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The Impact of AI on Creativity: Enhancing Human Potential or Challenging Creative Expression

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Abstract: The purpose of this study is to investigate how artificial intelligence (AI) can revolutionize creativity, aiming to determine whether AI enhances human creative potential or challenges established modes of creative expression. This study uses qualitative, quantitative, and theoretical methods, including mathematical frameworks and practical trials with computer simulations. By exploring the theoretical foundations of AI–creativity interactions, it analyzes the advantages and limitations of AI in creative domains such as art, music, and science. Computational creativity is examined using experiments that define metrics for evaluating AI systems, integrating emotional intelligence, generative theory, and creativity theory. This study leverages large language models such as BingAI, HuggingChat, BERT (Gemini), and GPT to assess creative tasks such as narrative collaboration, problem-solving, and writing. A mathematical approach is introduced to evaluate AI's creative intelligence, revealing its potential to rival human creativity in cost-efficient applications. The findings clarify the intricate relationship between AI and creativity, emphasizing collaborative creation and highlighting AI's dual role as both a catalyst and a disruptor. This study underscores the importance of individualism in human creativity and provides insights into evolving AI-driven creative processes. By systematizing literature reviews and experimental validations, this study advances understanding of AI's impacts and encourages further research into human–AI synergy.

Keywords: large language model, automation, creativity, artificial intelligence, computational intelligence

1. Introduction

Artificial intelligence (AI) is becoming increasingly important in reshaping the world of art by interacting with human creative potential. The current influence of AI on fields such as visual arts, music, and poetry highlights the merging of AI with creative practices. This fusion not only has the potential to enhance artistic abilities but also introduces intriguing challenges to traditional standards of creative expression. The primary questions focus on the future direction of the field and the potential of AI to achieve creativity comparable to that of humans. In addition, the creation of artworks that are indistinguishable from those made by humans is a topic of interest from a mathematical standpoint.

The concept of creativity and the intersection of human creativity and AI are intricate subjects that require a deep and comprehensive study to establish a valid theoretical framework. This study is multidisciplinary, encompassing fields such as cognitive science, philosophy of mind, and computational creativity (CC) to identify and understand the interaction between AI and creative expression. The idea of interplay raises central questions: Can AI replicate or exceed the depth and richness of creativity, or does its computational essence inherently constrain it? What optimizations can be applied to AI to enhance its creative output? In addition, how is creativity currently evaluated and measured? Exploring cognitive processes behind human creativity and examining the philosophical implications of AI-generated artworks are crucial.

1.1. Background: the progression of AI creativity

AI models encompass a variety of conceptual frameworks and architectures. Each year, there is a significant increase in the production of new research focused on multimodal and generative models. As AI models, such as large language models (LLMs) and generative algorithms, become more sophisticated and approach human language comprehension, they are capable of producing outputs that rival those of human creators. The concept of AI creating art and poetry is foundational to the early development of AI, where researchers aimed to understand whether machines can think and whether they possess a sense of creativity. These ideas lead to the development of CC theories. This development, in turn, facilitated the emergence of AI capable of generating subjects of human creative novelty, such art, music, literature, and even scientific theories and hypotheses. In addition to its role in understanding consciousness regarding creativity, innovation on understanding machines and their creativity created a darker side, raising philosophical questions and challenges concerning originality, authorship, and self-awareness in the era of AI. In today's age of LLMs, there is significant discussion regarding the impact of AI on the field of artistry. This brings attention to the tension between pushing boundaries through innovation and safeguarding the essence of creativity [1].

1.2. Ethical implications and collaborative frameworks

The capacity of AI to generate speech raises concerns among voice actors regarding their job security, leading to conversations in the industry regarding the future of their profession. The emergence of AI poses a dilemma for voice actors because it offers a potentially more cost-effective option for implementing text-to-speech technology in video games. This shift could result in the displacement of talent in this field. It is noteworthy that in the industry, there is ongoing discussion regarding the impact of AI on creativity and employment opportunities across various forms of media, such as films and animations. This

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discussion echoes themes from films such as "The Terminator," which influences people's mindsets, projecting a bleak and disastrous future with AI in control. To discuss the broader implications of AI in art, we can confidently assert that AI art generation mimics human learning by associating keywords with images, thereby demonstrating its potential to comprehend creativity itself. This raises important questions regarding the nature of art and originality. From a data perspective, we can identify that reliance on extensive datasets underscores the importance of quality and diversity in training data. These data are crucial for model development and can significantly influence the creativity and representation of each detail in the output. There is a new opportunity for artists to utilize LLMs as copilots to enhance their artistic creations. This approach introduces the concept of prompt engineering [2], which highlights the collaborative nature of AI art creation. It enables users to refine their inputs to achieve desired outcomes, akin to collaborating with a creative partner. However, AI-generated art frequently reflects societal biases present in training datasets, sparking discussions regarding representation and inclusivity in digital art.

1.3. Study overview

We can assert that AI is transforming the landscape of creativity and communication. However, it also necessitates a critical examination of its long-term implications for society and individual cognition. The experimental concept of the proposed study integrates a theoretical framework from cognitive science with a quantitative approach, incorporating elements from linguistics, the philosophy of mind, and CC. This study aims to investigate and understand the complex dynamics between AI and human creativity. We conducted a series of experimental modules based on several LLMs currently available in the market [3], analyzing the capabilities of AI models such as BingAI, HuggingChat, BERT (Gemini), and ChatGPT in various creative tasks. This study seeks to provide a comprehensive understanding of AI's role in the evolving landscape of creativity. The central question is to assess the current state of the art regarding these models' capabilities and to determine whether AI can genuinely emulate or surpass the depth and richness of human creativity or whether its computational nature inherently limits it. To achieve our goal, creativity—traditionally considered a uniquely human attribute—is now being analyzed in terms of machine performance, utilizing metrics such as fluency, originality, elaboration, and linguistic diversity. Moreover, this study aims to demonstrate tactics by applying reinforcement learning (RL) techniques, which provide AI systems with the opportunity to adapt and improve their creative processes through user feedback, thereby enhancing their ability to generate novel and useful content over time. Four prominent LLMs are evaluated across multiple dimensions of creativity. Tasks such as collaborative content creation, problem-solving, and creative writing are used to test these models. A mathematical framework for assessing creativity based on learning, problem-solving, communicative flexibility, and neural dynamics is additionally included in this study. To outline the proposed study, I will present the ideas in the form of objectives: 1) Evaluate the creative performance of several state-of-the-art LLMs using quantitative metrics. 2) Apply the principles of RL to model the optimization of AI creativity. 3) Develop a mathematical framework to assess AI creativity across multiple dimensions, providing a comprehensive view of how AI can contribute to creative processes. This study focuses on the possible advantages and difficulties of incorporating AI into the creative sectors in an effort to offer better insights into the role of AI in creativity. The framework for assessing artistic productions as "artifacts" with linguistic ramifications will yield results that add to the expanding corpus of research on AI-driven creativity and its consequences for human creativity in the future and human–intelligent system collaboration.

2. Literature Review

Humans have always possessed the urge to create beings that resemble themselves, to imbue inanimate objects with life and magic, and to depict the natural world through god-like figures. This inclination has given rise to legends and poems that explore the concept of nonliving entities gaining consciousness. For instance, the Jewish myth of the golem narrates the tale of a creature animated by human hands. In this context, the golem serves as a powerful symbol in relation to modern developments in AI, highlighting concerns regarding control, responsibility, and the unpredictable nature of human-made creations. Therefore, we can assert that AI represents a contemporary reimagining of the golem myth [4]. Another work that has gained popularity in modern pop culture is Mary Shelley's "Frankenstein," which, similar to the myth of the golem, explores the concept of a creature brought to life by human hands. We can speculate on various ideas and highlight significant ethical issues surrounding the creation of life, drawing parallels between Dr. Frankenstein's creation of the monster and the work of today's AI developers. The central metaphorical similarity of the main idea can be understood as a cautionary tale regarding the potential dangers of AI if not properly managed and the moral responsibilities that creators have toward their creations [5]. The foundational studies of AI are directly related to creativity, particularly in the development of artificial thinking machines that possess common sense and emotional capabilities similar to those of humans. In recent years, the intersection of AI and creativity has garnered significant attention, driven by advancements in machine learning, natural language processing (NLP), and generative models that facilitate innovative approaches to creative tasks. The use of AI to generate novel and valuable content in fields such as art, music, literature, and design is now a well-established phenomenon. This section reviews key studies that have explored AI's creative potential, the evaluation of AI creativity, and optimization strategies for AI-generated content. These works provide a historical, philosophical, and technical foundation for understanding how AI systems contribute to creative processes and highlight the gaps that the current research aims to address.

There have already been studies presented that primarily focus on how AI and its various applications can generate outputs based on creative metrics across different sectors. Anantrasirichai and Bull [6] showcased a broad range of applications in creative industries through a review approach, examining tools of creativity in art, design, and media. Five separate groups were introduced to segment creative applications in relation to the approaches used for AI. This work emphasized the increasing role of AI in automating creative processes and enhancing human creativity. Similarly, Moura et al. [7] conducted experimental validation in their research to demonstrate how AI-generated art is perceived in terms of creativity and value. The main objective was to test automation in production, compare individuals' changing views on product value, and identify influential metrics. The proposed findings suggested that AI is a valid companion in creative endeavors, but there are open questions regarding authorship and the authenticity of its outputs. LLMs significantly improved the use of AI in narrative development and creative writing. Early research by Boden [8] had a significant impact on the development of current LLMs such as generative pre-trained transformer (GPT). The paper showcased novel frameworks that demonstrated how AI could achieve creativity by generating original ideas. Natale and Henrickson [9] further developed this concept by proposing and investigating the core structure of machine creativity through the "Lovelace effect" to evaluate AI creativity, which serves as an alternative approach to the famous Turing test. The Turing test is the first proposed theoretical method for measuring machine creativity through role-play [10]. The work explores how judgments regarding AI creativity influence human biases and expectations, and it asserts that AI must possess the ability to understand the concept of creative generation. By producing novel and creative artifacts, it must comprehend the creative process that underlies their creation. These experiments have influenced the creation of LLMs that can generate high-quality, human-like writing, which is the current study's main purpose. Recent advancements in multimodal AI systems, such as Gemini Ultra [11], have redefined CC by enabling the seamless integration of text, image, and code generation. For instance, Gemini's ability to produce illustrated narratives from textual prompts exemplifies cross-domain creativity, effectively addressing the limitations of earlier single-modality models. The COFI framework [12] formalizes iterative human–AI collaboration, illustrating how real-time feedback can refine creative outputs, a principle applied in the RL experiments of this study.

The purpose of CC is to create AI systems that can independently produce original material or imitate human creativity. In the early days of AI development, the primary idea for creating intelligent systems was CC, which aimed to build robots with human-like thought processes and common sense. From the perspective of CC, Colton and Wiggins [13] identified it as one of the "final frontiers" for AI, emphasizing its role at the core of creative thinking. Their objective was not only to replicate human creative outputs but also to produce artifacts that are perceived as novel, original, and valuable according to societal metrics. The paper introduced frameworks for evaluating AI-generated outputs, referred to as machine-based artifacts, which were based on the FACE and IDEA models. Alongside Duch's [14] work on exploring CC through neural networks (NNs), these models have advanced the current understanding of AI creativity. They have also been essential for analyzing, measuring, and comprehending how outputs generated from machine learning processes are interpreted. To explore the foundational techniques represented in today's AI models, it is essential to mention the proposal and introduction of generative adversarial networks (GANs) by Saxena and Cao [15]. This groundbreaking concept enabled meaningful interaction with creative outputs generated by machines and accelerated advancements in the field of CC. The remarkable aspect of GANs lies in their game-theoretic approach, which can be described as a "minimax two-player game." AI systems can generate highly realistic, pixelated images and art—an important category of human-made creative artifacts—by pitting two NNs against each other. One model generates content while the other evaluates its authenticity, thereby optimizing individual payoffs. This method has been applied to a variety of creative fields, especially visual arts, where human and AI-generated art is frequently indistinguishable. Wu et al. [16] further developed this concept by demonstrating that AI does not independently create novel art that challenges ethical and value metrics. Instead, they explored human–AI cocreation models and frameworks, emphasizing the collaborative potential of AI systems in proposing and generating creative content alongside human creators. This collaboration opens new possibilities for human creators to enhance their workflows, introduce innovative ideas, and advance the understanding of hybrid creativity in society [17].

In CC research, assessing AI-generated creativity has evolved into a major challenge. To delve into history, we can observe that traditional metrics of creative behavior such as fluency, originality, elaboration, and flexibility were outlined and proposed by Guilford [18]. These metrics have since been adapted to assess the creative outputs of AI. Tyagi [19] explored the relationship between mathematical intelligence and mathematical creativity, which is fundamentally based on creative behavior. Therefore, we can propose that an AI model's ability to creatively solve mathematical problems, rather than merely following procedural equations, could serve as a proxy for creativity. Similarly, Simo et al. [20] proposed a framework for understanding the true characteristics of creative behavior. The main idea is to compare creative systems and, from that perspective, examine the details of how to measure the novelty and value of AI-generated outputs. The use of RL is the closest machine learning technique for enhancing creativity in the future. Research by Colton and Steel [21] demonstrated how feedback and the ability of AI systems to adapt based on that feedback could be used to optimize systems as well. This approach has been implemented in scientific problem-solving, particularly in natural sciences, and for content generation in video games, as explored by Still and d'Inverno [22]. RL is a crucial strategy for developing AI's creative authority because it allows AI to improve its creative process by identifying which behaviors result in the most creative outputs.

Despite tremendous advancements, there are still a number of gaps in AI creativity. One of the main drawbacks of the existing literature is the absence of a thorough framework for assessing creativity in LLMs across a variety of aspects. Without taking into account the entire range of creative qualities that go into a model's overall creative performance, the majority of studies concentrate on just one facet of creativity, such as originality or fluency. This identification process is crucial now that AI models are becoming a significant part of people's daily lives. The current proposed research aimed to enhance the creative measurement possibilities and address existing gaps by developing a comprehensive mathematical framework for assessing creativity in LLMs across various contexts, including learning creativity, problem-solving creativity, adaptive communication creativity, neural dynamics creativity, and graph-theoretical creativity. This study involved implementing RL in LLMs to sequentially and iteratively improve their outputs across different problems and stages of creative tasks based on feedback that leads to optimization. Finally, we selected several leading LLMs—BingAI, ChatGPT, BERT (Gemini), and HuggingChat—based on criteria such as cost, usability, and flexibility. Consequently, we combined the proposed mathematical framework with RL-based optimization techniques to quantitatively evaluate their performance.

Prior research has primarily focused on individual creativity metrics (e.g., originality as discussed by Tyagi [19]) or theoretical frameworks [20], often overlooking empirical validation with contemporary LLMs. Furthermore, existing human–AI collaboration models [16] lack clearly defined roles tailored to specific tasks. This study addresses these shortcomings by 1) introducing a multidimensional creativity measure (CM) that integrates metrics for problem-solving, learning, and communication; 2) validating these frameworks against empirical data from four LLMs; and 3) demonstrating how the unique strengths of each model (e.g., BingAI's originality and ChatGPT's fluency) facilitate targeted collaboration paradigms, thereby advancing Wu et al.'s [16] cocreation model. This study addresses these gaps by offering a more comprehensive and dynamic method of assessing and improving creative performance in LLMs, thereby adding to the expanding corpus of research on AI creativity.

3. Objectives

Examining how AI affects creativity and how these effects might influence human potential and creative expression is the aim of this motivated study. The study's primary goal is to determine whether AI improves human creative capacities or challenges conventional paradigms of creative expression. A conceptual examination of the dynamic interplay between AI and creativity is one of the specific goals, with an emphasis on assessing the advantages and disadvantages that AI may offer in various creative domains. Understanding the creativity of LLMs—which are currently the mirror of creativity and fear in the creative industries—and the proposed chatbots' capacity for producing original outputs are the objectives of the experiment. In addition, mathematical metrics will be developed to quantify these outputs and compare them to those produced by different AI models. The purpose is to identify ways in which AI could improve creativity without totally replacing humans and to evaluate the creativity, linguistic, and commonsense reasoning metrics of AI models. Research also hopes to shed light on the transformative opportunities and potential obstacles that arise when human artists and innovators undertake creative endeavors.

4. Research Methodology

4.1. Research design

The purpose of this study was to carefully evaluate the creative potential of AI models, investigate how AI affects creativity, and determine if AI encourages human creativity or challenges traditional forms of artistic expression. Independent analyses, theoretical investigations using mathematical formulas, and empirical experiments with computer simulations and test-like scenarios were incorporated into the study design. Through mathematical combinations and analysis, this study used integration models such as the theories of emotional intelligence (EI), generative theory (GT), and creativity theory. This study began with a comprehensive literature review that methodically developed knowledge regarding the different effects of AI on creativity. This study used LLMs, including BingAI, HuggingChat, BERT (Gemini), and GPT, to arrive at an inventive solution. Each language model received the same set of stimuli in a random order for the following activities:

1) Prompt creative writing assessment
2) Creative problem-solving
3) Collaborative storytelling
4) Creative test tasks.

The following creativity metrics for written content were applied:

1) Fluency
2) Originality
3) Uniqueness
4) Elaboration.

Fluency, originality, uniqueness, and elaboration—all well-known creativity metrics for written content—were utilized in this experiment to conduct a thorough analysis. In addition, a quantitative study was conducted to assess the linguistic diversity, syntactic complexity, and language richness of the generated responses. As a result, the study identified the language model that performed best in certain creative writing domains and compared each model in terms of text originality.

This study utilized original graphical user interface (GUI) versions of the following commercial and open-source models, accessed between March and June 2024: BingAI (Microsoft Copilot, March 2024 release), ChatGPT (GPT-4, OpenAI web interface, May 2024 version), Gemini (Google Gemini Advanced, April 2024 release), and HuggingChat (Hugging Face web interface, June 2024 iteration). These models were selected to represent the state-of-the-art commercial and open-source LLMs. The training data for proprietary models (BingAI, ChatGPT, and Gemini) include publicly disclosed corpora (e.g., web-scraped text, books, and codes) and proprietary datasets, and HuggingChat relies on publicly available open-source repositories. Evaluation protocols adhered to standardized creativity benchmarks (e.g., Torrance Tests of Creative Thinking) that were adapted for LLMs, with prompts randomized to mitigate order effects. Table 1 shows the evaluation setup of the utilized LLMs.

In the realm of digital experimentation, a unique environment was created using the Python programming language, and for the simulation platform, Google Colab Cloud was utilized. To optimize the digital proof-of-work framework, this cloud-based environment aids in the periodic examination of each metric, the identification of relationships, and visualization. It additionally makes easier to construct algorithmic systems based on mathematical equations. A scheme based on mathematical equations was used to assess the level of CC in the Turing test or its related models. In summary, this research design takes a holistic approach, making comparisons to the methods used in the study of AI in relation to creativity. Its objective is to unravel the complexities of the relationship between AI and creativity, providing valuable insights into the evolving dynamics of creative processes driven by AI.

4.2. Theoretical and methodological frameworks

This research design utilizes a multidimensional approach by combining independent studies, theoretical inquiries, and empirical trials to comprehensively assess the influence of AI on creativity. This study will determine whether AI fosters human creativity or poses novel challenges for conventional forms of artistic expression. An emerging topic of study that has the potential to transform creative work and obfuscate the distinction between human and machine artistry is AI in art, poetry, design, communication, and CC. The aim of this study is to quantify the creativity of modern LLMs and explore how AI can enhance human creativity by providing feedback, generating unique works, and assisting in the creative process. Various theoretical frameworks are incorporated into this study, such as creative theory, GT, and EI. These concepts form crucial foundations for comprehending the dynamic interaction between AI and creativity. The preliminary quantitative synthesis integrates foundational theoretical frameworks from EI, GT, and creativity theory in the experimental design. The objective is to establish a robust theoretical basis for comprehending the dynamic interplay between AI and creativity. To begin, a mathematically modeled EI framework was created. The goal of this framework is to investigate how EI components influence AI's creative capacities, with a focus on incorporating emotion into generated material, as shown in Equation (1):

$$EI_{AI} = \alpha \times C_{\text{prompt}} + \beta \times R_{\text{emotion}} \quad (1)$$

The theoretical framework for examining the generative mechanisms integrated in AI models is referred to as GT. It evaluates their ability to independently create and produce innovative artifacts. The mathematical representation that encapsulates these mechanisms is utilized for evaluation in Equation (2):

Table 1
Model specifications

Model	*Version*	*Access date*	*Platform/API*	*Prompts (n)*
ChatGPT	GPT-4 (May 2024)	May–June 2024	OpenAI Web Interface[1]	35
BingAI	Microsoft Copilot (Mar 2024)	Mar–Jun 2024	Web GUI	35
Gemini (BERT)	Gemini Advanced (Apr 2024)	Apr–June 2024	Google Web Interface	35
HuggingChat	June 2024 Release	Mar–Jun 2024	Hugging Face Web GUI	35

[1] chat.openai.com

$$\mathrm{GT}_{\mathrm{AI}} = \gamma \times \mathrm{N}_{\mathrm{novelty}} + \delta \times \mathrm{D}_{\mathrm{diversity}}. \tag{2}$$

Creative theory framework is used to evaluate AI-generated material against recognized creative criteria, aligning with the concepts of creativity theory as represented by this mathematical framework (3):

$$\mathrm{CT}_{\mathrm{AI}} = \theta \times \mathrm{F}_{\mathrm{fluency}} + \lambda \times \mathrm{O}_{\mathrm{originality}} + \mu \times \mathrm{E}_{\mathrm{elaboration}}. \tag{3}$$

The AI–LLM model, which leverages context vectors to affect creativity metrical outcomes, has been presented as a model for content analysis. The score for contextual creativity $\mathrm{C}_{\mathrm{contextual}}$ is defined in Equation (4):

$$\mathrm{C}_{\mathrm{contextual}} = \eta \cdot \mathrm{C}_{\mathrm{index}} + \zeta \cdot \mathrm{C}_{\mathrm{context}}. \tag{4}$$

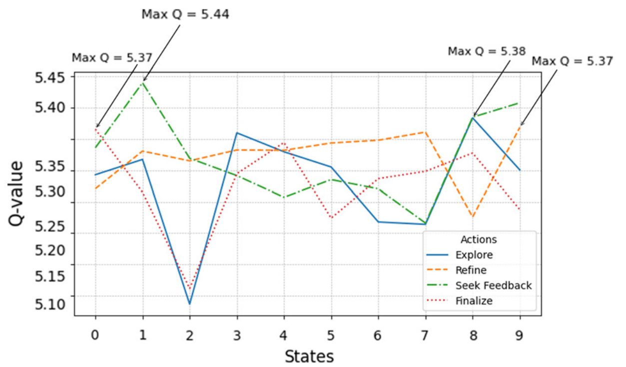
The equation $\mathrm{C}_{\mathrm{contextual}}$ represents the contextual creativity score, with η as the weight of the creativity index, ζ as the weight of context based on input–output metrics, and $\mathrm{C}_{\mathrm{context}}$ as the representation of the contextual factors influencing the overall creativity point.

RL techniques are applied to incorporate a user feedback metric into the foundational creative model that has been considered. The Q-value update for creativity $\mathrm{Q}_{\mathrm{creativity}}$ (s,a) is defined in Equation (5):

$$\mathrm{Q}_{\mathrm{creativity}}(\mathrm{s},\ \mathrm{a}) = \mathrm{Q}_{\mathrm{creativity}}(\mathrm{s},\ \mathrm{a}) + \alpha\left[\mathrm{r} + \gamma \max_{\mathrm{a}'} \mathrm{Q}_{\mathrm{creativity}}(\mathrm{s}',\ \mathrm{a}') - \mathrm{Q}_{\mathrm{creativity}}(\mathrm{s},\ \mathrm{a})\right] \tag{5}$$

In the equation model, the quality of action a in state s is represented by $\mathrm{Q}_{\mathrm{creativity}}$ (s,a), and r denotes the reward. In addition, the learning rate is denoted by α, and the discount factor is denoted by γ. The new state that arises from executing action α in state s is represented by s' in the model. Therefore, the maximum projected future Q-value of the new state s' and all feasible actions a' is $\max_{\mathrm{a}'} \mathrm{Q}_{\mathrm{creativity}}(\mathrm{s}',\ \mathrm{a}')$. This formula has been used to build a simulation where the initial states of each episode are chosen at random, such as the action to be taken and the reward for the action. Using this RL model, the simulation attempts to mimic how AI becomes more creative over the course of several episodes in response to user feedback (Figure 1). Figure 1 illustrates the evolution of Q-values across 10 discrete states (from State 0 to State 9) during AI-driven creative tasks. The Y-axis represents Q-values, which quantify the quality of creative actions. Peak values of 5.44 (in State 1) and 5.37 (in State 9) indicate optimal creative decisions during the refinement and finalization stages. Higher Q-values are associated with increased user engagement and enhanced creativity efficacy, demonstrating AI's ability to prioritize high-reward actions, such as "Refine" and "Finalize," through RL.

Figure 1
Q-value simulation output for creative actions across various states



The simulation's output plot displays the Q-values of every action in every state. On the basis of the incentives obtained, these Q-values show the acquired quality of every creative action in every condition. Higher Q-values (i.e., stronger user involvement or higher creativity) suggest acts that are more likely to receive positive feedback. As a result, the X-axis shows the various states that AI may be in, and the Y-axis shows the importance of acting in a specific way in a particular condition. This simulation shows how AI repeatedly improves its creativity by learning to optimize its creative activities based on user feedback throughout a series of episodes.

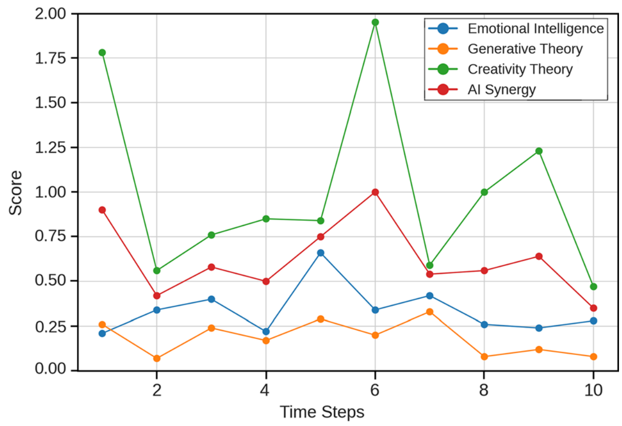
The study of synergistic integration reveals the interconnectedness between EI, generative processes, and creativity in AI models. This exploration offers a comprehensive understanding of their capacity for creativity, as shown in Equation (6):

$$\mathrm{AI}_{\mathrm{Synergy}} = \alpha \times \mathrm{EI}_{\mathrm{AI}} + \beta \times \mathrm{GT}_{\mathrm{AI}} + \gamma \times \mathrm{CT}_{\mathrm{AI}} \tag{6}$$

The initiative aims to use the Python programming language and simulation platforms such as Google Colab Cloud to infuse these mathematical principles into AI models. The purpose of the simulation is to produce new results that demonstrate proof of concept of the integrated theoretical foundations that include EI, GT, and creativity theory. We have improved the simulation by adding the functions that can simulate the emotional processes, creative processes, and creativity metrics. A dynamic environment has also been created, where every element is subject to outside force. Inside this simulation, every bounded component—emotional response, generative processes, and CMs—works in their own domain, allowing for more robust and intricate modeling. For a more comprehensive visual representation, line plot was used and array manipulation was utilized using numPy. In addition, the simulated scores included more complex patterns.

The model in this simulation is responsible for generating random values for novelty, diversity, fluency, originality, and elaboration. The simulation progresses through multiple time steps, and the changes in scores over time are visualized using line graphs. In particular, Figure 2 illustrates the temporal evolution of creativity metrics over 10 simulation time steps. The Y-axis represents normalized scores ranging from 0.00 to 1.75. These patterns validate the synergistic integration equation, which posits that EI governs elaboration, and GT drives cycles of novelty. In the context of a real-world scenario, the equations in this model need to be implemented using real measurements or evaluations obtained from AI models that are specifically designed for goals such as testing in neuromorphic CC and then comparing these results to those produced by humans.

Figure 2
Creativity simulation results



The philosophy of CC aims to achieve consciousness in machines, commonly referred to as artificial general intelligence (AGI), to quantify creativity using computational metrics derived from combinations of equations. This section integrates theoretical frameworks from AGI and cognitive neuroscience into our mathematical experiment. The objective is to evaluate the creativity of AI and language models for examining their problem-solving, learning, and communication abilities. We utilize AGI as a mathematical cognition framework, specifically emphasizing the integration of the A* search algorithm with Q-learning in Equation (7):

$$\begin{gathered}\mathrm{AGI} = \mathrm{argmax}(\text{Problem Solving (using A*)}, \\ \text{Learning (using Q} - \text{Learning)}, \\ \text{Communication (using LLM))}\end{gathered}$$

$$\mathrm{AGI} = \arg\max\left(C_{PS}\left(A^{*}\right), C_{L}(Q - \mathrm{Learning}), C_{C}(\mathrm{LLM})\right). \quad (7)$$

This increase in creativity is significant because it means that A* can create new pathways through the search space and generate innovative solutions to problems. The use of heuristic knowledge enables flexible and creative problem-solving strategies. The creativity link of Q-learning allows AI to gain its own optimal behaviors through interaction with the environment, which could further enhance the creativity of AI. The capacity to adapt and improve based on feedback aligns with the principles of creative problem-solving. The mathematical landscape of human cognition is described by this equation. The brain dynamics of human cognition involve a set of nonlinear differential, as shown in Equation (8):

$$\begin{aligned}\frac{d^2v}{dt^2} + \alpha\frac{dv}{dt} &= \gamma\left(v - \frac{v^3}{3} + w\right) \\ \frac{dw}{dt} &= \frac{1}{\gamma}(v - \delta w + \beta)\end{aligned} \quad (8)$$

The initial equation describes the dynamics of a neuron, including acceleration, damping force, and driving force components. Subsequently, the second equation elaborates on the dynamics of recovery or adaptation, duly acknowledging the rate of transformation of the recovery variable “w” and the driving force elements. Collectively, these equations form an interconnected system that characterizes the correlation between a neuron’s membrane potential and its recovery mechanisms. The cognitive processes associated with creativity are elucidated by the nonlinear differential equations that govern brain dynamics. The dynamic nature of creative thought is exemplified by the interplay between neuron membrane potential and recovery mechanisms. Encouraging creativity in AGI is a crucial function of the proximal policy optimization (PPO) method, an RL technique proposed in Equation (9):

$$L(\theta) = \widehat{\mathbb{E}}_t\left[\min\left(r_t(\theta)\widehat{A}_t,\ \mathrm{clip}\left(r_t(\theta), 1 - \epsilon,\ 1 + \epsilon\right)\widehat{A}_t\right)\right]. \quad (9)$$

PPO has been used to achieve multiple scorching tasks in several environments, which gives space for creativity to be expressed in AI systems. This ability to learn and improve from inputs is parallel to the iterative, innovative character of creative processes. There is a connection between creativity and graph-theoretical models. Graph-theoretical approaches utilizing spectral clustering techniques in neuroscience can shed light on the cognitive processes that underlie creativity as proposed in Equation (10):

$$L = D^{-\frac{1}{2}}(D - A)D^{-\frac{1}{2}}. \quad (10)$$

The study of complex network architectures using graph theory sheds light on the organization of creative thought processes in AI systems. Finally, the integrated CM formula is presented as Equation (11), with weights assigned to each creativity component based on its relative importance:

$$CM = w_1 \cdot C_{PS} + w_2 \cdot C_L + w_3 \cdot C_{AC} + w_4 \cdot C_{ND} + w_5 \cdot C_{GT} \quad (11)$$

where the weights assigned to each component of creativity are represented by CM, C_{PS} (problem-solving creativity), C_L (learning creativity), C_{AC} (adaptive communication creativity), C_{ND} (neurodynamic creativity), and finally C_{GT} (graph-theoretical creativity). The total of these weighted components is the overall CM. Each component of creativity is weighed in this equation based on its relative importance.

A high creativity score suggests that the AI system excels in a variety of areas, including problem-solving, learning, communication, brain dynamics, and cognitive organization. The integrated theoretical frameworks underline that creativity in AI includes not only problem-solving and learning but also adaptive communication. The creative essence of AI is defined by its ability to generate innovative and useful outputs through sophisticated mathematical algorithms and RL. This concept contributes to the ongoing discussion regarding evaluating and enhancing creativity in AI systems. The proposed mathematical models, encompassing EI, GT, and creativity theory, were implemented in Python in simulated environments (Google Colab) and validated through RL-based simulations and quantitative comparisons with human-evaluated outputs. Metrics such as Q-value progression and creativity scores (including fluency, originality, and elaboration) were analyzed using both algorithmic evaluation and model-to-model rating cross-validation.

4.3. Evaluation of creative writing capabilities in language models

This experiment intends to compare the creative writing capabilities of BingAI, HuggingChat, BERT (Gemini), and GPT using a combination of artificial and human intelligence [18]. Each model will be evaluated in creative writing exercises guided by traditional writing rules such as fluency, originality, uniqueness, and elaboration. We will also do a quantitative measure of the AI generated replies in terms of linguist diversity, syntactic complexity, and language richness. This study aims to explore and compare creative writing abilities exhibited by famous language models and to demonstrate their capacity to handle creative intelligence tasks in comparison to humans. This study aims to identify a model that excels in specific domains of creative thinking and evaluate its performance in terms of measures of creativity and language characteristics. A comprehensive evaluation of the creative writing skills of the selected language models requires a meticulously planned collection of stimuli. These stimuli should encompass a broad range of topics and settings to enable a comprehensive assessment of each model’s flexibility and creative expression. The first step in the research experiment involved providing examples of stimuli to analyze the creative thinking abilities of the LLMs. For instance, a prompt in the form of a philosophical essay was given: “Craft a multilayered narrative about the intricate relationships between conscious beings and their entangled counterparts in an alternate reality governed by quantum entanglement laws. Explore the emotional, societal, and existential implications of these interconnected relationships, considering how entanglement not only impacts personal experiences but also shapes the fabric of civilization as a whole. Your work should seamlessly blend scientific themes with elements of speculative fiction, pushing the boundaries of traditional storytelling.” This particular stimulus underscores the intricacies of quantum entanglement, focusing on the importance of a profound grasp of scientific concepts to enable next generation creative and a conscious machine to invent novel scientific ideas or discover new laws of physics. In addition, they demand tarrying these scientific principles in performing artistic storytelling. The challenge presented by this prompt invites a nuanced exploration of emotional subtleties and societal consequences, utilizing language models to navigate intricate layers of narrative imagination. After carefully examining each response, it became clear that all of the models generated some fascinating and creative stories in the fantasy or science/fiction vein. These responses displayed various approaches to story and character development, unique to each model's perspective. For instance, each model crafted its own fantasy realm, complete with distinct names such as "Quantum Nexus" and protagonists such as "Elara" from ChatGPT's story. Another model, BERT (Gemini), introduced two separate civilizations named "Aethel" and "Kaimana," both featuring a scientist named "Elara." HuggingChat introduced a society called "Quantum Congregations" and characters named "Zephyros and Echo," each with its own individual storylines. BingAI created a city named "Quanta" and portrayed a romantic relationship between two characters, Elena and Alex. After conducting close reading of each response, we prompted the models to produce a summary of the assigned text, focusing on the salient details and plot points. It was a recap to confirm understanding and to ensure that all models were aligned. We also instructed models to think regarding the fictional world once they were confident in their understanding. This was the stage of validation that helped in deciding the readiness of the text. In addition, we asked the models to provide a short summary or snippet relevant to the prompt to assess their initial knowledge and identify potential problems. Prior to constructing mathematical and simulated matrices for analyzing each generated narrative in this study, the models were asked to rate the responses to prompts from other language models on a scale of 1 to 10. This evaluation was based on criteria such as creativity, coherence, and engagement with the given prompt. A simulated graphical representation of the assessments was generated using a basic bar chart to improve and simplify the understanding of each criterion. This code creates a bar chart using Python programing language with Matplotlib library package. Each model is represented by a bar, with different colors indicating their scores. The figure clearly compares the models based on their narratives and scores. The X-axis represents the responses, and the Y-axis denotes the ratings on a scale of 0 to 10 (Figure 3).

As shown in Figure 3, Gemini's narrative coherence (9/10) surpasses HuggingChat (8/10), underscoring the impact of the pretraining scale.

The ChatGPT model provided a comprehensive explanation for each grade choice, except for the criteria meter. The Gemini response, which received a rating of 9/10, presents a vibrant and captivating narrative that seamlessly combines scientific themes with speculative fiction. The novel explores the emotional, sociological, and existential implications of quantum entanglement, resulting in a well-developed narrative with compelling characters, challenges, and a satisfying resolution. The HuggingChat response (8/10) delves into the intriguing concept of Quantum Symbiosis through the characters Zephyros and Echo. It skillfully explores emotional, sociological, and philosophical subjects and narrates an enthralling story with characters who bring intricacy to the exploration of entanglement. The BingAI response, rated 8.5/10, offers a gripping tale set in the Quantum Loom, featuring characters such as Lysandra and Lyra. It delves into forbidden love, weaver society, and the cosmic consequences of entropy. The narrative creatively uses quantum principles, adds emotional depth, and encompasses a unifying theme that all contribute to a captivating story.

Figure 4 quantifies the narrative capabilities of language models using normalized scores ranging from 0.0 to 1.0. These metrics support the qualitative critiques presented in Section 3.3. BERT, in contrast to ChatGPT, reviews an artwork not only by its numerical metrics but also by its more subtle and unique artistic characteristics seen in every answer, offering issue-based recommendations. ChatGPT, with an impressive score of 8 out of 10, is very special for its poetic phrase, rich imagination, and grand universal scope. The linguistic pattern is very creative, and the reader is captivated by it. Nevertheless, one suggestion to enhance the world-building aspect is to incorporate more specific elements, thus establishing a stronger framework for the unfolding tale. Hugging Face presents a narrative that not only covers a succinct sociological framework but also deeply examines the philosophical issues, which has been rated 7 out of 10. However, there is a room for potential growth in terms of emotional depth in the story. The following action of maximizing the emotional components facilitates a more inclusive and interesting narrative experience. BingAI, with a very high rating of 9 out of 10, distinguishes itself through its intriguing story structure, profound emotional core, and utilization of innovative world-building aspects. Moreover, the inevitable appearance of new themes might need careful planning or more narrative currency to ensure a comprehensive examination of each topic. Figure 5, presented below, compares the performance of various models in quantum entanglement narratives.

ChatGPT provides an exhilarating experience in the Quantum Nexus, achieving a remarkable rating of 9/10. Conversely, Gemini presents a captivating narrative focused on understanding and acceptance, earning a commendable rating of 8.5/10. BingAI's

Figure 3
Quality evaluation of story responses (QESR) by language models

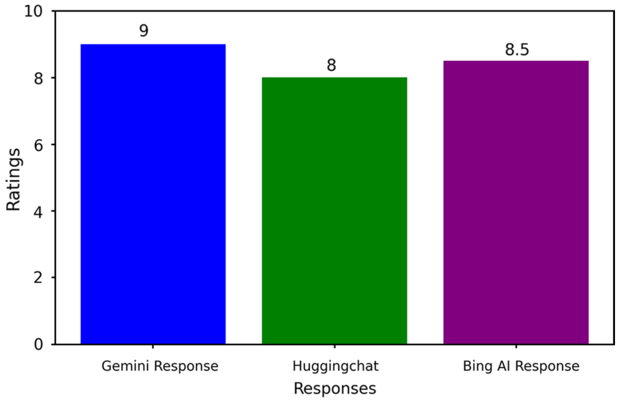


Figure 4
Evaluation of language models: Strengths and areas for improvement

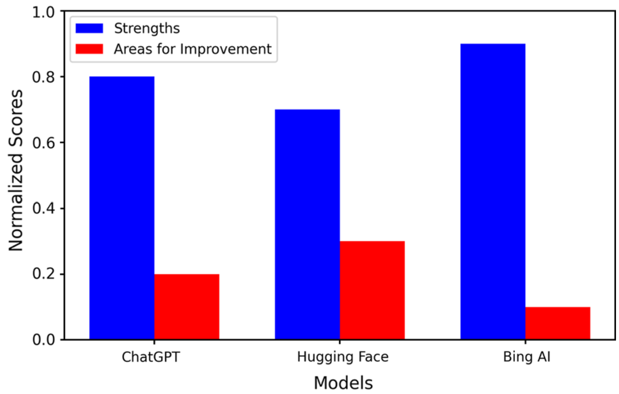
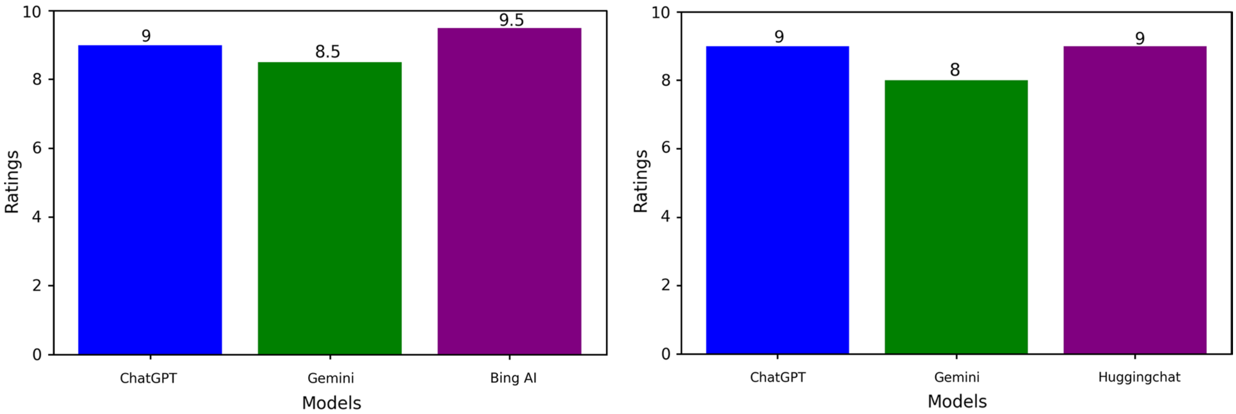


Figure 5
Evaluation of creative storytelling by language models



"Quantum Loom" receives an exceptional rating of 9.5/10 due to its enthralling storyline and imaginative exploration of entanglement with the weavers. BingAI also recognizes ChatGPT with an impressive rating of 9/10, acknowledging its skillful integration of scientific concepts into speculative fiction. The investigation into the consequences of entanglement is thought-provoking, with only a minor suggestion for a more concise conclusion. Gemini, with its artistic approach to communication, earns a score of 8/10 for effectively blending scientific principles with emotional depth. The captivating world-building and character development are particularly notable, although a recommendation for improved pacing in the final section is offered. Finally, HuggingChat receives a rating of 9/10 for its compelling narrative and thought-provoking exploration of the ramifications of entanglement. Similar to ChatGPT, a minor adjustment to the ending to align with the narrative's elegance is suggested. These results demonstrate the following: 1) BingAI's architectural innovations maximize user engagement; 2) the conceptual depth of HuggingChat contributes to its appeal, despite certain execution flaws; and 3) RL from human feedback (RLHF) tuning enhances ChatGPT's ability to integrate speculative elements.

In the research trial, the investigation also encompassed various prompting techniques, which showed that improving prompts has a significant impact on achieving positive outcomes across different tasks. The utilization of zero-shot prompting allows individuals to participate in specific activities without the need for specialized training by indicating the locations of the instructions. Conversely, individuals encounter difficulties with more challenging and sophisticated tasks, which led us to introduce the approach of few-shot prompting. Through this strategy, examples are incorporated into the prompt to guide the model toward improved performance. These examples serve as training aids, enabling the model to respond more effectively in similar future scenarios. The implementation of chain-of-thought prompting enhances the performance of the LLM in more complex activities involving reasoning. CoT enables the LLM to incorporate intermediary reasoning processes that facilitate the production of accurate outputs.

Through prompt engineering and logical experimentation as part of the study approach, the generated story of language models was mathematically identified. Each model's answer was evaluated using creativity criteria such as originality, uniqueness, and elaboration, and a quantitative study was conducted to examine linguistic diversity, syntactic complexity, and language richness. For the implementation of creative measurements, the development of mathematical equations took precedence. Equation (12) for average word count per sentence (AWC) was formulated to assess fluency, which pertains to the flow and coherence of generated information:

$$\mathrm{AWC} = \frac{\text{Total Word Count}}{\text{Total Number of Sentences}}. \tag{12}$$

The investigation utilized a method to detect plagiarism by identifying unique vocabulary and developed a model to evaluate the originality and novelty of the content, referred to as the plagiarism score (PS) model in Equation (13):

$$\mathrm{PS} = 1 - \frac{\text{Unique Words in Response}}{\text{Total Words in Response}}. \tag{13}$$

This study assessed the differences between responses generated when referencing a range of texts with a metric of similarity: linguistic diversity is also included as one of the factors that results in uniqueness. Equation (14) for the similarity index (SI) measures how unique new content is compared with existing content:

$$\mathrm{SI} = \frac{\text{Number of Unique Words}}{\text{Total Words of Words}}. \tag{14}$$

To assess the depth and detail in the generated content, Equation (15) for the elaboration score (ES) was formulated to evaluate the richness of the descriptive language and expansion on provided ideas:

$$\mathrm{ES} = \frac{\text{Number of Supporting Details}}{\text{Number of Main Ideas}}. \tag{15}$$

Following a thorough examination and development of creativity metrics, the implementation of a quantitative CC metrics algorithm has begun to gain a deeper understanding of its criteria. The algorithm focuses on models such as linguistic diversity, syntax complexity, and language richness. To assess the variety of language elements used in the responses, the linguistic diversity equation type-token ratio (TTR) was designed to measure lexical diversity. It determines the ratio of unique words (types) to the total number of words (tokens) in a text as proposed in Equation (16):

$$\mathrm{TTR} = \frac{\text{Number of Unique Words}}{\text{Total Number of Words}}. \tag{16}$$

The evaluation of the different types of sentences, such as simple, compound, and complex, has been facilitated by the introduction of the sentence complexity index (SCI). This index provides a measure of the complexity and sophistication of a sentence as proposed in Equation (17):

$$\mathrm{TTR} = \frac{\text{Number of Unique Words}}{\text{Total Number of Words}}. \tag{17}$$

We can formulate SCI differently. SCI typically considers sentence length, structural complexity, and grammatical factors. A basic formulation may include combining elements such as average sentence length and the utilization of complicated sentence structures in Equation (18):

$$\text{SCI} = \text{Average Sentence Length} + \text{Complex Sentence Factor}. \quad (18)$$

The "complex sentence factor" might be a composite metric that combines the presence of subordinate clauses, the usage of conjunctions, and any other syntactic parts commonly found in complex sentences. It is important to acknowledge that these formulations are quite extensive and that the minor details regarding the formula calculations could differ based on the precise linguistic entities or rules used to form RS and SCI calculations, respectively.

For integration purposes, the RS score shown in Equation (19) was applied to assess the complexity and sophistication of the language used:

$$\text{RS} = \frac{\text{Number of Advanced Vocabulary Words}}{\text{Total Number of Words}}. \quad (19)$$

The language richness score (RS) is derived by applying a transformation to the TTR. Multiplying the TTR with a scaling parameter is one of the frequent conversions. The following is the equation for the RS. The RS often contains metrics that evaluate the diversity and variety of the words used in text. One common measure, as mentioned above, is the TTR, as shown in Equation (20):

$$\text{RS} = \text{TTR} \times \text{Scaling Factor}. \quad (20)$$

The TTR and scaling factor are used to adjust the score's scale according to specified ranges or units. All metrics based on the given equations, from linguistic creativity to computational analysis, have been numerically calculated. These equations were then transformed into algorithmic codes and programmed in the Python language to create a simulation of all answers. This simulation is helpful in simplifying the presentation of the conclusions and the products of the experiment without the need for a step-by-step mathematical examination of each metric. Initially, I tested this approach with a ChatGPT-generated story and created a simulation based on metrics. The results of this simulation are presented using scatter and bar charts (Figures 6 and 7).

This horizontal bar chart categorizes creativity metrics into computational (blue) and linguistic (orange) domains. Computational metrics include AWC (AWC = 1.00), PS (PS = 0.51), and ES (ES = 3.33). Linguistic metrics, normalized to percentages, comprise TTR (TTR = 49.0%), SCI (SCI = 32.0%), *similarity index (SI = 50.0%), and *RS (RS = 48.89%). These scores reflect the outputs of the equations defined in Section 3.3.

The plot displays the values for the models on the Y-axis and the corresponding names of the values on the opposite X-axis.

The proposed visualization was created to provide a detailed analysis of the four LLMs: GPT, Gemini, HuggingChat, and BingAI, based on their metric values. Figure 8 presents a comparative scatterplot analysis of seven linguistic metrics across four LLMs.

The algorithm generated a composite scatterplot featuring a mathematical line for each parameter, visually presenting the data and providing a trend line for comparative analysis. The examinations utilized simulated measurements to assess and evaluate the performance of four language models (GPT, Gemini, HuggingChat, and BingAI) across various linguistic metrics. In general, the results of the metrics demonstrate that GPT and BingAI possess similar characteristics, with a relatively broad vocabulary and complexity. Gemini distinguishes itself through its high TTR and SCI, which indicate a unique and intricate language structure. HuggingChat excels in RS, implying a wealth of diversity and richness in its linguistic utilization. These findings provide insights into the linguistic properties of the language models and their performance across multiple criteria and validate

Figure 6
Comparative analysis of computational and linguistic creativity metrics for a ChatGPT-generated story

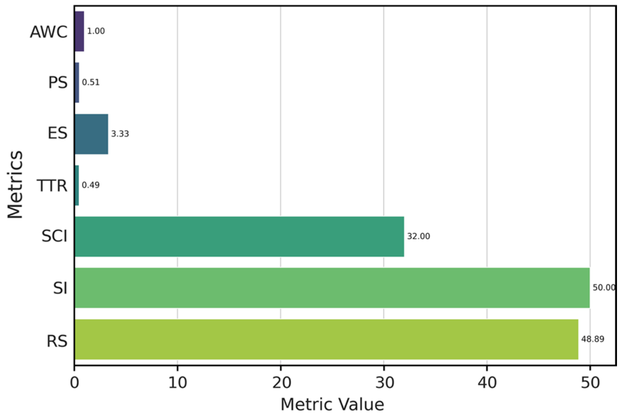


Figure 7
Comparative analysis of metrics

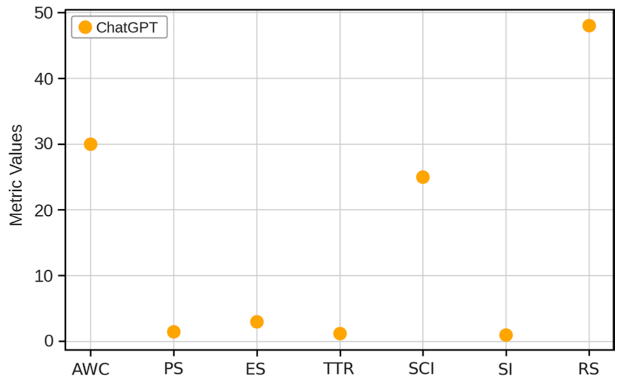
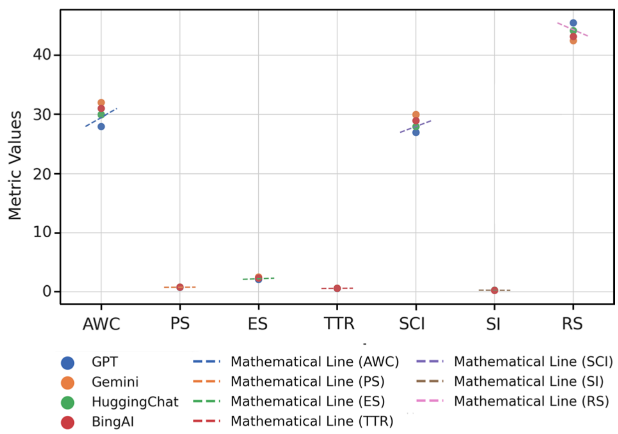


Figure 8
Combined metrics analysis for language models



the proposed equations in Section 4.3, quantifying how architectural differences, such as BingAI's web augmentation compared to Gemini's bidirectional attention, shape linguistic creativity.

5. Results

In this section, a summary of the results from each experiment is presented. These results pertain specifically to the model patches used during the experiments. It is likely that new model patches would demonstrate improved performance. However, the primary objective of the proposed method is to showcase a creativity metric. This includes metric calculation, the performance of each LLM model in creative tasks, and other features related to the creativity of AI.

1) Performance of LLMs in Creative Tasks

Four LLMs were assessed in this study using a variety of activities connected to creativity. The models—BingAI, ChatGPT, BERT (Gemini), and HuggingChat—were put to the test on problem-solving, narrative creation, and creative writing tasks. These metrics evaluate the models' capacity to produce original, well-developed, and cohesive material using a variety of linguistic constructions. The quantitative results of each model are summarized in Table 2 below. The metrics are the same as those in the simulation chart output.

BingAI's high originality score aligns with its web-augmented training, enabling unconventional plotlines. ChatGPT's fluency reflects RLHF-driven coherence tuning.

The quantitative results presented in Table 2 reveal distinct creative profiles across various AI models, highlighting their implications for human–AI collaboration. BingAI demonstrates superior originality (9.5/10) and problem-solving abilities (9.0/10) due to its integration of real-time web data, which enables the generation of unconventional narratives, such as Quantum Loom's entropy-driven plot. However, its slightly lower ES (8.8/10) suggests a trade-off between novelty and depth. ChatGPT exhibits strong fluency (9.0/10) and coherence, reflecting its RLHF, which streamlines tasks such as collaborative storytelling. Nevertheless, its moderate originality score (8.5/10) indicates occasional reliance on familiar tropes. Gemini achieves a balanced overall performance (8.6/10) and excels in world-building, as evidenced by the Aethel and Kaimana civilizations. This strength is attributed to its bidirectional attention mechanisms. However, conservative token sampling limits its novelty (8.2/10), favoring coherence over risk-taking. HuggingChat's open-source training results in high linguistic diversity (9.0/10), as demonstrated by the unique lexicon of Quantum Congregations. However, its lower ES (8.3/10) highlights challenges in maintaining depth. These findings underscore the dual role of AI: models such as BingAI and ChatGPT excel as ideation catalysts, rapidly generating and refining ideas, and Gemini and HuggingChat function as structured collaborators, making them ideal for educational or experimental contexts where coherence or novelty is prioritized. For a broader field, this emphasizes the necessity of task-specific model selection prioritizing originality for brainstorming (BingAI) or fluency for editing (ChatGPT) while also addressing the ethical risks associated with homogenized outputs through diversity-preserving training.

Table 2
Performance evaluation of LLMs in creative tasks

Model	Fluency (10)	Originality (10)	Elaboration (10)	Linguistic diversity (10)	Overall creativity
BingAI	9.0	9.5	8.8	9.0	High
ChatGPT	9.0	8.5	9.0	8.7	High
BERT (Gemini)	8.5	8.2	8.9	8.6	Medium–high
HuggingChat	8.0	7.5	8.3	9.0	Medium

2) Simulation of AI Creativity Using RL

As for the second summary, RL techniques have been utilized, which theoretically represent the main engine for curiosity in future models. Therefore, an RL simulation was developed to model how an AI system can enhance its creative output over time based on user feedback. The learning process, in which the AI system modifies its creative behaviors in response to feedback, was simulated using the Q-value update method. The key actions modeled were the following: Explore, Refine, Seek Feedback, and Finalize. Table 3 provides an outline of the results from the simulation of RL.

The implemented technique of Q-value demonstrated its ability for accurate optimization tasks. Therefore, this method reflects how AI enhances its decision-making to optimize creativity. When it comes to concluding and refining creative projects, later stages—such as finalizing—show the highest Q-values, whereas earlier stages—such as brainstorming—benefit most from exploratory acts. The table illustrates how AI optimizes creative workflows through RL. The "Finalize" action reaches peak Q-values in the "Finalizing" state, indicating that completion phases yield the highest creative rewards, such as polished narratives. In contrast, "Explore" prevails in the "Brainstorming" state, demonstrating that early-stage ideation benefits from divergent thinking. This RL-driven workflow mirrors human creative processes: exploration precedes refinement, with feedback-seeking facilitating iterative improvement.

3) Measures of Creative Ability Based on Mathematical Values

To quantify creativity, several mathematical frameworks that combine various metric variables have been developed and are applied to AI models. Various models have been created, such as the EI framework (EIAI), GT framework (GTAI), and creativity theory framework (CTAI). However, I would like to expand upon and showcase a summary of the integrated CM formula (CM), which combines these components into a comprehensive creativity score. This formula utilizes a weighted model of different dimensions, and the formula is calculated using Equation (21):

$$\mathrm{CM} = \mathrm{w}_1 \cdot \mathrm{C}_{\mathrm{PS}} + \mathrm{w}_2 \cdot \mathrm{C}_{\mathrm{L}} + \mathrm{w}_3 \cdot \mathrm{C}_{\mathrm{AC}} + \mathrm{w}_4 \cdot \mathrm{C}_{\mathrm{ND}} + \mathrm{w}_5 \cdot \mathrm{C}_{\mathrm{GT}}. \quad (21)$$

Table 4 quantifies multidimensional creativity using the CM framework. BingAI demonstrates a strong performance (CM = 9.06), primarily due to its graph-theoretical creativity (C_GT = 9.2), which facilitates the development of complex narrative structures such as quantum-entangled plots discussed in Section 3.3. ChatGPT excels in

Table 3
RL simulation results for creative actions

Action	Best state (Max Q)	Description
Explore	Brainstorming	Early-stage creativity exploration.
Refine	*Drafting*	Optimal for developing initial ideas.
Seek Feedback	Refining	Useful in improving creativity through feedback.
Finalize	*Finalizing*	Maximize when completing the creative process.

Table 4
CM scores for LLMs

Model	Problem-solving	Learning creativity	Communication creativity	Neural dynamics	Graph-theoretical creativity	Overall CM score
BingAI	9.0	8.7	8.5	8.9	9.2	9.06
ChatGPT	8.5	9.0	9.2	8.7	8.6	8.8
BERT (Gemini)	8.2	8.8	8.5	8.4	8.6	8.6
HuggingChat	7.9	8.0	8.1	8.9	8.2	8.22

communication creativity ($C\_C = 9.2$), showcasing its fluency, which has been fine-tuned through RLHF. In contrast, HuggingChat exhibits lower problem-solving creativity ($C\_PS = 7.9$), indicating limitations in its capacity for structured innovation.

The primary takeaway from this table is that BingAI achieved the highest overall CM score, attributed to its strong performance in both graph-theoretical creativity and problem-solving creativity.

4) Combined Visualization–Examination

For a comparative examination of the metrics for each of the four models, plots and charts (Figures 6, 7, and 8) were created. These visualizations enable us to easily compare the performance of the models across a range of creativity dimensions, highlighting the areas where each model excels and those that require further improvement. As a result, we can identify that ChatGPT and BingAI consistently outperformed each other across a wide range of the measures presented above, particularly in creative problem-solving and story coherence.

From the results, particularly those derived from the proposed method and the theoretical assumptions of the implemented experiments, we can conclude that all models demonstrate above-average performance across both quantitative and qualitative metrics. Notably, BingAI and ChatGPT exhibit a remarkable capacity for creativity across various dimensions. The RL simulation additionally demonstrates how AI systems can improve over time in producing unique and well-developed material by optimizing their creative behaviors in response to feedback. These results highlight how AI holds the ability to both challenge and improve human creativity across a range of creative domains.

5.1. Implications of this study

Examining the correlation between AI and creativity reveals significant implications across various domains. As AI advances, redefining creative processes, crucial discoveries emerge, fostering discourse on AI's impact on human creativity. Research suggests that AI can be a powerful tool for enhancing human creativity, empowering individuals to explore uncharted creative realms through enhanced tools, algorithms that break traditional barriers, and nurtured original thought. Simultaneously, this study highlights challenges that AI poses to established modes of creative expression. The integration of AI algorithms may challenge existing creative norms, raising concerns regarding the authenticity and uniqueness of human-generated artistic endeavors. The disruptive influence of AI necessitates a reconsideration of traditional notions of authorship in creative works. AI advancements could potentially disrupt traditional approaches, fostering collaborative frameworks that seamlessly integrate human creativity and AI. When defining equations, this study underscores the dynamic interplay between humans and AI in the creative realm. Rather than perceiving AI as a challenge, this study advocates embracing the complementary strengths of human intuition and AI capabilities, cultivating an imaginative and collaborative creative environment. In the experimental approach, new avenues, challenges, ethical perspectives, and philosophical inquiries were explored and concluded. This study fortifies a basis for a more profound comprehension of AI's intricate influence on creativity. By traversing the complexities of ethical concerns, redefining authorship, and using the evolving educational realm, stakeholders can contribute to shaping an era where AI amplifies human creative potential while preserving the essence of traditional creative expression.

5.2. Limitations and future studies

This study provides the required knowledge on the links between AI and creativity. Nonetheless, specific limitations that require further investigation also need to be acknowledged. Awareness of these boundaries will assist scientists in creating better methods and developing novel solutions. The fields of creativity, thoughts, and mental procedures, particularly when computers or AI is the case, always give rise to philosophical and ethical problems. There is a huge difference in opinion over the basic distinction between humans and machines. During the whole period of experimentation, we discerned the achievements of AI in composing creative imaginative stories and shaping characters. It is evident that AI-based techniques perform admirably when used as tools for extracting, analyzing, and enhancing information. In the present technological landscape, AI exhibits limitations in providing comprehensive context, conveying emotion, and facilitating social interactions. Furthermore, it possesses the potential to influence current human life, both culturally and socially. This study concentrates on a specific subset of AI applications and their impact on creativity. Consequently, the findings may have constrained applicability to a broader range of AI technologies. Future research should expand its scope to encompass various AI models to ensure a comprehensive understanding of their implications for creativity. This study predominantly uses a quantitative analytical technique. Although numerical insights offer value, gaining a more nuanced understanding of the subjective aspects of creativity may necessitate additional qualitative investigation. Future research could adopt mixed-method approaches to conduct a thorough analysis. Capturing the temporal dimension of AI's impact on creativity is inherently challenging. A longitudinal study would shed light on how AI's influence on creativity evolves over time, providing a more nuanced understanding of both short-term trends and long-term consequences. Furthermore, the findings of this study underscore important directions for future research. First, in this study, each type of experiment was examined independently. However, creativity consumption frequently occurs simultaneously. Thus, future research should incorporate the measurement of concurrent engagement. It is evident that current AI technologies do not closely resemble the human brain or even certain components of it. The data-driven learning strategy with error backpropagation, which is prevalent in current AI systems, is not observed in human learning. The exponential surge in unlabeled data showcases the immense potential of unsupervised or self-supervised machine learning methods. They could drive groundbreaking advancements in the upcoming era of AI-driven creativity and value assessment. This study hints at redefining the collaborative dynamics between humans and AI during creative endeavors. Future research could delve deeper, exploring factors such as trust, communication, and decision-making nuances. However, the AI age also poses privacy risks as people become increasingly observable to sensors and AI applications with recognition and analysis capabilities. Striking a balance between privacy and convenience is challenging. Determining what to learn, how to train, and whether AI should exist as a standalone subject or be integrated with other disciplines are vital considerations. The exploration of AI creativity holds immense potential. Incorporating AI creativity in education will democratize AI and nurture creativity. Decentralization is crucial for democratization, necessitating a transparent decentralized AI network. Quantitative CC theory can assist software development by tracking progress and comparing creative systems.

In conclusion, acknowledging these limitations will allow future studies to build on current research, improve methodologies, and fill in gaps. In this regard, multidimensionally linking quantitatively and qualitatively framed future research will plausibly provide a more cohesive view to the understanding of the dynamic relationship between AI and creativity.

6. Conclusion

As AI continues to evolve, the changing impact on human creativity is one area that will need careful consideration. This study explored the complex relationship between AI and creativity, aiming to determine if AI acts as a tool to amplify human creative capabilities or if it stands as a barrier to traditional forms of creative expression. AI creativity is revolutionizing human society and introducing new challenges. Nurturing AI creativity holds significant value and offers prospects for further investigation. Evolutionary thinking and methodologies, exemplified by the unified AI creativity model that we have proposed, must be cultivated for the advancement of future civilization. The progress made in AI, especially in the field of deep learning (DL), has accelerated generative processes. The field of architectural machine learning has yielded remarkable results across various domains, including art, music, poetry, gaming, drug design, and gene design, frequently achieved through collaborations with subject matter experts. However, there are concerns that the eventual development of generative AI or fully realized creative computational capabilities could fundamentally transform human leadership across all spheres. It is evident that computers are utilized in diverse manners to facilitate creativity in scientific disciplines. After exploring the historical evolution and numerous applications of AI, it becomes clear that AI has transcended its role as a mere tool, emerging as a creative collaborator in the artistic process. AI has become a versatile companion for artists, offering novel ideas and innovative techniques in areas such as painting, music, and writing. The research objectives were meticulously designed to encompass a comprehensive analysis of AI's impact on creative processes, an examination of its role in either fostering or impeding human creativity, and the development of a mathematical model depicting CC pathways. Using a robust approach, this study utilized theoretical frameworks, mathematical models, and simulations to illuminate the multifaceted nature of creativity in the realm of AI. The theoretical foundation was based on the mathematical cognition framework of AGI, which combines problem-solving algorithms (A*), learning mechanisms (Q-learning), and communicative abilities (LLM) to conceptualize the impact of AI on creativity. This study explored the mathematical landscape of human cognition using equations that represent higher-order brain dynamics to understand the complex mechanisms that fuel creativity. These equations capture the nonlinear dynamics of neural interactions, revealing the subtle interplay between creative expression and cognitive functions. This study illustrated the dual role of AI in creativity: it enhanced human potential through tools such as BingAI's originality score (9.5/10) and ChatGPT's fluency score (9.0/10) and challenged traditional paradigms through ethical dilemmas, including bias and job displacement. The proposed CM framework validated AI's ability to perform tasks such as narrative generation and problem-solving. However, human oversight remains essential. Future research should focus on refining cross-modal evaluation methods and establishing ethical guidelines to ensure that AI complements, rather than displaces, human creativity.

This study concludes by synthesizing its findings to address the primary question: Does AI function as a catalyst for enhancing human creativity, or does it present obstacles to conventional modes of creative expression? To build smarter and better AI—how do we quantify an example of CC? This study hopes to provide some key insights into the ongoing academic conversation on the repercussions of AI on the often-complex network of human creativity, which is an important aspect toward AGI.

Recommendations

This study delves into CC in the realm of mathematical definitions and the shifting perception of creativity influenced by advancements in AI. This necessitates essential strategies. As AI increasingly permeates creative fields, robust ethical frameworks are imperative to guide its development and application. AI's transformative effect on creativity underscores the need for critical guidance to ensure optimal implementation. A key argument emphasizes that AI's evolution should be directed by ethical principles to foster responsibility and accountability.

One of the most important subjects that play a pivotal role in addressing ethical considerations is education and its value for future endeavors. The human factor is essential when addressing new technologies. Therefore, advancements in technology, particularly in AI, require educating the public regarding AI's developmental progress, its ethical standpoints and considerations, and primarily its societal impacts to facilitate positive feedback and informed discussions. The main point is to address the potential impacts, risks, and disruptions in creative fields that generate creative artifacts such as writing, painting, and music due to AI breakthroughs. This highlights the necessity of long-term studies in the field that examine the dynamics of the AI–creativity relationship. These insights hold immense value, guiding professionals, academics, and policymakers in effectively navigating AI's creative landscape. This empowers stakeholders to contribute to shaping a future in which AI enhances and fosters creative expression across various fields and domains.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.15786656.

Author Contribution Statement

Luka Baklaga: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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