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A Unified Cognitive Framework for Artificial Creativity: Modeling Divergent Thinking and Conceptual Blending

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Abstract: Artificial creativity has been a difficult research issue because of the inability to reduce the high-level cognitive theories to computationally testable models. This paper hypothesizes a universal cognitive approach to artificial creativity combining ideas of divergent thinking, conscious/unconscious processing, and blending of concepts at a layered computational architecture. The framework is inspired by the literature on cognitive and neuroscience and separates exploratory (divergent) and evaluative (convergent) processes and models these processes in terms of semantic expansion, concept blending based on similarity and concept convergence filtering. A proof-of-concept implementation of the method is provided using large-scale textual knowledge in the form of the Wikipedia encyclopedia and classical semantic representations such as TF-IDF, Latent Semantic Analysis, and Explicit Semantic Analysis to show that it is feasible. The outputs depict how the intended architecture is capable of producing and optimizing new combinations of concepts in a directed and understandable way. Instead of proposing complete validation of creativity, this contribution creates a rigorous computational basis upon which cognitive theory and empirically testable models are connected, which can serve as the foundation of future empirical testing, multimodal extrapolation, and human-in-the-loop creativity testing.

Keywords: Artificial Intelligence; Computational Creativity; Neuroscience; Cognition; Conceptual Blending; REM; Divergent Thinking

1. Introduction

Artificial intelligence has gained remarkable advancements in the last decade. With the rise of artificial intelligence (AI), the field of creativity is encountering new opportunities and challenges. As the research field attained a certain level of maturity, its sibling, computational creativity, is in its phases of development. Artificial intelligence and Computational Creativity both are characterized as parallel to each other in the sense that:

AI studies how the task is being performed, which depicts human-level intelligence, whereas Computational Creativity studies performances/behaviors that depict creativity if performed by a human. The main objectives of Computational Creativity are either to enhance creativity by using computational methods or to model/simulate human creativity. Creativity is a sensation that is not exclusive to the human species; it can be considered the directional force in the evolution of our entire universe [1] [2].

So, Computational creativity is concerned with a practical and theoretical understanding of issues that arise while studying creativity. Theoretical work emphasizes proper definition and the focus on variant aspects essential for computational creative systems, in parallel with practical work regarding implementing these computational modules in more general and complex architectures so that the entire system can exhibit human-level creativity. However, creativity is controversial in psychology, neurosciences, physiology, and cognitive science. Creativity is the human ability to think, solve problems, and develop products.

Creativity is one of the most complex and debated concepts in the academic world, even though it is universally recognized as one of the pillars of human intelligence. Researchers in fields ranging from psychology to neuroscience to physiology to cognitive science have long sought to understand its origins, mechanisms, and implications, but often have conflicting perspectives and interpretations.

In psychology, creativity is most commonly associated with divergent thinking — the capacity to devise many possible solutions to a problem. However, no consensus exists on whether creativity is a separate cognitive process or an expression of general intelligence. Guilford, Torrance, and others have proposed measuring capacity for creativity using standardized tests, while critics claim such tests do not adequately capture creative thought's multi-dimensional and context-dependent nature.

Creativity is also debated in neuroscience to determine neural correlates. Some of them mentioned the success of spontaneous idea generation produced by the default mode network (DMN) and others reported the strength of the executive control network for the evaluation and refinement of ideas. This dual-process point of view asks the relationship between these two networks and whether creativity results from their interaction or competition.

1.1. Artificial Intelligence

The extent of GAI use in our lives today is changing our working, communication and innovation [3]. Generalized Artificial Intelligence (GAI) represents a new and innovative technology that helps the machine to successfully analyze and learn on available information to respond to new and unpredictable events. The importance of this central technology to organizations is increasingly growing over time as it is able to rationalize the automated decision-making processes, identify the complex patterns in large volumes of data, and enhance overall efficiency of operations. [4]. This paradigm shift has brought about a reorganization of the work dynamics whereby the workers are now forced to re-orient their attention to confront more complex and creative jobs which are founded on human ingenuity and problem solving skills. A fuzzy inference system of QoS was also introduced in [5] to optimize the migration of virtual machines in the cloud to achieve service availability.

As GAI continues to accelerate, there exists a possibility of this technology performing complex duties, which had only been done by humans. This has created an explosion of interest in exploring the way GAI can be used to support and stimulate human creativity. This discussion starts with the convergence of technology and human ingenuity, trying to discover the synergistic exploitation of GAI as an instrument of enhancing and perfecting the creativity of individuals and society [6]. Scientific literature, however, offers a more specific perspective of creativity, and these include a variety of issues as to how creativity engages in formulating problems, generating ideas, select ideas, and implementing an idea.

There has also been increased interest in the discipline of artificial intelligence because of the introduction of new and trending tools such as ChatGPT (https://chatgpt.com/), MidJourney (https://www.midjourney.com/home), Microsoft, and Bing (https://www.bing.com/) and Google, Bard (https://blog.google/technology/try-bard/). But the debates regarding AI have been going on. The latter may be dated to ancient times, where the Greek mythology and the philosophical contemplation of the nature of consciousness contained the mention of non-human agents.

Artificial intelligence (AI) has undergone an unbelievable evolvement in the 10 years, promising thrilling opportunities and challenges in computational creativity. Computational creativity is a branch of AI that focuses on the development of systems that can produce or support creative behaviours, and is intended to imitate or support human creativity. Early studies on the relationship between AI and creativity investigated such topics as symbolic AI and pipelined systems that might reproduce creative processes by using a set of rules and logic. These methods were not, however, very adaptive to new, unstructured environments.

1.2. Computational Creativity

Computational creativity that is creation of computational systems capable of exhibiting creative behavior. The discipline is an offshoot of Artificial Intelligence, and it represents a broad field, covering cognitive sciences, in which such systems can generate ideas or produce objects. These artificial intelligence tools are not confined to classic creative fields such as science, mathematics, poetry, and narrations, music, images, graphics, and industrial design [7] [8].

Creativity should be studied as it is one of the things that make humans stand out and it must be appreciated. Since the inception of modern computing, scholars have been debating on whether machines can be creative in their behaviors. Sir Geoffrey Jefferson, a prominent neuroscientist, is an example of such a person to have posed such questions.

A machine is incapable of writing a sonnet or writing a concerto due to chance accidental fall of symbols and thoughts and feelings experienced, this is because we could not accept that machine be equal to the brain.

The first attempt to develop a theoretical framework of studying the artificial creativity was produced by researcher Margaret Boden [9]. The work has had an enormous influence of the philosophy of Computational Creativity [29]. Plucker came up with a commonly acknowledged definition of creativity, which involved aptitude process in which a person or a group of people generate a perceptible product that is both new and useful as it is determined in a social environment. [10]. Equally, this practical and realistic meaning of creativity as new and useful [11] is the most common one. Researchers have in recent years already prepared significantly to ensure that machines are creative such as having tools Murf.ai (https://murf.ai/ text to speech generator), and beatoven.ai (https://www.beatoven.ai/ royalty-free music generator). Machines, robots, and systems of AI can be identified as creative without copying human attitudes, behaviors, and actions. They rather imitate the cognitive process and the product in order to attain something that seems new and beneficial [12].

In this regard, the emergence of machine learning and deep learning technologies has provided a radical shift in the discipline whereby systems learn to identify patterns as well as generate outputs without much human participation. The adoption of neural networks as creative purposes was one of the key twists. In a similar manner, the Generative Adversarial Networks (GANs) are capable of creating real images, music, or even text, which demonstrates the huge opportunities of unsupervised learning in the world of creativity.

These findings were expanded by newer studies that investigated AI and creativity. As the higher-level functions of natural language generation shown by gpt-based models (e.g., ChatGPT), support of creative writing, storytelling, and ideas. All these models have made breakthroughs of surprise in the interaction of humans with machines throughout the whole sphere of artistic success, with analogues such as OpenAI DALL·E and MidJourney flourishing in the creation of visual art using the prompt provided in natural language.

To go with these artistic uses, scholars have also speculated AI in science discovery and problem solving. Systems that are controlled using artificial intelligence have been applied to formulate hypotheses, enhance the design process, and generate novel chemical compounds. These are only a portion of a bigger picture of computational creativity which is viewed as being able to enhance human creative practices by assisting in streamlining menial tasks in the creative process so that people might be able to concentrate on the high level creative processes.

Nevertheless, after all these improvements, there are still significant issues [30-33]. In fact, even the definition of the very notion of creativity is difficult to determine and varies according to the field of study and the situation. The argument of whether the machine creativity or human creativity is better or not is still going on. Moreover, the issue of ethics in implementing AI in the creative sphere, that is, in terms of authorship and intellectual property rights, needs to be considered carefully.

The present paper, in its turn, builds upon those advances, exploring the cognitive processes that facilitate the conception of divergent ideas, and provides a unifying model which can be used to build artificially creative agents. These conceptualizations will enable us to reduce the gap between computational models and human-like creativity by synthesizing the results of fields such as neuroscience, psychology, and artificial intelligence, which will bring clarity to the development of really intelligent, creative systems.

1.3. Central Questions:

Theoretical contributions: This study highlights the mechanisms and processes that explain divergent idea generation in the context of artificial creativity. In order to do so, I explore the following specific research questions:

1. What is the interplay between conscious and unconscious cognition during divergent idea generation?
   - How do these processes function in creative thinking, and how do they support problem-solving and ideation?
   - How is this interaction modeled in computer programs for human-like creativity?

2. What do we know about the cognitive and neural correlates of divergent thinking?
   - What brain regions and networks are involved in divergent idea generation?
   - What are the ways in which these networks interface with physiological states such as sleep (for example, REM cycles) to shape creativity?

3. How can we effectively embed associative thinking, in particular via conceptual blending, into an artificial creative agent?
   - How does the conceptual blending works in AI systems (give the computational methods)?
   - But how do these techniques allow for the creation of new, useful output?

4. How do emotional and motivational factors play a role in creating creative outcomes?
   - What role do feelings and desires play in the creative process, from the conscious to the subconscious levels?
   - Is it possible to mimic or incorporate these aspects into the design of artificial creative agents?

5. But how are divergent ideas then turned into convergent but actionable solutions?
   - How are ideas evaluated, refined and converged upon in human cognition and artificial systems?
   - How can we adopt and implement these mechanisms to help make creative agents perform even better?

Conception about the Proposed Model (Working of Internal Stimulus: The Science Behind Divergent Idea Generation)

Creativity, intuition, and insight are distinct forms of thinking that rely primarily on the unconscious mind. These areas have been awarded a privileged status in psychology, and the study of creativity and problem-solving has gained tremendous momentum, resulting in innovative approaches to investigating topics previously thought to be beyond our capacity to comprehend. We aim to develop a comprehensive solution for creating an artificially conscious creative agent. This agent will be constructed based on scientific and philosophical elements of consciousness, with a dual aspect of cognitive and operational correlates. [13]. The proposed model has been designed to provide an agent with the capability to create its own independent experience, with the generation of novel motivations, goal setting, and efficient performance evaluation. It is a multi-layer structure that mimics an agent's external (conscious) and internal (unconscious) phenomena. Organising the elements aims to achieve intelligent and conscious behavior using existing knowledge (seed knowledge) for self-evaluation. All cognitive units are spread over 2- layers, the upper layer represents the conscious layer and reveals its correlates, whereas the bottom layer represents the unconscious jargon, as shown in Figure 1, which displays a single entity working collaboratively in parallel to achieve the final goal.

2. Literature Review

Making it one of the first systematic theories of creativity, the seminal work of Odens defines the latter as the skill to generate novel, surprising, and valuable ideas. She divided creativity into combinational, exploratory and transformational creativity, claiming that creative novelty is produced by structured manipulation of conceptual spaces and not by randomness. This paradigm has had a significant impact on the study of computational creativity and has been directly inspirational in the focus of the current work on semantic recombination and conceptual blending in limited representational spaces [1].

Wiggins expanded the theory offered by Boden and suggested a formal computational approach to creativity that separates the concept of generative processes and evaluating mechanisms. He clearly formalizes the search space, traversal strategy and evaluation function in his model and emphasizes the need to decouple divergent idea generation and convergent filtering. This differentiation has much in common with the layered architecture that was suggested in the present study, representing divergent exploration and conscious evaluation as interacting processes, but functionally separate ones [2].

Fauconnier and Turner developed the conceptual blending theory in which humans create new meaning by using selection in integrating different elements in more than one mental space. Their effort that offers a mental basis to explaining creative thinking as an emergent process that develops as a result of a systematized conceptual combination. This theory has been used extensively in research in computational creativity and the current research has operationalized conceptual blending based on semantic similarity and expansion methods based on large-scale textual knowledge [3].

New discoveries in cognitive neuroscience have given empirical data in favor of dual-process models of creativity. Beaty et al. showed that creative thought is a dynamic interaction between the default mode network (DMN), which is connected with spontaneous and associative thought, and the executive control network (ECN), which is the one that is in charge of evaluation and goal-directed control. These results substantiate the architectural isolation between unconscious exploration of the environment as well as conscious evaluative processes that have been assumed in the framework suggested [4].

Hassabis et al. studied the part of imagination, memory replay, and dream-like process in intelligence and claimed that offline cognitive states, including the state during REM sleep, allows creative recombination of experiences. According to their work, internally motivated unconscious processes are very important in creating new ideas and theoretically, this explains why they include REM inspired exploratory processes into artificial creativity systems [5].

Colton and Wiggins critically assessed systems of computational creativity and pointed out a common limitation: much of the work does not provide any clear definition of creativity and do not relate theoretical perspectives to practical realizations. They have given more importance on open structures that explicitly define the way creativity is created, assessed, and understood. The objective of this critique is a direct informant on the study at hand, which aims at mapping the constructs of cognitive creativity to tangible computational processes [6].

The Latent Semantic Analysis (LSA) methods were proposed by Landauer et al. as a technique to extract conceptual meaning in large text collections, and it proved to be able to identify semantic associations, which are similar to those of humans. Equally, Gabrilovich and Markovitch had offered Explicit Semantic Analysis (ESA) that exploits structured knowledge sources like Wikipedia to express meaning explicitly. Computational creativity research has been able to use these semantic models to aid associative thinking and conceptual blending and the models form the foundation of the proof-of-concept implementation described in this study [7,8].

Although these advances have been made, the current literature focuses mostly on creativity as a phenomenon that is viewed in isolated perspectives, either as a theoretical, neuroscientific or algorithmic phenomenon. Not many studies are aimed at the incorporation of the cognitive theory, unconscious-conscious processing and computational realization into one unified framework. The current paper attempts to fill this gap by suggesting an operational cognitive architecture that strategically fills in the gaps between creativity theory and computational processes that can be implemented.

3. Materials and Methods

The model of creativity proposed has separate levels of improvement of cognition that are dynamic and merge consciousness and unconsciousness. The figure shows the architecture of a Meta-Cognitive System (MCS) which combines multiple memory systems, learning processes and motivational drives to replicate cognitive processes. The model consists of two main modules including an Ontogenetic Module (top half) and a Phylogenetic Module (bottom half) that are connected to environmental inputs, effectors, and cognition.

Ontogenetic Module: External Inputs Xenobiome: First, the external inputs are represented in sensory memory, where they are filtered out to exclude irrelevant characteristics, and the relevant snippets are conveyed to the Workspace. The Gym of Temporary Storage Working Memory (WM): WM is dynamic interaction with the workspace. Convergence, which is the integration of information that is made in order to facilitate future learning, takes place in working memory. This leads to Explicit Learning, which encourages well-organized knowledge that is stored in the Explicit Knowledge Repository. CorElementary knowledge in the Declarative Memory is further divided as Semantic Memory (facts and general knowledge) and Episodic Memory (personal experiences).

Planning and Goal setting: This is the process that involves the setting of action plans that are achieved by the interaction between the Planning module, working memory and the declarative memory.

Pattern Analysis Module (PAM): Here the basic pattern recognition and extraction is done and the results are passed on to other modules such as Dreams, Spatial Memory and Self-Evaluation modules to help in cognitive reflection and creativity.

This model explains that behavior and cognitive attention are influenced by hierarchical motivations (instinctual drives) and secondary motivations (learned desires). Behaviour and cognitive attention is heavily dependent on emotions and this is aided by this model. Inquiry of Implicit Learning and Implicit Knowledge: Unconscious processing of information leads to the formation of Implicit Knowledge Repository, which is a component of Domain Competency, and which is crucial in the acquisition of adaptive behavior.

Knowledge: Previous knowledge is a starting point to new growth and development.

The Long-Term Memory (LTM) functions as an intermediary between two modules through which the information storage and retrieval take place.

Iterative Learning: Adaptation and integration of explicit and tacit knowledge systems are utilized via the system through feedback loops, which promotes continuing the learning process. In general, such an architecture is a simulated complex, self-reflective cognitive architecture with dynamic learning, task identification, flexibility, and alike to human intelligence.

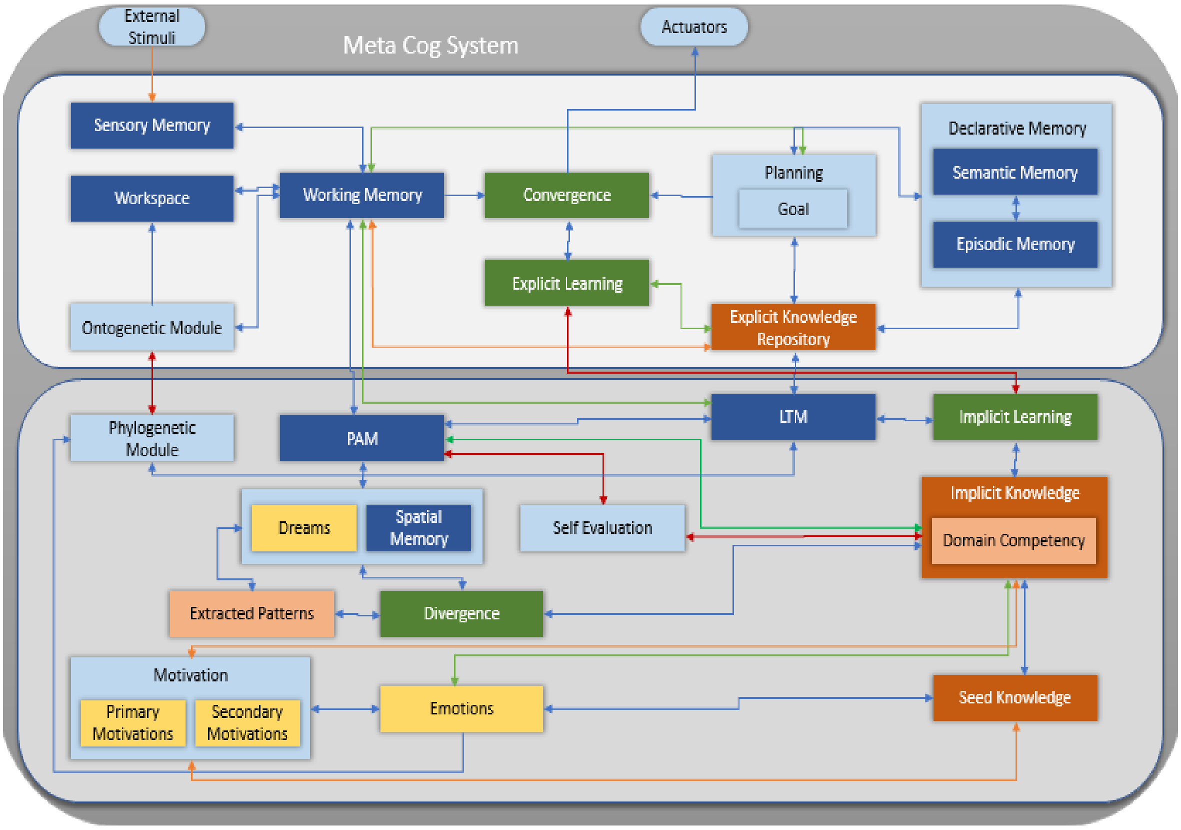


Figure 1. Layered and Cognitive View of Model

3.1. Conscious Layer

Represents systematic, goal-oriented processes employed to refine, evaluate, and carry ideas through. It plays a significant role in targeting attention, logical reasoning, and integrating information to create things that can be acted on.

3.2. Associated Brain Regions:

Prefrontal Cortex (PFC): Related to decision-making, planning, and self-control.

Anterior Cingulate Cortex (ACC): Attention-regulation and conflict-resolution.

Posterior Parietal Cortex: Exciting for directional action and conscious Seeing.

3.3. Unconscious Layer:

Embodies spontaneous, associative processes that happen inadvertently and without design. Enables more divergent thought, leading to ideas formed as free associations and non-linear trains of thought.

3.4. Associated Brain Regions:

Default mode network (DMN): Regions such as the medial prefrontal cortex (mPFC) and posterior cingulate cortex (PCC) are involved in periods of the mind-wandering and creative ideation.

Hormones: Most unusual, with very localized effects and sluggishness; generally favouring creative ideas, but could also bias them toward unconscious ideation at certain times.

Hippocampus: Involves in memory retrieval as well as the formation of links between unrelated ideas.

The role of conscious and unconscious processes in the creative process

3.5. Unconscious Processes:

Act as the “ideation engine”, producing new and out-of-the-ordinary ideas by accessing memory, emotion and sensory experiences. In a state of REM sleep, REM sleep dyssynchrony is dominant, no longer constrained by the logic of the waking world, filtered out in lucidity, formed by associative ideas. For example: Dream states where emotional memories and visual associations collide to produce novel experiences.

3.6. Conscious Processes:

The conscious layer acts as the “refining mechanism,” evaluating, filtering, synthesizing the ideas produced in the unconscious layer into workable, practical solutions. By allowing structured thought, enabling people to narrow down on relevant information and aim towards goal-directed creativity.

Sample Output: Ideation sessions, where raw ideas are sharpened and formulated as actionable plans.

3.7. Findings from Brain Science

It has been shown that in highly creative individuals, there is high connectivity between the default mode network (DMN) and the executive control network (ECN), suggesting that successful creativity requires the need to balance spontaneous ideation with task-centered control (Beaty et al, 2021). The better problem solving and creative insight have been related to the high levels of limbic activation in the process of REM sleep.

Great painters and Nobel Prizers all through history have emphasized the great part that the unconscious mind plays in promoting creativity. Despite the fact that conscious activities are paramount, unconsciousness usually comes up with a lot of very extraordinary and original thoughts. This school of thought holds that creative ideas are generally the results of a conscious thought made to take a rest.

Successively, without any conscious effort, the solution or generated idea presents itself spontaneously. This stage is commonly known as incubation, where one refrains from conscious thinking and allows the unconscious to take over. Recent neurological studies suggest that dreams can aid in self-renewal, emotionally driven behavioral learning, and creative solutions to the problem. Furthermore, our proposed model explores the concentrated areas of the brain that switch between active or inactive regions during the generation of divergent ideas (Divergent Creativity) [14].

While generating diverse ideas, our coherent thoughts, episodic memory, and physical and motor functions become inactive. Instead, unique combinations of brain centers such as emotions, the spatial memory (visual association cortex), and other unconscious brain localities become functional. The absence of logical thinking leads to unfiltered, non-linear dreams that can alter episodic memory. However, it may exclude the memory of the waking life episode that activated the dream. The emotions and memories associated with the waking events remain accessible and are processed by the highly active limbic system, the emotional brain. During dreams, the amygdala and the limbic system are highly active. This suggests that dreams play a role in selectively processing emotionally relevant memories. The cortex and limbic system work together to facilitate this process. The limbic system is also vitaln organizing dream activity and establishing associations between dream images and emotional memories [15].

Dream imagery refers to what is visualized by the active visual association cortex which is the representation of emotions. It reveals the unconscious interpretation of conscious lives. The brain is busy in creative problem solving and learning during Rapid Eye Movement (REM) sleep. Rapid Eye Movement (REM) Sleep is the process in which vivid dreams are realized, and it is related to the functions of understanding (learning) as well as retention, among other functions. This makes it difficult to identify the definite role of the dreams as we perceive them irrationally. The unique characteristic of dreams has been lately credited to a unique interaction of the active and inactive brain areas. By dreaming, our conscious mind rests and sleeps. This enables the brain areas that process the information that is unconscious to work. These areas are undergoing a complicated inner dialogue with each other, thus creating links within a hyper-connective mode of association. This creates an increased degree of information processing all of which occurs on top of our conscious mind. [16]. Our unconscious mind finds a major way of speaking through dreams. Perceptual Associative Memory (PAM) is used in detecting inconsistencies, predicting consequences, choosing responses, overseeing results and modifying behavior hence helping in problem solving and decision-making [17].

Creativity has been described as the ability to use the available knowledge in different combinations so as to get new solutions. Numerous researches have proposed that creativity can be supported by unconscious mental activity. They have suggested that dreams, and those developed during the Rapid Eye Movement (REM) sleep are significant contributors to divergent thinking in which we are able to free associate [4850]. In dreams, the brain also integrates emotionally salient memories and creates new combinations of things that have never been put together. PAM is a cognitive process that helps monitor inconsistencies, create associations, and adjust behavior. Therefore, exploring and understanding how unconscious processes create creativity is important. PAM forms an important part of the mechanisms within the brain that allows it to couple emotional memories with sensory and conceptual information, which is essential for problem-solving and ideation.

This paper explores the interrelated contributions of dream and PAM to idea generation, including the following:

REM SLEEP MAKES YOUR BRAIN WARM UP FOR CREATIVITY By Engaging Emotion and Memory Networks

The role of PAM is to track and adjust associations, allowing for new perspectives during both dreams and waking. We suggest framework underlying the artificial creative agents. The brain regions responsible for generating different ideas work together and are linked to adjacent structures such as the basal ganglion. The basal ganglion is responsible for reward-based learning and helps determine which of several possible behaviors to execute. The hypothalamus is involved in emotions and motivations, while the orbitofrontal cortex regulates planning. The frontal polar cortex is responsible for processing information generated internally, which is used for abstract and analogical reasoning. The study in [18] developed a CNN-based fungal disease diagnosis model to enhance medical precision, while utilized ensemble learning to mitigate dataset specificity in deepfake detection. On the other hand, the medial prefrontal cortex is involved in goal-directed behavior. In addition, the brain functions like self-monitoring, self-referential and social activities, memory consolidation, information retrieval, optimization, and information encoding, are crucial for learning and storing the ideas that have been generated.

Dreams can help us maintain our sense of self and achieve a higher level of consciousness. Dreams can reinforce existing connections or create new ones to align our internal and external realities better. Dreams act as an emotion-driven learning processadaptable, and highly interconnected [19]. Dreams help our brains create new connections and integrate new information into our memories, which can give us a unique and broader understanding of the world and problems around us [20].

4. Conceptual Blending

Conceptual blending is a mental operation that helps create new insights, meanings, and conceptual solidity. It is important in the arts, sciences, and the behavioral and social sciences to create meaning in everyday life. The process involves selecting and constructing a partial match between two inputs and projecting those selective inputs (features) into a unique blended mental space, developing dynamically evolving structures [21]. Conceptual blending is a cognitive theory developed by Gilles Fauconnier and Mark Turner, which states that elements from diverse scenarios are blended in a subconscious process. These elements are assumed to be present in everyday thoughts and language [22] [23].

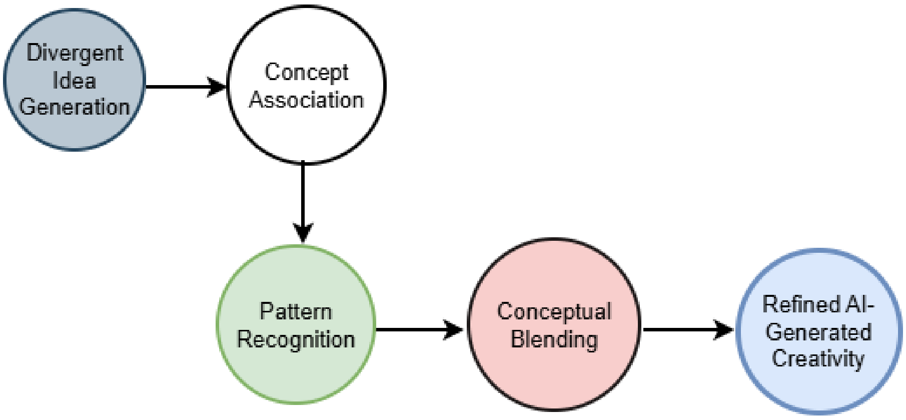


Figure 2. Conceptual Blending in AI

The AI mimics human creative thinking start with divergent idea generation as explained in Figure 2 This is the first step that produces a range of disconnected ideas. Concept Association connects these ideas semantically, and then Pattern Recognition recognizes the hidden patterns. Integrating them all into a coherent foundation establishes Refined AI-generated creativity through Conceptual Blending, where artificial intelligence generates all new material.

The cognitive behavior of human beings inspires our proposed framework, and the underlying cognitive correlates during idea generation are explained. To computationally realize these cognitive principles, we have taken the notions of conceptual blending and implemented blending in an association-based(combinatorial) workflow. Creativity is a blend of unfamiliar combinations in a novel, familiar way, explaining how divergently generated ideas are onverted into convergent ideas [24].

By considering this free-fall nature of divergent idea generation during sleep, we have taken the general data as a Wikipedia article so, to validate our proposed paradigm, we utilized a mixed approach comprising Word Embedding,(Latent Semantic Analysis) LSA, (Explicit Semantic Analysis) ESA [25]. This approach involves the following steps:

4.1. Text Preprocessing

It is important to carry out text preprocessing before conducting a comprehensive analysis to achieve accurate results. This stage involves removing all stop words and punctuation marks, such as full stops. By doing so, common words are eliminated, and the text is transformed into plain text that can be easily processed further.

Figure 3 depicts the sequence of steps involved in text processing. It begins with Raw Text Data that is then Preprocessed to remove stopwords and punctuation. Tokenization divides the text into meaningful pieces, then TF-IDF Calculation gives word importance. Apart from understanding contextual relationships, semantic analysis contributes to concept extraction to identify the most relevant key ideas.

4.2. Wikipedia's Articles:

The ESA (Explicit Semantic Analysis) technique requires access to a lot of information about the world to work effectively, i.e., it requires a large amount of text to be processed. So, we chose to use Wikipedia's articles as they are the largest collection of text available on the internet and available in numerous languages. These articles are highly organized and constantly updated with human knowledge, resulting in an increasing amount of information over time.

Figure 4 represents how textual content from Wikipedia articles is processed for semantic understanding. The workflow begins with Wikipedia Articles, which undergo Text Preprocessing to remove unnecessary data. Then, Keyword Extraction identifies key terms, followed by Entity Recognition to classify names, locations, and concepts. Semantic Relationships are established to connect different concepts, leading to Conceptual Understanding, where meaningful insights are derived

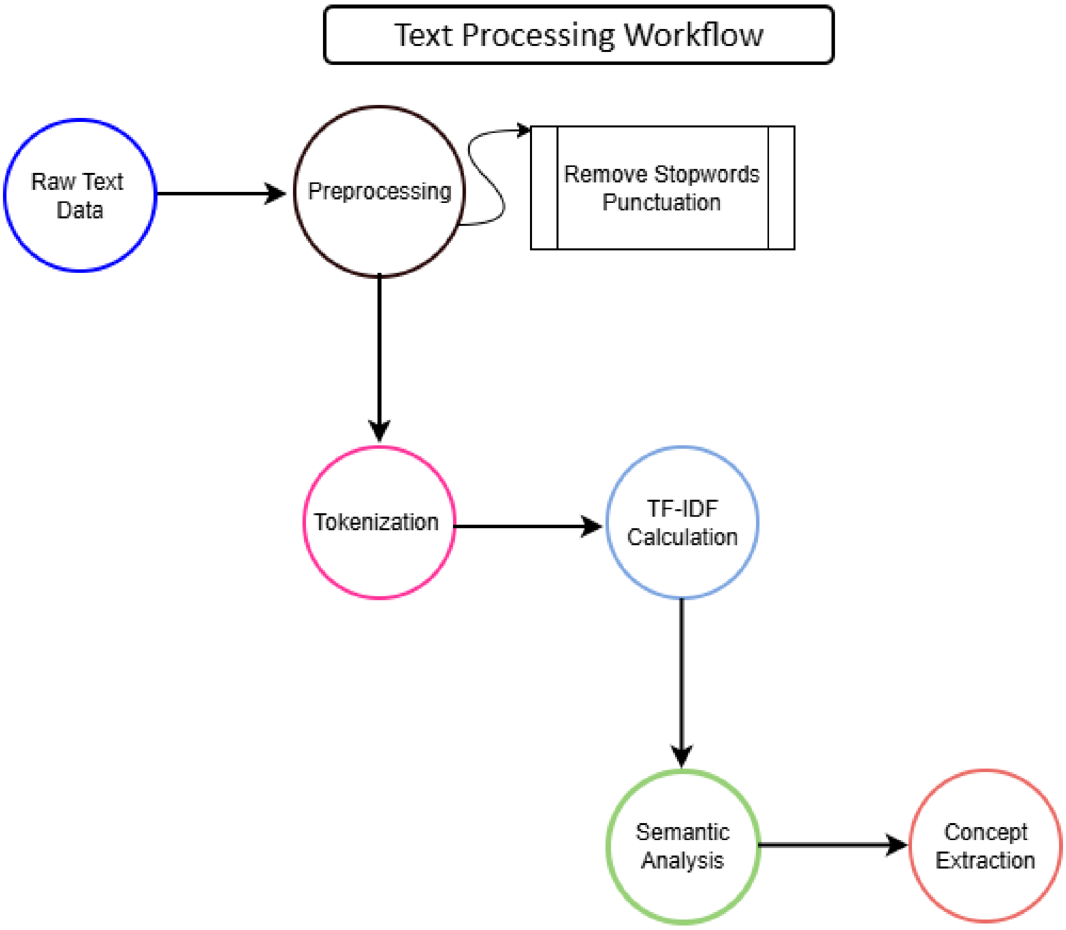


Figure 3. Text Processing Workflow

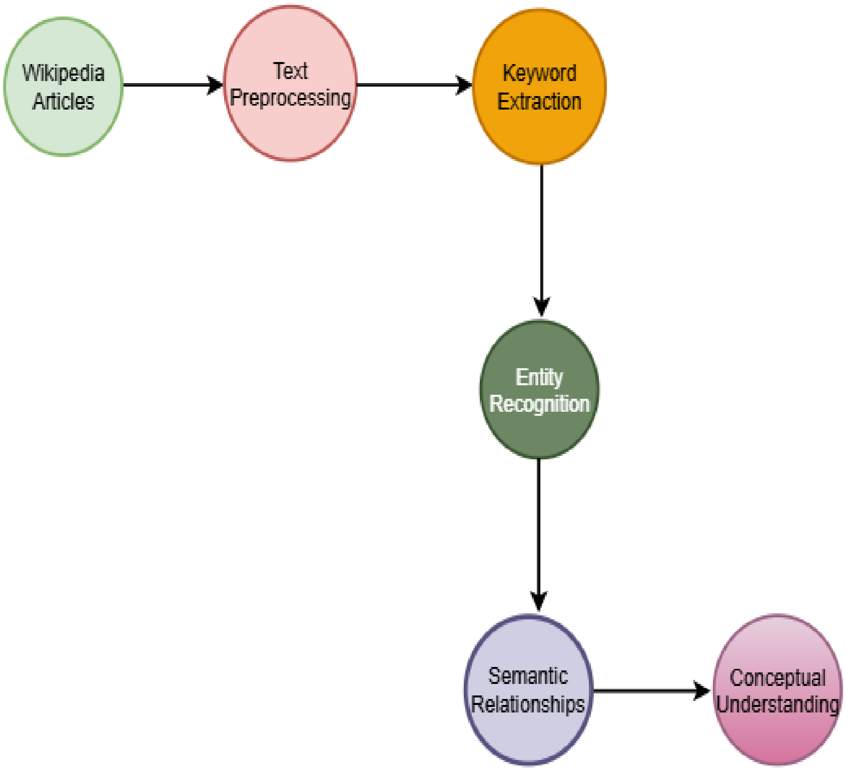


Figure 4. Wikipedia's Article Semantic

4.3. TFIDF Score of Articles

Once preprocessing is done, each article's tokens will be represented as a matrix. In the generated matrix, each column represents an article, and each row represents a token. The count of tokens in each document is recorded in the corresponding column. This is a critical step in representing the overall information within the matrix in mathematical form. Henceforth, the count matrix is modified with a TFIDF score.

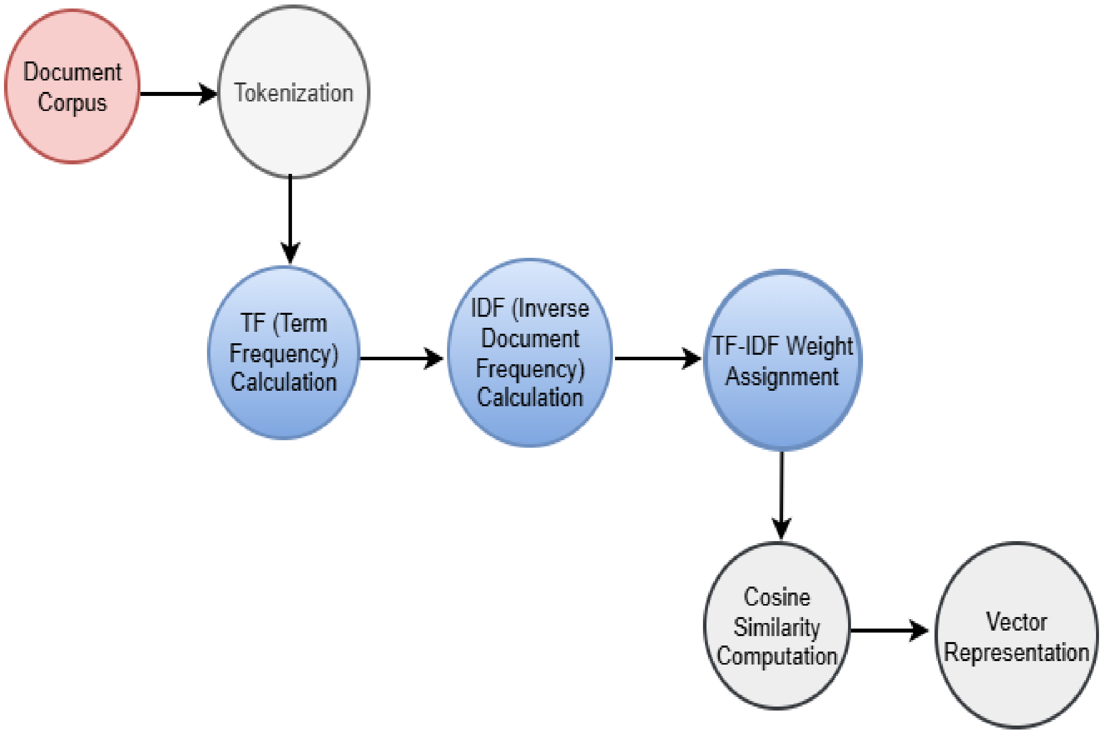


Figure. 5 TF-IDF Calculation & Cosine

To assess text similarity, it's important to know how much weight a word is given before conducting a similarity analysis. Before we dive into the process, it all starts with a Document Corpus, where the Tokenization step is tokenized, as shown in Figure 5. TF calculation counts word occurrences, while IDF calculation measures how important a particular word is. TF-IDF Weighting gives a numerical value to words, depending on how important they are. Followed Word Vector Representation, turning words into mathematical representations, and Cosine Similarity Computation computing the text similarity.

Cosine similarity is also an important method used in this study to determine the semantic relationships between words based on a multi-dimensional space. This approach computes the cosine of the angle between two vectors in a vector space, allowing for measuring how contextually relevant the terms are to each one another. This research thus utilizes cosine similarity to determine the connection between the keywords and the entities, therefore helping to classify and determine meaningful connections. Words are represented as vectors based on how often they appear on a webpage, using term frequency-informative document frequency (TFIDF) scores that can position words in a high-dimensional space. In this space, each dimension corresponds to a given word in the corpus, and the vector value represents the frequency and importance of that word within that document. The cosine of the angle between these vectors thus measures how alike or different terms are. The identified patterns and conceptual relationships become the framework for this paper's semantic analysis and hierarchical keyword extraction processes. This dependence on cosine similarity highlights the vectorized representations and how they influence the context of terms within textual data.

Figure 6 Process of structured keyword extraction Tokenization of Raw Text Data into words TF-IDF Weighting assesses the importance of a word before applying Semantic Analysis to extract meaning from the text. Concept Identification consists of detecting the overarching themes, followed by Hierarchical Keyword Mapping, which catalogs the extracted keywords into categories.

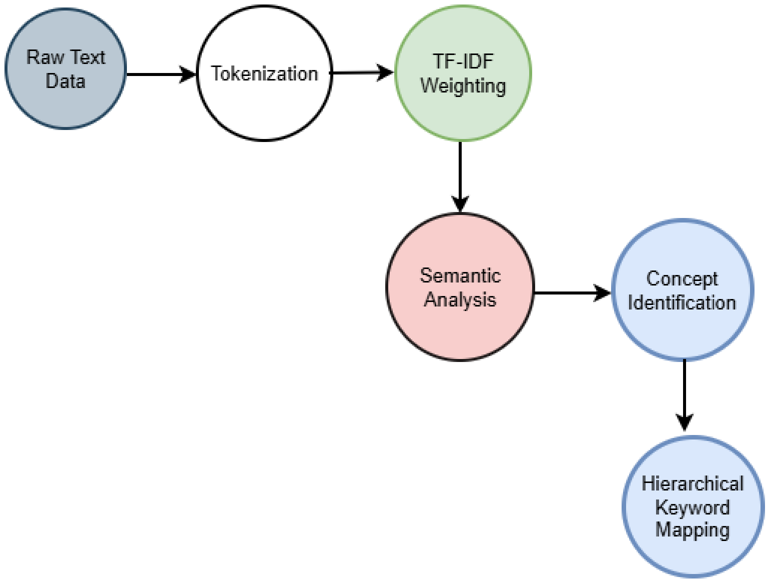


Figure 6. Hierarchical Keyword Extraction

Central to this creativity conundrum is the challenge of making sense of how free associative divergent thinking—where many options are on the table as possibilities for a solution—eventually gets refined and synthesized into a workable solution. Divergent thinking is characterized as spontaneous flow of large and seemingly unrelated ideas, driven by conceptual blending and associative memory mechanisms. Creativity flows quite freely from these unconscious ideas, devoid of strict logic. However the conscious layer is responsible for filtering, evaluating, and integrating such ideas into coherent, goal-directed solutions.

The TFIDF score is a way to measure the importance of words in a document. It assigns a higher value to words that are less common than those that are commonly used. The highest TFIDF score is given to words frequently appearing in the document, making them more significant. Conversely, a low point score indicates the word hardly appears in the document [26][27].

$$(TFIDF)_{w,d} = tf_{w,d} \times idf_w$$

We utilize an already-trained model called BoomTrain to calculate the semantic score of each source token. The trained model measures the cosine similarity among two words, which correlates words with the cosine angle between their vectors. This similarity is rated on a scale of -1 to 1 like humans as shown in Table 1.

Table 1. Similarity Scale

Range	Interpretation
1	Strongly Related
-1	Negative Related(No strong Impact)
0	Neutral

4.4. Process of Convergence

The convergence process can be seen as a several-step workflow:

Dynamic Phase 1: Ideation (Divergent Phase) — Exploring ideas freely, from memory, emotions, and sensory experiences. e.g. will you map how disparate concepts could solve your problem — e.g. “natural growth”,”mechanical efficiency” / a new robotics design?

Filter (Selection Phase): This is where the ideas that have been generated are assessed for their real-world relevance, feasibility, and alignment to the identified goal. This is where reasoning and contextual knowledge enter the equation. For example, ideas that are not practical or possible are eliminated [28].

Integration (Convergent Phase): In this phase, the best ideas synthesises, and divergent ideas (fragments) are integrated into a more ordered solution. An example of this is coming up with bio-inspired robotic systems by taking the "natural growth" concept and merging it with "mechanical efficiency".

Validation (Solution Phase): The converged solution is tested or validated to make sure that it is feasible. He can, if necessary, further refine this from here, iterating until he gets what he wants.

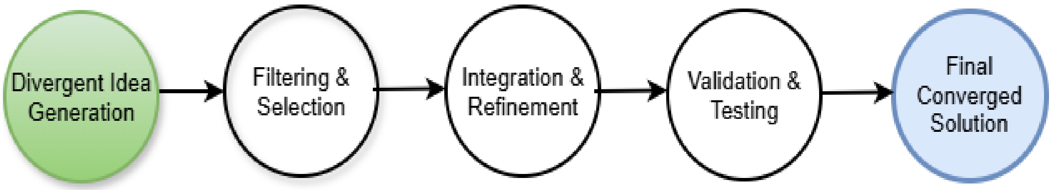


Figure 7. Process of Convergence

Figure 7 shows the jumbled ideas we have become a streamlined solution. Everything start at the Divergent Idea Generation with open many paths. Then, we move to Filtering & Selection and discard irrelevant ideas. Then, we finally go to Integration & Refinement, which combines the best ideas into a structure. The process of Validation & Testing that checks feasibility leads to the Final Converged Solution that is the well-defined output.

Concrete Example: Eco-Friendly building design:

They generate ideas like using recycled materials, vertical gardens, solar panels and biomimicry. The FIRST of these filters is a no-brainer, but I'm already old and rigid, so I should probably explain it: Filtering: Costs do NOT matter, and I mean that very seriously, but you have to set your climate proposals in a context that makes sense.

Intermingling: The rest of the ideas, vertical gardens, solar panel, etc are intertwined to design a building that combines sustainability with look.

Validation: Simulations are performed to prove the building's energy performance is compliant.

To illustrate, let's consider the cosine similarity between "goat" and "milk" which may be 0.6, whereas the similarity between "goat" and "wood" is only 0.2. To demonstrate the entire process of the adopted method as explained earlier, to train the network Wikipedia page on "Computers" is used as the mentioned link https://en.wikipedia.org/wiki/Computer (visited: 22-1-2024), and it indicates the following results.

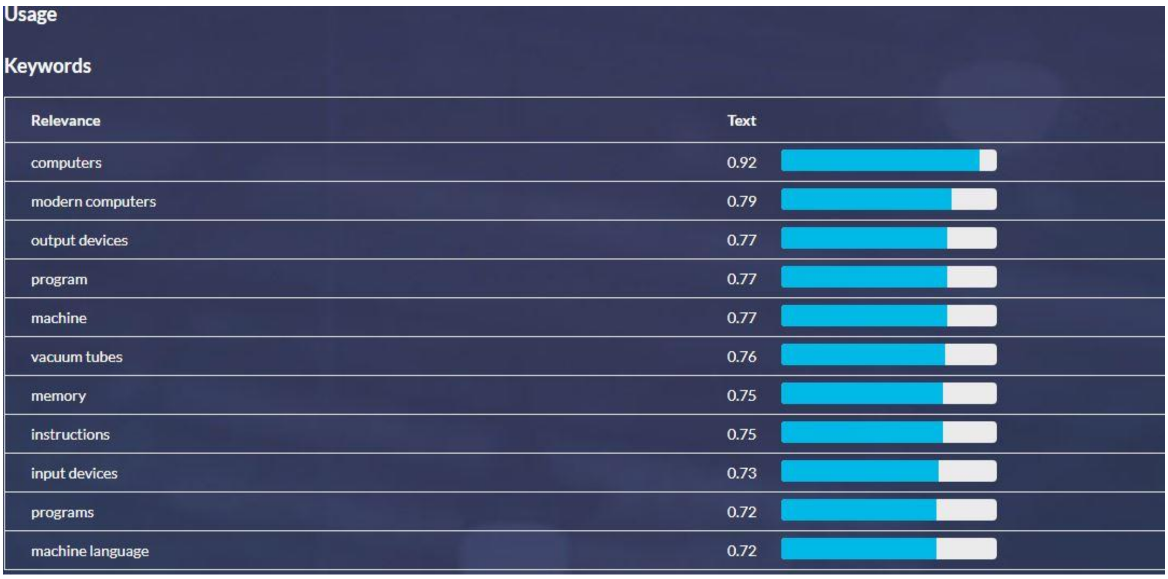


Figure 8. Convergent Keywords Hierarchy

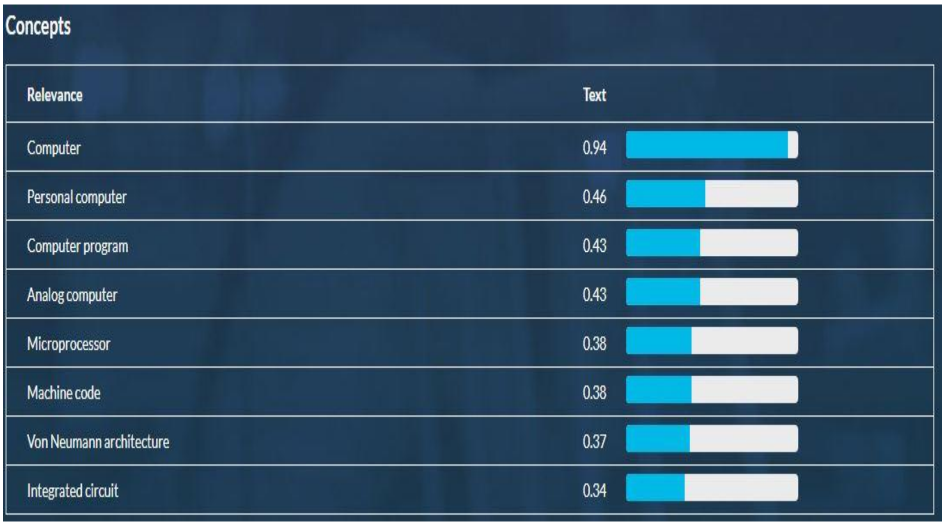
Figure 8 represents the relevance of keywords related to computing, with terms like "computers" (0.92) and "modern computers" (0.79) ranked by importance and relevance. The bar graph visually indicates the relative significance of each term in the analyzed content. We analyzed the text of the article on "Computers" on Wikipedia. Firstly, we identified the essential features or keywords used in the article such as I/O devices, programming, and machine language. We then determined the frequency of these keywords throughout the document. The keyword "Computers" occurred 0.96 times. These keywords helped us to identify tokens and concepts that represent the main ideas in the article.

Entities

Relevance	Text	Type
JobTitle	Electronic Numerical Integrator and Computer	0.49
Company	RAM	0.45
Person	Charles Babbage	0.4
Person	Sir William Thomson	0.39
PrintMedia	Oxford English Dictionary	0.38
Location	United States	0.38
JobTitle	programmer	0.37
Person	Vannevar Bush	0.37
Organization	ENIAC	0.35
Company	Colossus	0.35
HealthCondition	calculi	0.34

Figure 9. Entity founded on Keywords.

Figure 9 highlights the relevance of identified entities such as "Electronic Numerical Integrator and Computer" (JobTitle, 0.49) and "Charles Babbage" (Person, 0.40). Each entity is categorized by type and ranked based on its significance in the analyzed content. After identifying the relevant keywords, we created a list of entities or tokens that demonstrate the importance of those keywords. For example, different companies and individuals have produced computers and their accessories at various locations across the globe. Furthermore, several organizations have advertised job openings related to this field at different locations. We used semantic analysis to establish all these relevant connections, as shown in Figure 9.



Concepts

Relevance	Text
Computer	0.94
Personal computer	0.46
Computer program	0.43
Analog computer	0.43
Microprocessor	0.38
Machine code	0.38
Von Neumann architecture	0.37
Integrated circuit	0.34

Figure 10. Conceptual Development

Our system utilizes "Keywords" and "Entities" to generate concepts based on word semantic relationship. This led to the development of the first analog computer on Von Neumann's architecture. Once the computer design was established, scientists focused on creating the language of the computer, which is known as machine code and helps in operating the system. With the advancement in technology, analog computers were replaced by microprocessors. The idea behind the development of microprocessors was also divergent. This divergent idea converged by assembling different parts of the computer based on their spatial features, resulting in the computers we use today, as shown in Figure 10.

Figure 11 illustrates the categorization, labeling, and evaluation of ideas generated by computer hardware, software, computing, and technological advancements.

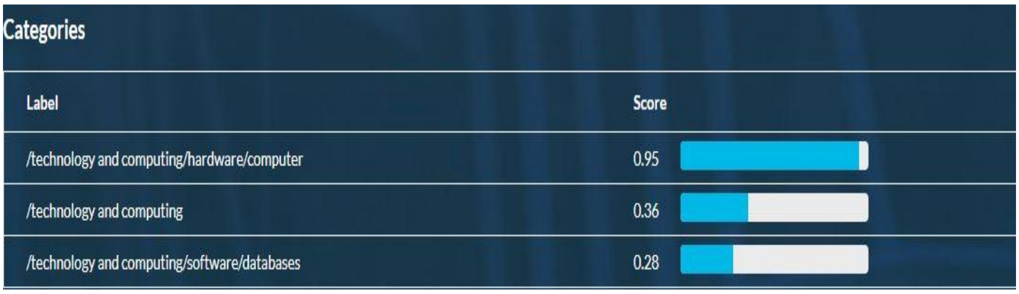


Figure 11. Segmentation

5. Discussion

In this study, one of the important factors to consider is the reliability of Wikipedia as a source of data. Wikipedia, despite being a very resourceful and available source of information, could be prone to certain inaccuracies as it was a user-generated platform. Articles may indeed contain factual errors, unverifiable edits, or out-of-date information, undermining the integrity of research that depends on its data. Moreover, many of the English Wikipedia articles are written or edited by people who are not native speakers, often using translation software. By referring to translation software, this practice adds other complications, since translation software can also write in embedded algorithmic biases or misrecognize linguistic nuances, incorrectly translating in terms of implication or context. These biases arise from the dependence on training data that does not adequately reflect industry-specific jargon or cultural nuances. As a result, human errors and biases in algorithms play a role in distorting the correctness of the data and analysis. To reduce these risks, researchers are encouraged to implement strong validation strategies, including cross-checking Wikipedia-derived information against peer-reviewed literature, utilizing domain experts for review, and employing preprocessing methods to filter and verify data accuracy. However, by addressing these issues, the potential impact of disparate and unreliable data sources and algorithmic biases on the integrity of research outcomes can be minimized so that a more reliable and credible analysis is ensured.

6. Conclusion

This paper concludes with a unified framework that supports the science behind the divergent idea generation, and an explanation of metaphysical concepts such as consciousness, the significance of cognition, neuroscience, and general intelligence in the creative process. The creative agent model proposed is founded on the cognitive aspects of humans such as emotions, motivations, dreams, awareness, and consciousness. This model facilitates the generation of diverse ideas by implementing neural, cognitive, and functional correlates of consciousness. We explain how these generated ideas, which are generated in a divergent manner, converge to form a coherent solution validated through the provided results. This research has the potential for further exploration through the implementation of cognitive correlates at conscious and unconscious levels.

Supplementary Materials: The following are available online at www.jcbi.org/xxx/s1, Figure S1: title, Table S1: title, Video S1: title.

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