cognition Approach.," 1995). This ambiguity also complicates the use of neuroimaging to study creativity. Neuroimaging can only detect well-defined, operationalized cognitive processes, but creativity, as currently defined, is too complex and poorly specified for clear detection. Without a solid theoretical foundation, neuroimaging data related to creativity remains difficult to interpret (Dietrich, 2007b, 2019d)

Creativity also poses additional challenges caused by its cognitive processing that is often characterized by its unconscious nature, where ideas and solutions emerge seemingly without deliberate effort or awareness such as in the case of incubation (B. T. Christensen, 2005; Smith, 2011). It is also common for creative individuals, when describing their work habits or the process of creative problem solving, to refer that creative ideas result of the absence of conscious effort (Ritter & Dijksterhuis, 2014). This unconscious aspect complicates the study of creativity, since the mental processing occurs outside of conscious awareness, making it challenging to observe and measure directly. Traditional research methods, which rely heavily on introspection and self-reporting, may not fully capture these spontaneous and unintentional creative moments.

Despite these difficulties there is some reasonable definitional agreement in the field. According to the definition first proposed by Barron (1955), we can define creativity as the process that leads to the production of a novel, useful idea or product. This is the definition that has been most used and accepted in the field (Runco & Jaeger, 2012). However, for the purposes of this research, we will focus specifically on the novelty aspect—the generation of original ideas—, as the utility component often proves problematic when broken down. This is because the usefulness of an idea is highly subjective and can vary across different contexts or historical periods (Amabile, 1996;

Sternberg & Lubart, 1999). An idea considered uncreative in one context may later be recognized as highly creative, and vice versa (Simonton, 1999). This variability suggests that usefulness is not a reliable measure of the underlying cognitive processes involved in creativity, which should be considered independent of the context in which they are evaluated (Sternberg & Kaufman, 2010). This phenomenon is particularly evident in the work of geniuses and artists whose contributions were initially dismissed but later celebrated (Csikszentmihalyi, 1997). The cognitive processes behind these works were creative from the start, regardless of their initial reception. Moreover, the criterion of usefulness does not always apply, especially in the case of artistic creativity, where the value of a work often transcends traditional notions of utility (Schubert, 2021).

The present study aims to address the key challenges that have contributed to fragmentation in the field of creativity research. We identified three major unresolved issues:

1. Definitional: There is a lack of a well-articulated definition able to encompass the diversity of creativity manifestations.
2. Methodological: The heavy reliance on the use of divergent thinking to measure creativity leaves us without an understanding of how the same cognitive architecture can give rise to both creative and non-creative thinking.
3. Processual: the lack of a clear cognitive mechanism able to account for the transient and non-volitional aspects of creativity does not present in other cognitive functions such as language comprehension or reasoning.

These problems stem from the absence of a concise and robust model of creativity. To tackle these questions, we will propose a model that offers a biological and cognitive explanation of how distributed brain processes are integrated to give rise to creativity.

1.2. Memory

We will begin by discussing one of the most important aspects of the model: Memory. For all uncertainty about what processes are or are not involved in creative cognition, memory has most certainty an indispensable role, since new ideas do not come ex nihilo, rather they arise from meaningful variations and recombination of available knowledge (Benedek & Fink, 2019;

Gabora, 2010; Schubert, 2021). The combinations of more unrelated concepts hold the key for the formation of original ideas and among which creative ones reside (Mednick, 1962).

Semantic memory is the human memory system that stores categories and concepts, generalizing across distinct facts and experiences from our lives, independent of time or context (McRae Michael Jones et al., 2013; Patterson et al., 2007; Saumier & Chertkow, 2002). The way meaningful new associations can arise is in relation to the concepts stored in semantic memory has supported the traditional hypothesis that its structure can be characterized as an associative network model (A. M. Collins & Loftus, 1975; A. M. Collins & Quillian, 1969), which can be represented through the framework of connectionism.

Connectionism relies on two primary elements: nodes and links. Nodes, which represent concepts, are analogous to neurons in the brain (Rumelhart & McClelland, 1987a). These nodes are connected by links, also referred to as weights, which are akin to synapses. These weights determine the strength of the connection between nodes, with stronger links facilitating more efficient communication between related concepts (Hinton, 1989). A fundamental principle of connectionism is that learning occurs by adjusting these weights based on experience, through processes like backpropagation and Hebbian learning (Rumelhart & McClelland, 1987a).

The present model's connectionist conceptualization requires some simplification. In the connectionist framework, knowledge is structured hierarchically and distributed within a network. Nodes represent basic perceptual or conceptual features, often referred to as microfeatures (Churchland & Sejnowski, 1992). These microfeatures can be perceptual, such as lines, angles, colors, or shapes, or conceptual, representing associations of these basic features, forming higher-level concepts like "paw" or "tail." The combination of these features gives rise to more complex categories, such as "dog," which in turn belong to even broader hierarchical categories like "Animals." This distributed representation enables spreading activation between concepts via shared microfeatures (Gabora, 2010).

For the purposes of this study, however, we will conceptualize each node as representing more complex cognitive representations, such as objects or animals. These correspond to privileged categories, which contain information that is accessed directly rather than through spreading activation along the hierarchy (Rogers & Mcclelland, 2003). Privileged categories exist at an intermediate level of the hierarchy, maximizing both informativeness and distinctiveness (Rosch et al., 1976). This allows for efficient memory access and retrieval, making them ideal for the study's focus on semantic networks.

It is important to note that this simplification does not disregard the underlying hierarchical structure of knowledge. While we will primarily address nodes as elements belonging to privileged categories, the underlying structure still plays a crucial role in connecting related concepts via shared microfeatures. This structural complexity is captured in the weights of the network, which reflect the level of shared distributed features in the strength of the connections.

1.3. Semantic inhibition model

Using this framework, we propose a model in which creativity emerges from the integration of two cognitive mechanisms that on their own are not necessarily creative: spreading activation in semantic memory and inhibitory control mechanisms.

Spreading activation is the process through which activation of one concept in the mind can trigger the activation of related concepts allowing for the retrieval of related ideas and providing contextual information for the concept. When a particular node is activated (through thinking about or encountering a concept), the activation spreads along the links to connected nodes, activating related concepts (A. M. Collins & Loftus, 1975). For example, when the concept "dog" is triggered, activation spreads through the semantic associative network to neighboring concepts like "bark" or "pet." The strength and distance of the connections determine how far and how strongly the activation spreads.

In contrast, inhibitory mechanism concerns the necessary pruning or restriction limiting which associated concepts become activated. This pruning is necessary because, although distant and weakly related concepts may provide useful insights, they are not always optimal for efficient everyday thinking (J. R. Anderson, 1988). For the brain to process the entire network of associations for a given concept each time it is activated would consume an excessive amount of time and cognitive resources. Therefore, inhibitory control reduces the number of associations to those that are most common or contextually relevant, enhancing processing efficiency (Dietrich, 2019b).However, this comes at a cost: by narrowing the search space, the mechanism also limits the potential for novel or creative connections (A. M. Collins & Loftus, 1975; Dietrich, 2019b; Kahneman, 2011).

It is important to mention that these two mechanisms, spreading activation and inhibitory control, are aligned with the long-standing distinction in psychology between insight problem-solving and analytical search strategies (Dietrich, 2015, 2019b; Gabora, 2010). Analytical approaches often involve a more methodical, step-by-step evaluation, while insight relies on spontaneous, novel connections. Previous models have also recognized the need to integrate these two mechanisms, since they often describe creativity as the result of alternating between the two processes (Gabora, 2010). Typically, an exploratory phase (maximizing spreading activation) is followed by an analytic phase (engaging inhibitory processes), where the expanded solution space is evaluated and filtered to leave only viable solutions (Smith, 2011; Smith & Blankenship, 1991). Although this approach acknowledges the importance of both mechanisms and their integration, there has been little articulation of how these cognitive processes map onto neural mechanisms (Dietrich, 2019b). Additionally, neither of the phases alone is sufficient to consistently generate novel associations and a simple sequential integration does not account for the unpredictable and erratic nature of creativity since once understood this simple algorithm, creativity should become a relatively manageable cognitive function.

The model addresses the key challenges in creativity research already mentioned by incorporating well understood yet highly flexible mechanisms that allow for a wide range of creative outputs as well as both creative and non-creative processing. The model also emphasizes the unconscious processes that occur even during active information processing, establishing it as a necessary but not sufficient part of creativity shedding light on the causes of the non-volitional and transient nature of the creative process.

Lastly, the model focuses on the originality aspect of creativity, allowing us to circumvent definitional issues that arise when creativity is defined based on the usefulness of creative products, which can be highly subjective.

The interactions between the two components allows for three types of creativity to be distinguished, depending on the level at which each of the processes is involved: Analytical creativity, associative creativity and inspirational creativity.

Analytical creativity is characterized by larger dominance of inhibitory mechanisms and a low level of spreading activation. It is linked to conscious processing, feelings of agency, executive or top-down attention, effort, volitional control, purposeful memory retrieval, intentionality, and planning. These functions are typically associated with the prefrontal cortex which is responsible for the inhibitory control of maladaptive cognitive behaviors (Benedek & Fink, 2019; Dietrich, 2004). This type of creativity is typically employed in solving structured problems, such as in mathematics or engineering (Dietrich, 2019b). Moreover, in this mode, thinking is focused and sequential, with conscious attention given to evaluating each possible association (Dietrich, 2019b; Gabora, 2010). However, analytical creativity is inefficient in two major ways. The first one is due to the sequential nature of the process, analyzing large solution spaces one by one is time and resource intensive. Second, the very top-down mechanisms that govern this type of creativity are designed to inhibit the abstract, atypical characteristics where truly novel associations, central to creative solutions, tend to form (Gabora, 2010). This selective inhibition can lead to functional fixedness (Runco et al., 2011), where creative solutions are excluded from consideration because they fall outside the predefined search space. For example, in the structured layout of semantic memory, where concepts overlap across categories, the node for “dog” might belong to both the “pet” and “mammal” networks. Top-down inhibitory control selects the most relevant context based on the perceived solution space: if “pet” is deemed more relevant, associations like “parrot” or “fish” are prioritized over closer but less relevant ones like “wolf” (McClelland & Rogers, 2003; Rumelhart & McClelland, 1987b). As a result, when analytical creativity happens it is not produced through its dominant mechanism but rather despite it, making the process highly inefficient.

Spontaneous creativity, in contrast, is characterized by a low level of inhibitory control and consequently by a large range of spreading activation. It is associated with unconscious processing, a lack of agency, inattention or bottom-up attention, no volitional control, effortlessness, undirected memory retrieval, and the eventual emergence of insight in working memory, often experienced as surprising, intuitive, and accidental (Dietrich, 2019b; Ritter & Dijksterhuis, 2014; Salvi et al., 2016; Weisberg, 2013). In this form of creativity, there is almost no top-down control, allowing for a freer spreading of activations across semantic networks. This opens the potential for new and original associations to form (Dietrich, 2004; Wang et al., 2018). Spontaneous creativity is more efficient than analytical creativity in some respects, as it operates in parallel rather than sequentially, allowing activations to spread in multiple conceptual directions at once. However, because this process happens when the prefrontal inhibitory areas are deactivated it also misses some important processes that also happen there like attentional control and working memory (Dietrich, 2004), this lack of mental guidance makes the process more difficult. As a result, while it facilitates the discovery of novel ideas, it is still an inefficient form of creative thinking (Dietrich, 2019b; Gabora, 2010).

It is important to note that within this model these two types of creativity exist on a continuum, with varying degrees of each process contributing to the overall level of associative novelty (Gabora, 2010), and in the extremes, neither purely associative nor analytical processes can archive creativity, some involvement of both is always necessary. Paradoxically, an increase in one component will inevitably lead to a decrease in the other, given that they play opposite functions in terms of regulating the extension the associations made within semantic memory, this contradictory nature of semantic processing, holds the key to understand the elusive nature of the creative process.

Finally, the interaction of these mechanisms allows us to conceptualize a third type of creativity, which we call inspirational creativity. This term is borrowed from the historical conceptualization of inspiration, where creative insight was thought to come from an external source, such as the muses of ancient Greece (Dacey, 2011). Inspirational creativity is characterized by the simultaneous and optimal engagement of both analytical and associative mechanisms, and the consequent optimization of the creative process. This type of creativity is activated when a stimulus, idea, or perception is processed and recognized as creative. When this occurs, it demands the association of previously unconnected concepts within the semantic space. These new associations are necessary to fully understand and integrate the creative stimulus.

During this processing, the top-down inhibitory mechanisms must temporarily relax to allow new associations to form. At the same time, other attentional and directive mechanisms remain active to allow the idea to be processed effectively. This delicate balance between relaxation and focused attention creates a state in which the brain is more receptive to forming original ideas. This is possible because the mental processing of ideas takes place in the same network architecture and obeys the same principles as idea generation, hence they are mirrored processes (Schubert, 2021). The same patterns of activation that allow for creative ideas to be processed allow for creative ideas to be generated. In other words, the processing of creative stimuli induces ("inspires") a mental state prone to the generation of creative ideas.

To fully understand this mechanism, we must explore how information is perceived as creative. This perception of creativity arises from the efficient integration of information when an optimal level of novelty is present (Schubert, 2021). Information exists on a continuum, ranging from fully established concepts to completely novel information. If an idea is familiar, pre-existing connections will be used, and it will not be interpreted as creative. On the other hand, if the idea is entirely novel, like the learning of new concept, processing it will require the mobilization of new nodes (neurons in the biological system), While this leads to new knowledge, it is experienced as learning rather than creativity. Creativity occurs when the information being processed possesses an intermediate level of novelty, necessitating the establishing of new associations within an established network of knowledge to be understood. Additionally, we argue that this type of information encoding is more efficient because it allows for the encoding of a similar amount of information without the mobilization of too many additional resources, thus we expect the brain to prioritize the creative type of encoding whenever possible. This allows us to explain the positive affect often associated with creative insight, the brain rewards the efficient integration of new information with existing knowledge, reinforcing creative processing (Bledow et al., 2013; Henderson, 2004; Kubovy, n.d.).

It is important to mention that despite the process of comprehension of the stimulus, idea, or perception is an active and conscious one, the relaxing of the top-down control is still an unconscious process leading to the same non-volitional sensations as the associative type of creativity. As previously established the least efficient forms of creativity are the ones that rely more on analytical processing thus it is expected that most new insight come about though some level of unconscious processing, we point this as the main cause of the non-volitional and transient nature of the creative process.

The present model also allows us to conceptualize another dimension of creative diversity: the distinction between general and domain-specific creativity (Baer, 2010). With two levels of influence in the creative process, creativity can emerge at both the micro and macro levels. At the macro level, generalized creative patterns of thought arise from the top-down regulatory mechanisms that govern overall cognitive processes. At the micro level, domain-specific creativity emerges from the unique ways in which specific domains of knowledge are encoded, operating independently of other domain structures. This dual-level influence explains how creativity can be both a general ability and one that is tailored to specific fields of expertise.

1.4. Present study

The present study will focus on the exploration of inspirational creativity as it offers the potential for an ideally efficient processing of creativity. We hypothesize that processing optimally novel stimuli will lead to a relaxation of inhibitory control and an increase in spreading activation, without having to disengage other forms of prefrontal top-down control, like working memory that help guide the associative process. This balance of relaxation and attention will enable the activation of broader semantic fields and more distant concepts, opening the possibility to of original associations to form.

This processing will be induced through the interpretation of original metaphors. The processing of original metaphors heavily relies on the activation of broad semantic fields and the integration of concepts that may have distant semantic relations integration of distant concepts to provide meaning (Rutter, Kröger, Hill, et al., 2012; Rutter, Kröger, Stark, et al., 2012; Yang, 2014). The effects of metaphor interpretation will be compared to those of literal sentences interpretation.

We will measure the effects of this relaxation directly by measuring the way information propagates in the semantic network, for this we will make use recently developed network science methodologies (Siew et al., 2019), that allow us to use networks to represent and study the cognitive process taking place in the brain, these networks will be built making use of a verbal fluency task. We expect the levels of connectivity within these networks to increase as the result of a less constrain spreading activation even without the disengagement of prefrontal activity like in states of relaxation or inattention. We will also measure these effects indirectly, using an

Alternative uses task where we expect the increased reach of activations will unlock the potential for novel association to be formed and consequently novel uses to be generated.

Additionally, we will build on the work made on the area of creativity using these methodologies (A. P. Christensen et al., 2018; Kenett et al., 2013, 2014; Rastelli et al., 2020), where the network properties of post-hoc groups (e.g. low vs high creativity) have been compared. We will apply similar methodologies to compare the control group to the experimental group before and after the metaphorical/literal sentences interpretation. With this we hope to demonstrate the potential for these network science methodologies to measure group level alterations caused by an experimental manipulation.

2. Method

2.1. Participants

The sample consisted of 66 participants (23 male, 43 female) with a mean age of 22.67 years (SD = 2.82). All participants were university students and native Portuguese speakers, recruited through face-to-face interactions at the university. The experiment was conducted in a supervised, empty room in the university library, and all participants responses were digitally recorded as audio files for later transcription.

2.2. Materials

2.2.1. Metaphor Exposure Tasks

This task intends to stimulate the participants of the experimental group to connect distant semantic concepts while asking them to make sense of new metaphorical sentences; meanwhile, the control group is exposed to sentences expressing connections between concepts with connections that are already well established.

For this task, we created 42 sentences organized in 14 triplets. In each triplet, the sentences had the same structure, but three different verbs were selected that rendered the sentence to be either literal, nonsensical or metaphorical. An example of a triplet can be found in Table 2.1. and a full list of all the sentences in Portuguese can be found in the appendix A. The originality of the metaphor was also taken into consideration to assure the optimal novelty principle; thus, metaphors commonly used in everyday language were not included, as their interpretation would not fulfill the novelty criterion. The metaphors were evaluated by two juries to ensure they followed the necessary criteria.

Condition	Phrase
Metaphor	O sol **orquestra** as sombras. (The sun **orchestrates** the shadows)
Nonsensical	O sol **fecha** as sombras. (The sun **closes** the shadows)
Literal	O sol **cria** as sombras. (The sun **creates** the shadows)

Table 2.1 Example phrases for the three experimental conditions. Critical words are printed in bold. The literal English translation of the example phrases is presented in brackets. A complete list of the stimuli is listed in the Supplementary material.

For each triplet, we create two types of sentence pairs: “metaphor vs nonsensical” and “literal vs nonsensical”, contrasting a meaningful sentence (either literal or metaphorical) with a nonsensical one. Each participant of the experimental group was presented with the 42 sentence pairs of the “metaphorical vs nonsensical” type, while the participants of the control group were exposed to the 42 sentence pairs of the “literal vs nonsensical” type. Phrase pairs and the order of presentation of the stimuli pairs was randomized for each participant.

All the participants were asked to identify out of each pair which was the sentence that makes sense, and to select their option using either the left or right control key on a keyboard (corresponding to the side of the monitor where the sentence was presented).

2.2.2. Alternative Uses Task (AUT)

Divergent thinking tests are arguably the most frequently used approach for assessing everyday creativity (Clapham, 2011). In these tests participants are asked to produce multiple ideas in response to a specific stimulus (Carroll, 1968).We applied a task based on the alternative uses task

(AUT) (Guilford, 1967). AUT is typically scored on four dimensions that capture different aspects of divergent thinking, namely:

- Fluency: This refers to the total number of ideas or responses generated by a participant.
- Originality: This dimension measures the uniqueness of the responses.
- Flexibility: This measures the variety of categories represented by the responses.
- Elaboration: This refers to the level of detail in the responses.

One minute is given to each participant to generate the maximum number of uses for common items. We used as stimulus the following items: “Clip”, “Brick”, “Wood board”, “Plastic bag”, “Post card” and “Glass bottle”.

As the focus of the study is the formation of original ideas, we designed a scoring method specifically centered on the originality component of the responses. For this, we first classified the responses into broader categories to reduce the functional redundancies (e.g. using the clip to “open a door lock” and using the clip to “open a padlock” were grouped under “opening locks”), using the methods of (Dippo et al., n.d.). Then, we gave each category the score of 1 and divided it amongst the total of individual answers classified into that category to obtain a generic average score for this category. Thus, lower scores are given to categories associated with more answers. We then added up all use scores for each object, giving us an object score for each participant. In this step multiple uses of the same category were still counted, rewarding the total number of uses produced in the minute, although, through to the previous step the score for very popular categories with many uses the amount these repeated category items counted to the final score was greatly reduced. Finaly, we averaged the three object scores in each moment.

The use of this purely statistical measure allowed us to circumvent some issues. First, it allowed us to give a bigger weight to originality in the final score; in the original AUT scoring procedure, 1 or 2 points are rewarded for originality with the bigger contribution to the final score being the number of item produced, in our scoring the originality has no upper limit to its contribution and plays a bigger role that the sheer amount of items produced since repetition is not rewarded as much as original responses. Secondly, it allowed us to circumvent the issues regarding appraisal discussed in the introduction.

2.2.3. Verbal fluency tasks

To assess the semantic memory network, we used the participants' responses to a verbal fluency task, a widely used neuropsychological test that assesses the ability of lexical retrieval, and the structure of semantic memory (Ardila et al., 2006). The semantic version of this task (semantic verbal fluency task, SVF) requires the generation of words according to a specific semantic category. Among the different semantic categories used in the literature, the criterion "animals" appears to be the most frequently used category, as it is associated to early learned knowledge, with a well-defined taxonomy showing minor differences across different languages (Goñi et al., 2011a). According to the standard procedure, the participants had one minute to generate as many names of animals as they could think of. For each participant, repetitions, morphological variations (by gender, number or size) and non-category members were excluded from further analyses.

In addition to the "animals" category, we added two more semantic categories, "foods" and "body parts", to test their adequacy to explore the structure of semantic memory.

2.2.4. Network Analysis

The data from the verbal fluency task was analyzed using a network science approach, a well-established method for quantitatively examining the dynamics of semantic memory at a cognitive level (Rastelli et al., 2020). Network science has increasingly been applied in cognitive research (Baronchelli et al., 2013; He et al., 2020; Patterson et al., 2007; Siew et al., 2019) and shares fundamental concepts with connectionism—both frameworks model cognitive processes using interconnected nodes and links, with weights governing the strength of these connections.

One widely used model for studying complex systems is the Small-world Network (SWN) model (Kleinfeld, 2002; Watts & Strogatz, 1998). SWNs are highly efficient, enabling fast communication between any two nodes with relatively few connections (Humphries & Gurney, 2008). This efficiency aligns well with how semantic memory operates, where concepts are represented by distributed patterns and activations spread across interconnected nodes. The features of small-world networks map onto key characteristics of semantic memory, providing a useful framework for understanding how ideas are stored and retrieved.

Using the network science framework, the output of the verbal fluency task can be modeled as a network. While individual networks cannot be explored at the participant level, group-level differences in conceptual structures can be examined by analyzing co-occurrence patterns across participants (Kenett et al., 2013). Several features of Small-world Networks (SWNs) will be used to analyze these networks:

1. Clustering Coefficient (CC): This measure reflects the network's overall degree in what nodes' neighbors tend to co-occur and be related. A higher CC signifies better local organization and stronger interconnections (Humphries & Gurney, 2008).
2. Average Shortest Path Length (ASPL): This measure indicates the average minimal number of steps between two nodes. A lower ASPL allows faster access to diverse concepts, enhancing spreading activation (Kenett et al., 2014; Siew et al., 2019).
3. Modularity Index (Q): This index quantifies how well a network divides into sub-networks, reflecting the organization of knowledge in separate domains (Fortunato, 2010; Newman, 2006).
4. Small-world-ness Measure (S): Combines local clustering (CC) and global efficiency (ASPL) into a ratio, characterizing a network's efficiency and flexibility (Humphries & Gurney, 2008; Marupaka et al., 2012).
5. Spread (Custom Metric): To further capture the dynamics of spreading activation, we computed this new metric, designed to simulate within the formed networks, the way activation spreads through biological systems (Siew et al., 2019). This simulation follows these rules:
    - All node activations start with a value of 1.
    - Activations travel to neighboring nodes that have not been previously activated, weighted by the strength of the link and a fixed decay factor.
    - As the activation travels further from the initial node, the decay factor reduces its strength, making it harder for distant nodes to activate.

- A node is activated if the sum of activations it receives exceeds a specific threshold, at which point it propagates the activation to its own neighbors.
- The process continues until activation can no longer spread.

This simulation is made for each node in the network. The range of activation for each simulation is recorded, and then average across all nodes, resulting in the Spread value. A higher Spread score indicates greater overall accessibility of information within the network. In the context of semantic memory, a high Spread metric means that more distant concepts can be activated after stimulating an initial concept, supporting the generation of more original ideas.

2.3. Procedures

The implementation of this experimental study was divided into three parts. In the first part the participants performed the semantic fluency task for the three selected categories, followed by the alternative uses task for a set of three different objects: “Clip”, “Brick”, “Wood board”).

In the second part, the participants were randomly split into two groups (the experimental and the control group) and were asked to perform the interpretation task. This part corresponds to the manipulation phase of the experiment, exposing the experimental group to sentences that make only sense metaphorically and the control group to sentences that made sense literally. This was the only part of the study that differed between the groups. During this interpretation task, each sentence pair was shown on the right and left of the screen and participants were asked to identify which of the phrases makes more sense, using the left and right control keys on a keyboard to give their answer. The participants were instructed to take as long as necessary to read all phrases carefully and then to make the decision. The two initial pairs of sentences were used for training and to guarantee that the task is fully understood.

Finally, the third part the study consists in the repetition of the tasks performed on the first part, namely participants repeated the verbal fluency task (using again the same semantic categories) and the alternative uses task (now with three new objects: “Plastic bag”, “Post card” and “Glass bottle”).

2.4. Network processing

2.4.1. Semantic network construction

We constructed the semantic memory networks based on participants responses to the verbal fluency tasks. Contrary to the category “animals”, the networks based on data from the other semantic categories (“foods” and “body parts”) revealed themselves inconclusive. As such we will consider solely the networks obtained from the category “animals” taking advantage of the fact that this is the most well established in literature. The possible causes of the contradictory results from the other two semantic categories will be further analyzed in the discussion section.

First, we translated the word responses from Portuguese to English and then excluded non-words and lemmatized the remaining responses (e.g. gender or number noun variations were combined, turning dogs and dog into just dog), using the SemNetCleaner package for R (A. P. Christensen & Kenett, 2021). Next, data was organized into a j x i matrix, with each column representing each word response generated by the entire sample, and with each row containing all the responses of a single participant. Each cell of the matrix contains a 1 when j-th participant produced the i-th word in the verbal fluency task, and 0 when that participant did not. Four matrices were created, for each group: experimental before the metaphoric task, experimental after the metaphoric task; control before the metaphoric task and control after the metaphoric task. Following this step, each of these rectangular j x i matrices were converted into an i x ii word similarity matrix, where i depicts the nodes (words), and the cells depict the similarity between each pair of words. As a measure of similarity, we applied the cosine similarity measure using the LSA package in R. Although Pearson’s correlation was used in previous studies (Kenett et al., 2014, 2016), we followed the reasoning of Christensen and colleagues (A. P. Christensen et al., 2018) that underlines the advantage of the cosine similarity measure not assuming a negative association between two responses, always ranging from 0 to 1. Next, we filtered the similarity matrix using the Triangulated Maximally Filtered Graph (TMFG) algorithm (Massara et al., 2017), which is able to remove spurious connections and retain high association within the original graph (Kenett et al., 2011), thus revealing the most important links between nodes within the network while preserving the network nodes. The TMFG filtering method was applied using the ‘Network Toolbox’ package in R (Christensen 2019, Kenett et al. 2014).

It is important to note that the networks generated in this study differ in several respects from those in previous work (Beaty et al., 2021; A. P. Christensen et al., 2018; Kenett et al., 2013, 2014; van Wijk et al., 2010).

Firstly, the resulting networks were not binarized, meaning that the edge weights were preserved, yielding an undirected, weighted network rather than one where all edge weights are set to one. This process is usually applied, so that only the structural properties of the network are maintained. By keeping the weights, we can study not only the structural properties of the networks (how nodes connect) but also their functional properties (how the information circulates in the network). These functional properties are particularly relevant for the current study since we are exploring possible differences between equivalent networks (constructed from the same sample) in two moments (baseline and post task administration). Therefore, any structural differences observed between the networks are likely to result from changes in how information within the structure is accessed.

Secondly, the network sizes were not equated, meaning the four networks contain different numbers of nodes. In some previous studies, size differences have been eliminated to avoid potential confounding factors, ensuring more straightforward comparisons across networks. However, since we are comparing networks constructed from the same sample across time, the number of nodes is a critical characteristic to consider. For instance, in the experimental group, we expect to see more uncommon animals being named after the manipulation, which would increase the total number of nodes in the network. While this may complicate between-group comparisons, it allows for a more reliable assessment of changes within groups, from baseline to post-task administration.

2.4.2. Network Measures Estimation and Validity

For each network, we calculated the respective network metrics, considering the inclusion of edge weights. Additionally, the metrics were normalized to mitigate the influence of differing network sizes. Normalization was performed using random networks, constructed to have the same degree sequence as the original networks. This ensured that each node in the random networks had the same connectivity (number of edges) as the corresponding node in the original networks. The edges in the random networks were then weighted by shuffling the original network's edge weights.

The metrics were calculated as follows.

1. The clustering coefficient (CC) was calculated using (Barrat et al., 2004) definition for weighted networks and normalized by dividing the observed CC by the CC of equivalent random network (Watts & Strogatz, 1998).
2. The Average Shortest Path Length (ASPL) was calculated using(Dijkstra, 1959) algorithm and normalized by dividing the observed ASPL by the number of nodes in the network, providing a per-node measure (Watts & Strogatz, 1998).
3. The modularity index (Q) was computed using a multi-level modularity optimization algorithm for weighted networks (Blondel et al., 2008), and it was normalized using a similar approach to the CC using random networks and applying the formula Q normalized = (Q observed – Q random)/ (1- Q random), (Newman, 2006).
4. The small world-ness measure (S) was calculated using the respective weighted and normalized CC and ASPL values (Humphries & Gurney, 2008). Here the normalized ASPL value was also obtained with the use of random graphs by dividing the observed ASPL by the random ASPL rather than dividing by the number of nodes.
5. The Spread metric is already calculated with the network weights, and it does not need be normalized since when calculating the average we divide by the number of nodes, giving us a normalization like that of the ASPL. Still there is the risk of the metric being influenced by the network size, in cases where the activation spreads through the entire network. To prevent this, we manipulated the threshold and decay factors, so that the maximum number of nodes activated in any simulation was always smaller than the smallest network total size.

These metrics were used to describe and compare the obtained networks. However, inferential statistical procedures were also used to further validate the differences between networks. Two complementary approaches were followed.

First, in order to statistically test whether the network metrics were significant and did not result from a random network, we simulated 1000 random networks, using the same procedures as for the normalization, we then calculated the non-normalized metrics for these random networks, and finally compared the average of these random metrics with the metrics from the original network using a significance Z-Test (Rastelli et al., 2020). Significant results will indicate that the functional parameters of the original network are reliably different from the parameters of a random network as well as providing support for the accuracy of the normalization process.

Secondly, to test the significance of the differences between networks, we used the bootstrap method to obtain sampling distributions of the global network metrics. This approach works by sampling N participants with replacement from the respective group, meaning that some participants may be included more than once in each replication, while others may not be included at all. For each replicate sample, the network construction method was applied and then the global network metrics – CC, ASPL, Q, S and Spread —were computed. This process was repeated 1000 times to get a sampling distribution for all metrics taken from each group network. These central tendencies of such distributions (means) were then compared using a repeated measures ANOVA analysis,

The networks were visualized using the force-directed layout of the CYTOSCAPE software (Shannon et al., 2003) (version: 3.10.2). the networks for the control group can be found in figures 2.1A and 2.1B for before and after the interpretation task respectively; and for the experimental group in figures 2.2A and 2.2B for the before and after the interpretation task respectively.

3. Results

3.1. Alternative Uses Task (AUT)

Normality assumptions were tested using the Shapiro-Wilk test, which indicated that the data for both groups were not normally distributed ($p < 0.01$). As a result, non-parametric tests were used. The Friedman test was employed to examine differences over time within each group, followed by post-hoc Wilcoxon signed-rank tests for pairwise comparisons.

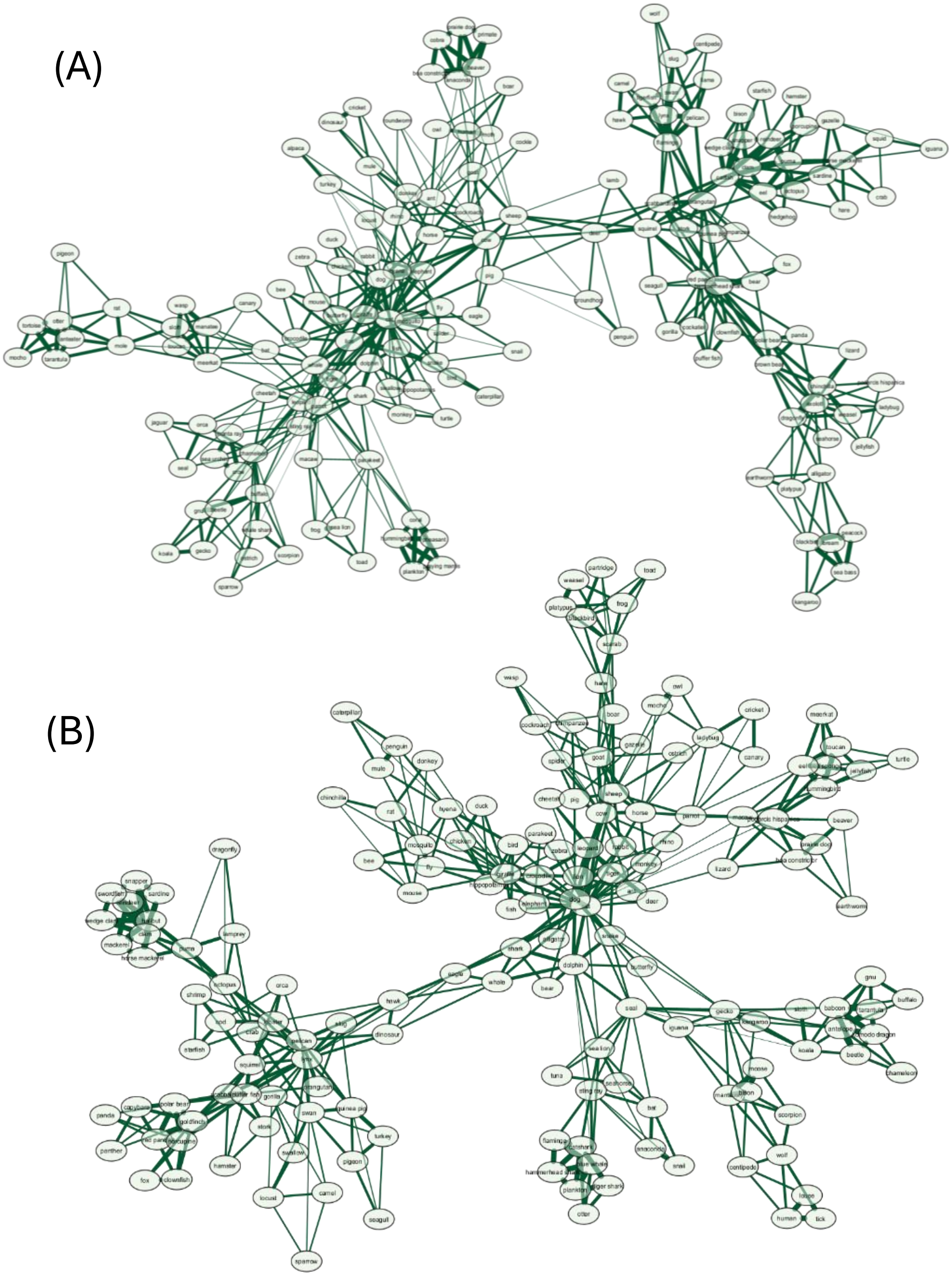

Figure 2.1. Semantic networks 2D graph visualizations of the control group (**A**) at the baseline moment and (**B**) at the post-task moment. The graphs are weighted and undirected, with nodes (word responses) represented as circles, the links between them (edges) represented as symmetrical similarities and the strength off the similarity (weights) represented by their thickness.

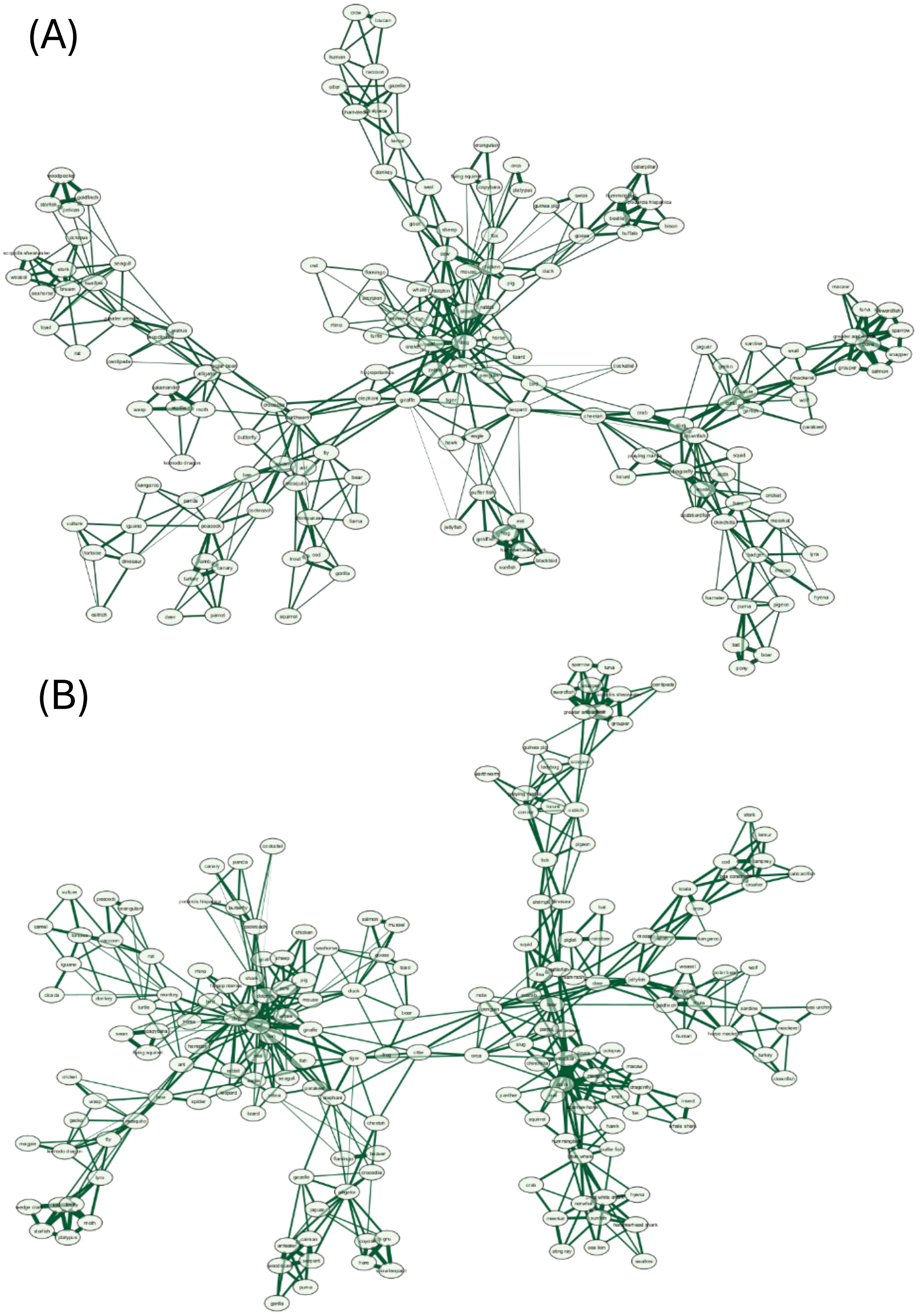

Figure 2.2. Semantic networks 2D graph visualizations of the experimental group (**A**) at the baseline moment and (**B**) at the post-task moment. The graphs are weighted and undirected, with nodes (word responses) represented as circles, the links between them (edges) represented as symmetrical similarities and the strength off the similarity (weights) represented by their thickness.

The results of the Friedman test revealed a significant difference in scores across time points for the control group χ2(1) = 6.818, p = 0.009, but not for the experimental group χ2(1) = 0.273, p = 0.602. Post-hoc analysis with the Wilcoxon Signed-Rank Test indicated that the scores significantly decreased from before the intervention to after the intervention in the control group (Z=−2.064, p=0.039). The interaction between the averages of the groups can be seen in image 3.1.

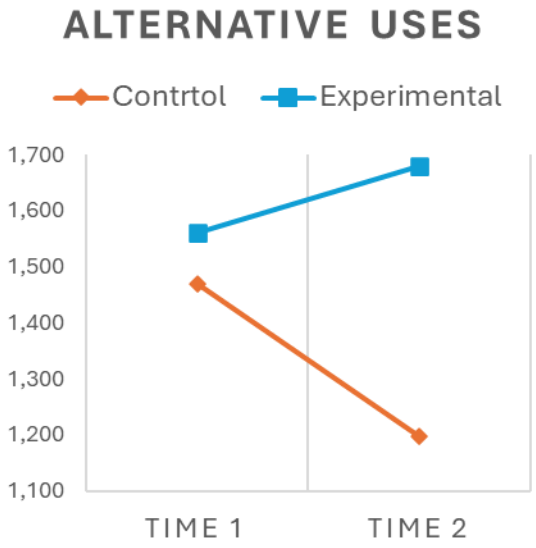

Figure 3.1 Plot of the means of Alternative Uses Task scores for the control and experimental groups before and after the sentence interpretation task

3.2. Network validation

To ensure the significance of the networks generated for the four groups (experimental before – experimental after, control before – control after), a Z test was performed comparing the metrics of the obtained networks to those of k = 1000 randomly generated networks. The results indicated that all network metrics significantly differed from those extracted from the random networks (p < 0.001), confirming the validity of the networks generated based on the verbal fluency data collected this study. The summary of the network's metrics, the random networks metrics and the Z scores can be found in Table 3.1.

Z- test

Condition	Metric	Network Value	Random Network Mean	Random Network SD	Z-score	p
Control Before	CC	16,892	0,058	0,006	160,691	<,001
	ASPL	0,058	3,548	0,052	98,103	<,001
	Q	0,678	0,292	0,009	55,360	<,001
	S	6,383	0,016	0,002	60,321	<,001
	Spread	100,434	172,998	0,006	-16885,291	<,001
Experimental Before	CC	16,763	0,052	0,006	165,119	<,001
	ASPL	0,060	3,622	0,052	120,636	<,001
	Q	0,672	0,294	0,009	54,052	<,001
	S	6,281	0,014	0,002	54,745	<,001
	Spread	96,591	166,998	0,006	-17733,000	<,001
Control After	CC	16,963	0,057	0,006	157,940	<,001
	ASPL	0,060	3,570	0,053	101,467	<,001
	Q	0,680	0,293	0,008	57,679	<,001
	S	6,357	0,016	0,002	56,510	<,001
	Spread	98,099	165,999	0,004	-22307,774	<,001
Experimental After	CC	18,572	0,049	0,005	174,758	<,001
	ASPL	0,058	3,615	0,048	126,979	<,001
	Q	0,692	0,298	0,008	61,585	<,001
	S	6,558	0,014	0,001	59,823	<,001
	Spread	98,895	186,996	0,010	-12119,312	<,001

Table 3.1. Network metrics values for the original and random networks. The table shows the metrics calculated for the original networks, the average network metric values for the random graph and the Z-score, and p-value for each group at each moment.

3.3. Network analysis

We conducted mixed 2 x 2 ANOVAs to assess the effects of the experimental manipulation on each network property. Separate analyses were performed for the Clustering Coefficient (CC), Average Shortest Path Length (ASPL), Modularity Index (Q), Small-world-ness (S), and Spread metrics.

These analyses focused on the interaction between group (experimental vs. control) and time of administration (pre-task vs. post-task), aiming to determine whether the experimental manipulation influenced network properties over time. The primary focus was on the interaction effects and the results of the corresponding post-hoc analyses, which were adjusted for multiple comparisons using the Bonferroni correction. The complete ANOVA table can be found in Table 3.2 while the table with post-hoc comparisons is provided in appendix B.

The experimental manipulation had a significant effect on the CC, reflected on the large interaction effect [F (1, 1998) = 1854,353, p <,001, partial-eta squared = 0,481]: while the CC metrics were similar for the control group before and after the metaphorical exposure (mean difference = -0.071, p = 0.013), the networks from the experimental group show a significant increase in CC after being exposed to the metaphorical task (mean difference = -1.809, p < 0.001) with a large effect size, d = -1.81. This effect can be observed in Figure 3.2A.

The experimental manipulation had a significant effect on the ASPL, reflected on the large interaction effect [F (1, 1998) = 259,429, p <,001, partial-eta squared = 0,115]: while the ASPL metrics increased significantly for the control group before and after the metaphorical exposure (mean difference = -0.002, p = 0.001) with a medium effect size, d = -0.49, the networks from the experimental group show a significant decrease in ASPL after being exposed to the metaphorical task (mean difference = 0.002, p < 0.001) with a with a medium effect size, d = 0.47. This effect can be observed in Figure 3.2B

The experimental manipulation had a significant effect on the Q, reflected on the large interaction effect [F (1, 1998) = 648,751, p <,001, partial-eta squared = 0,245]: while the Q metrics were similar for the control group before and after the metaphorical exposure (mean difference = -0,002, p = 0,029), the networks from the experimental group show a significant increase in Q after being exposed to the metaphorical task (mean difference = -0.02, p < 0.001) with a large effect size, d = -1.43. This effect can be observed in Figure 3.2C

The experimental manipulation had a significant effect on the S, reflected on the medium interaction effect [F (1, 1998) = 168,915, p <,001, partial-eta squared = 0,078]: while the S metrics were similar for the control group before and after the metaphorical exposure (mean difference = 0,026, p = 0,117), the networks from the experimental group show a significant increase in S after being exposed to the metaphorical task (mean difference = -0,277, p < 0.001) with a medium effect size, d = -0.64. This effect can be observed in Figure 3.2D

Source	Metric	SS	df	MS	F	p-value
Between-subjects						
Group	**CC**	546,817	1	546,817	340,103	<,001
	ASPL	0	1	0	5,719	0,017
	Q	0,007	1	0,007	27,432	<,001
	S	2,426	1	2,426	11,429	<,001
	Spread	2319,969	1	2319,969	26,022	<,001
Residual (Error)	**CC**	814,148	1998	0,407		
	ASPL	0,032	1998	1,62E-05		
	Q	0,273	1998	0		
	S	270,727	1998	0,135		
	Spread	112237,459	1998	56,175		
Within-subjects						
Time	**CC**	884,286	1	884,286	2170,126	<,001
	ASPL	2,582E-07	1	2,582E-07	0,016	0,899
	Q	0,112	1	0,112	816,082	<,001
	S	15,742	1	15,742	116,178	<,001
	Spread	0,24	1	0,24	0,004	0,948
Group * Time	**CC**	755,614	1	755,614	1854,353	<,001
	ASPL	0,004	1	0,004	259,429	<,001
	Q	0,089	1	0,089	648,751	<,001
	S	22,888	1	22,888	168,915	<,001
	Spread	5377,917	1	5377,917	95,735	<,001
Residual (Error)	**CC**	3212,382	1998	1,608		
	ASPL	0,04	1998	0,00002005		
	Q	0,492	1998	0		
	S	424,2	1998	0,212		
	Spread	178131,957	1998	89,155		
Total	**CC**	5399,099	1999			
	ASPL	0,044000258	1999			
	Q	0,7	1999			
	S	465,256	1999			
	Spread	185830,083	1999			

Table 3.2. Analysis of Variance (ANOVA) results for the effect of Group (Experimental vs. Control), Time (Pre vs. Post sentence interpretation) and Time x Group interaction on the metrics calculated for the bootstrapped networks (N = 100 samples). The table shows the degrees of freedom (DF), sum of squares (SS), mean square (MS), F-statistic (F), and p-value for each source of variance.

Finaly, the experimental manipulation had a significant effect on the Spread, reflected on the small interaction effect [F (1, 1998) = 95,735, p <,001, partial-eta squared = 0,046]: while the S metrics show a significant decrease for the control group before and after the metaphorical exposure (mean difference = 2,335, p <,001) with a small effect size, d = 0.28, the networks from the experimental group show a significant increase in S after being exposed to the metaphorical task (mean difference = --2,304, p < 0.001) also with a small effect size, d = -0.26. This effect can be observed in Figure 3.2E

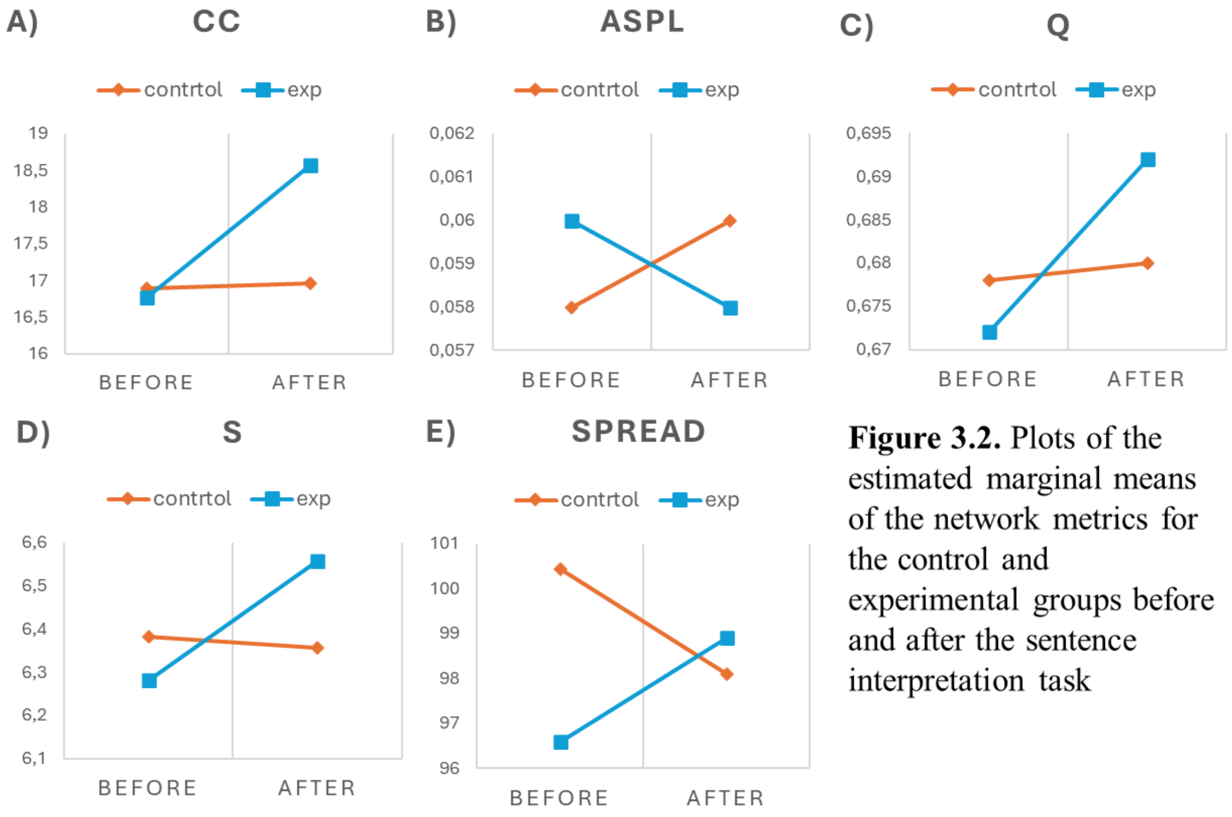

Figure 3.2. Plots of the estimated marginal means of the network metrics for the control and experimental groups before and after the sentence interpretation task

3.4. Correlation analysis

Finaly, a Pearson's correlation was conducted to assess if the changes in AUT performance can be explained by increases in spreading activation, as measured by the connectivity metrics of the networks. The results can be observed in Table 4. These indicated a significant positive correlation between AUT scores and all network metrics except for ASPL that showed a significative negative correlation since these metric decreases as the network becomes better connected. This suggests that as network connectivity increases, AUT scores also tend to increase. Additionally, the magnitude of the correlations increased in the after moment, indicating that after the task the relation between the metrics and the AUT score got accentuated. The results of this analysis are presented in Table 3.3.

	Before	After
Metric	Correlation with AUT (r)	Correlation with AUT (r)
CC	,186**	,461**
ASPL	-,105**	-,208**
Q	,202**	,374**
S	,080**	,201**
Spread	,204**	,141**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3,3. Pearson correlations between the network metrics and the AUT group score before and after the metaphor interpretation task

4. Discussion

4.1. Alternative Uses Task (AUT)

We initially expected the AUT scores to increase in the experimental group while remaining relatively stable in the control group. However, the results showed no significant change in the experimental group, while the control group experienced a notable decrease in AUT scores.

Although these findings do not fully support the study's hypothesis, they can be explained by differences in the difficulty of the object sets used in the second round of testing. It is possible that the objects in the second set had more limited potential uses, leading to lower scores for both groups. However, the metaphor interpretation task in the experimental group may have mitigated this effect, resulting in no significant change in their scores. In contrast, the control group, without the benefit of increased spreading activation from the relaxation of inhibitory mechanisms, showed a greater decline in performance.

To address this issue in future studies, one possible solution would be to counterbalance the object sets. Half of the participants in each group could use one object set in the first round and the other set in the second round. This approach would help ensure that difficulty is evenly distributed across both time points.

4.2. Network analysis

We begin by addressing the semantic networks derived from the semantic fluency results for the categories "Foods" and "Body parts". These categories were selected to determine if they are suitable for network construction and analysis, and whether they exhibit the same structural properties as the "Animals" category. Our aim was to enhance the robustness of semantic fluency tasks in network construction by incorporating a broader range of categories. The "Food" and "Body parts" categories were chosen for their potential to occupy similar intermediate hierarchical levels to "Animals", featuring multiple sub-categories and building on similar microfeatures as well as belonging to higher categories that allow for the spreading of activations to other adjacent concepts.

Regarding the "Food" networks, the results exhibited minimal changes and variability across groups and over time. We hypothesize that this could be caused by lack of specificity in the elements of this category and so, not belonging to a preferred category as discussed previously. By belonging to category of a higher hierarchical level it allows for the grouping of elements that on their own are not similar and thus do not share many features, this corresponds to the informativeness aspect of the privileged categories (Rosch et al., 1976). One possible way of verifying and preventing this issue would be to use a more specific category within food domain like “vegetables”, these would share enough microfeatures for the spreading activation to propagate in and reach related but distant concepts.

Another possibility is that the organization exists but is not sufficiently standardized across individuals. This limitation arises from constructing the network at the group level, where differing organizational strategies among individuals prevent a specific organization pattern from emerging.

The "Animals" category is more robust in handling these issues because animals are organized in well-defined hierarchical structures that are consistent across people and cultures (Goñi et al., 2011b).

For the "Body parts" category, we did observe changes. However, the metrics tended toward those of random networks in the post-task administration, especially in the control group. Low levels of clustering, average shortest path length, and modularity aligned with the properties of a random graph. We hypothesize that these changes can be explained by re-test effects and the unique nature of the "Body parts" category. Unlike the other categories, "Body parts" has a physical model available for reference. After the initial exploration of elements during the baseline application, participants could enumerate category elements by following the body's structure rather than relying solely on semantic knowledge and its underling structure. This led to element selection resembling a random draw from a pool of options.

With regards to the “Animals” category the results we obtained from the constructed networks support the study hypothesis. In the experimental group, the post-task administration revealed a better-connected structure compared to baseline, indicated by higher clustering coefficients and lower average shortest path lengths. Consequently, there was a significant increase in the small-worldness of the network. Small-world properties give the network a more flexible structure, enabling a more efficient search through semantic space (Marupaka et al., 2012; Marupaka & Minai, 2011) and facilitating the search and retrieval of associations in memory (E. G. Anderson & Parker, 2013). The experimental network also got an increase in the Modularity index. Traditionally associated with more rigid networks (Kenett et al., 2014; Newman, 2006); modularity measures the network's propensity to be divided into distinct communities. However, in this study's context, the increased modularity reflected the strengthening of connections within communities rather than weaker links between them. This interpretation is supported by the Spread results, networks that are too fractured into communities tend to resist the spreading of activations as the weaker links between communities make it difficult for activations to propagate from a community to the other, however this was not the case as the activation range actually increased showing that the modularity increased not as result of weaker links between communities as they still connected the communities in an efficient way, but rather as the result of the strengthening of the connections within the networks.

These findings suggest a positive effect of metaphor interpretation on the facilitation of spreading activations in semantic memory, and a more efficient retrieval of concepts in memory leading to an increase in the distance between all the concepts that can be associated and used in the generation of original ideas.

The control group showed an opposite tendency, while the Clustering coefficient did not present significant changes the average shortest path length goth larger resulting in a decrease in the Small-worldness levels pointing to a network less interconnected. This trend was also reflected in the spread values, which decreased. Although the study did not directly manipulate the control group results, it is plausible that the interpretation of literal sentences had an inhibitory effect on information spreading in semantic memory, by reenforcing the inhibitory mechanisms responsible for ensuring adequate responses. Alternatively, these results may be attributed to factors such as fatigue, which could further constrain the range of activations to concepts more related, making information retrieval more efficient under limited cognitive resources. It is important to note that the effects observed in the experimental group would likely also have to compensate for such factors before demonstrating increased interconnectedness. Moreover, it is arguable that metaphor interpretation, being more cognitively demanding, may require additional resources, potentially exacerbating these effects.

4.3. Correlation analysis

Finaly, we conducted a correlation between the network analysis and the network metrics. To circumvent the limitations of the present network science method that produces only group level results, we repeated the bootstrapping procedure using the same samples to produce a group level measure of AUT scores as well. The results of this analysis showed a positive correlation between the metrics measuring network flexibility and connectivity. In the specific context or this analysis this indicated that in a resampling where individuals with higher AUT score were selected and lower AUT were excluded, the resulting network presented higher connectivity properties. This supports the interpretation that the changes in AUT scores can be explained by the changes experienced in semantic memory as measured by the network metrics.

The correlations also increased in the second moment, this points in the direction of the AUT results being influenced by the top-down inhibitory mechanism via the spreading activations in semantic memory: where in the first moment this influence was relatively neutral the polarization or the networks towards more rigid networks in the control group interpretation group and more flexible networks in the experimental group, made this influence more salient.

5. Conclusions

Before drawing broader conclusions, it is important to acknowledge certain limitations of the present study. First, there are the methodological limitations of network science approaches already mentioned that produce only measures at the group level.

Secondly, during the metaphor and literal sentence interpretation we did not ask participants to provide their interpretation of the sentence chosen as meaningful. As such, there is the possibility that some participants have chosen as meaningful the nonsensical sentence targeted as nonsensical; or that the sentences were not given adequate attention for proper, invested interpretation; or that the interpretation given to the metaphorical sense was trivial or even literal. These issues can be in part ignored since the interpretation of the sentence targeted as incorrect necessitates the same conceptual expansion process to occur, possibly to an even bigger extent since the concepts are more distantly related, enough to be considered nonsensical. Still, this issue can be mitigated by incorporating an appropriateness rating for metaphors, as done in previous studies (Rutter, Kröger, Hill, et al., 2012; Rutter, Kröger, Stark, et al., 2012).

Despite these limitations and although not conclusive, the results showed support for the model. Interpretation sentences caused differentiated and opposite changes in the network properties for the group interpreting sentences with metaphorical meaning compared to the group interpreting sentences with literal meaning. The differences in the resulting changes in network metrics align to those observed in previous studies comparing high versus low creative post-hoc groups (Beaty et al., 2021; A. P. Christensen et al., 2018; Kenett et al., 2013, 2014; Rastelli et al., 2020), supporting the interpretation that these changes in network metrics are able of measuring process changes in mechanism associated with creativity.

These same differentiated changes in the groups were also observed for the AUT, with the group that interpreted the metaphorical sentences showing a higher score in the second moment compared to the group that interpreted the literal sentences.

Together these findings support the hypothesis that the creative process is regulated by top-down inhibitory processes and that these mechanisms can by passively influenced by the type of information being processed inducing a necessity for distant concepts to be connected for the processing of stimulus with an optimal novelty level. By virtue of the processes of interpretation and production of these novel associations sharing the same cognitive architecture these influences in processing can extend to creative production.

Additionally, the study employed a new paradigm using network science methodologies to an experimental design, allowing us to measure the changes induced through experimental manipulation. The findings support the suitability on this approach to complement the traditional measures of creativity like divergent thinking tasks,

In addition, the study demonstrates the value of integrating network science methodologies into experimental designs. This approach allowed us to measure changes induced by the experimental manipulation, offering a complement to traditional creativity measures, such as divergent thinking tasks. By allowing us to directly measure specific mechanisms, rather than using the final output of the several, different and widely distributed mental processes involved. This approach can help provide a more detailed and robust modelling of the neurocognitive mechanisms underlying creative thinking.

There is also room for further refinement and expansion of this approach. Beyond the previously mentioned recommendations, future studies could include more detailed measures of relationships within the network. For example, incorporating the order and timing of item activation in the network could provide insights into how readily related nodes are activated, offering a more precise measure of the flow of information in the network.

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7. Appendices

Appendix A – list of Metaphorical, non-scenically and literal sentences grouped into triplets, used in the interpretation task, the two initial triplets were used for training and to guarantee that the task is fully understood.

	Metaphor	Nonsensical	Literal
1	O telescópio despiu o universo.	O telescópio escovou o universo.	O telescópio revelou o universo.
2	O outono amordaçou as cigarras.	O outono reconheceu as cigarras.	O outono silenciou as cigarras.
3	O vento fazia cócegas nas árvores.	O vento escrevia nas árvores.	O vento derruba as árvores.
4	O oceano abraçou o barco.	O oceano esqueceu o barco.	O oceano envolveu o barco.
5	O artista pariu a obra de arte.	O artista calçou a obra de arte.	O artista criou a obra de arte.
6	A brisa rebocou as folhas pela calçada.	A brisa vacinou as folhas pela calçada.	A brisa arrastou as folhas pela calçada.
7	Os meteoritos autografaram o céu.	Os meteoritos trancaram o céu.	Os meteoritos atravessaram o céu.
8	O inverno raptou o jardim.	O inverno ouviu o jardim.	O inverno congelou o jardim.
9	A chuva maquilhou a cidade.	A chuva arrancou a cidade.	A chuva cobriu a cidade.
10	A barragem censurou o rio.	A barragem analisou o rio.	A barragem parou o rio.
11	A melodia dissolveu-se no ar.	A melodia feriu-se no ar.	A melodia propagou-se no ar.
12	O vento penteou as dunas.	O vento fritou as dunas.	O vento varreu as dunas.
13	O surfista domesticou as ondas.	O surfista encadernou as ondas.	O surfista surfou as ondas.

14	O terremoto lavrou a cidade.	O terremoto enlatou a cidade.	O terremoto devastou a cidade.
15	O sol ceifou a poça.	O sol colou a poça.	O sol secou a poça.
16	A gravidade seduziu a lua.	A gravidade batizou a lua.	A gravidade prendeu a lua.
17	O vulcão desabrochou.	O vulcão escorregou.	O vulcão explodiu.
18	A tempestade declamou os relâmpagos.	A tempestade secou os relâmpagos.	A tempestade gerou os relâmpagos.
19	As estrelas infetaram o céu noturno.	As estrelas arrefeceram o céu noturno.	As estrelas preencheram o céu noturno.
20	A maré sequestrou a praia.	A maré leu a praia.	A maré cobriu a praia.
21	O orvalho coroou as folhas.	O orvalho roubou as folhas.	O orvalho molhou as folhas.
22	A neve apagou o chão.	A neve dividiu o chão.	A neve tapou o chão.
23	As nuvens galoparam sobre os campos.	As nuvens recortaram sobre os campos.	As nuvens pairaram sobre os campos.
24	O amor naufragou.	O amor sapateou.	O amor desapareceu.
25	A luz derramou-se no chão.	A luz lavou-se no chão.	A luz iluminou o chão.
26	O sol orquestra as sombras.	O sol fecha as sombras.	O sol cria as sombras.
27	Os pirilampos incendeiam a noite.	Os pirilampos incentivam a noite.	Os pirilampos iluminam a noite.
28	O avião invadiu o céu.	O avião ligou o céu.	O avião cruzou o céu.
29	Os pinceis beijam a tela.	Os pinceis cozem a tela.	Os pinceis pintam a tela.
30	Os seus olhos despenharam-se nela.	Os seus olhos barbearam-se nela.	Os seus olhos focaram-se nela.
31	O despertador roubou o silêncio do quarto.	O despertador regou o silêncio do quarto.	O despertador interrompeu o silêncio do quarto.

32	A brisa sussurrou o cheiro do mar.	A brisa grelhou o cheiro do mar.	A brisa transportou o cheiro do mar.
33	O maestro engomou a sinfonia.	O maestro calçou a sinfonia.	O maestro guiou a sinfonia.
34	Os pássaros narraram a manhã.	Os pássaros folhearam a manhã.	Os pássaros cantam de manhã.
35	As ondas trincaram as falésias.	As ondas acenderam as falésias.	As ondas erodiram as falésias.
36	As pessoas ensoparam as ruas.	As pessoas beberam as ruas.	As pessoas encheram as ruas.
37	O mergulhador vestiu o mar.	O mergulhador desinfetou o mar.	O mergulhador entrou no mar.
38	O medo exilou o movimento.	O medo agasalhou o movimento.	O medo impediu o movimento.
39	O verão prescreveu a praia.	O verão pesquisou a praia.	O verão favoreceu a praia.
40	Os seus lábios orbitaram-se.	Os seus lábios sentaram-se.	Os seus lábios aproximaram-se.
41	O vento embriagou as ondas.	O vento marinou as ondas.	O vento agitou as ondas.
42	As nuvens arquivaram o sol.	As nuvens lamberam o sol	As nuvens taparam o sol.

Appendix B – Pairwise comparisons between the network metrics before and after the experimental task; and between the experimental and control groups. The values are based on the estimated means and the analysis was performed using the Bonferroni correction to account for multiple comparisons.

Pairwise Comparisons Moment					
Measure	Group	Mean		Mean Difference (T1-T2)	Sig.b
		Time 1	Time 2		
CC	Control	16,892	16,963	-0,071	0,013
	Experimental	16,763	18,572	-1,809	<,001
ASPL	Control	0,058	0,06	-0,002	<,001
	Experimental	0,06	0,058	0,002	<,001
Q	Control	0,678	0,68	-0,002	0,029
	Experimental	0,672	0,692	-0,02	<,001
S	Control	6,383	6,357	0,026	0,117
	Experimental	6,281	6,558	-0,277	<,001
Spread	Control	100,434	98,099	2,335	<,001
	Experimental	96,591	98,895	-2,304	<,001

Pairwise Comparisons Group					
Measure	Time	Mean		Mean Difference (Control - Exp)	Sig.b
		Control	Experimental		
CC	1	16,892	16,763	0,129	0,003
	2	16,963	18,572	-1,609	<,001
ASPL	1	0,058	0,06	-0,002	<,001
	2	0,06	0,058	0,002	<,001
Q	1	0,678	0,672	0,006	<,001
	2	0,68	0,692	-0,012	<,001
S	1	6,383	6,281	0,102	<,001
	2	6,357	6,558	-0,201	<,001
Spread	1	100,434	96,591	3,843	<,001
	2	98,099	98,895	-0,796	0,043