The Art of Positivity in Drawing: Unveiling the Impact of Positive Mood States on Visual Creativity via Deep Learning

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Abstract

This study integrates visual creative tasks with artificial intelligence techniques to study the flexibility pathway proposed by the dual pathway to creativity model. According to this model, positive activating moods enhance originality—the uncommonness of ideas, solutions, or products—by increasing cognitive flexibility, which facilitates the switching between thoughts and supports the exploration and connection of diverse ideas. Diverging from the predominance of verbal tasks, this study employs the Incomplete Shape Drawing task to track both the dynamics of the creative process indicative of cognitive flexibility and the originality of the final completed drawings. Using validated film clips for mood induction, I randomly assigned 90 participants to one of three groups: *High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control*. Participants then completed three rounds of the Incomplete Shape Drawing Task (with qualitatively distinct stimuli), each followed by a section to provide a written narrative on their thought process. Flexibility was assessed through two modalities: (1) stroke-level drawing behavior using the Compositional Stroke Embedding model to compute entropy and Bhattacharyya distance; and (2) semantic-level flexibility using Divergent Semantic Integration to quantify the integration of conceptually distant ideas in participants' narratives. Originality was evaluated using AuDrA, a deep learning model trained on human originality ratings from the same task. The results indicated that while mood induction effectively altered participants' self-reported arousal and valence, no significant differences in flexibility or originality were observed across mood conditions. However, correlational and multilevel regression analyses suggested two distinct modes of flexibility: persistent exploratory breadth and adaptive switching. Crucially, only adaptive switching flexibility measures significantly predicted originality. Together, these results raised caveats on transient mood manipulations in creativity research, while illuminating the value of process-level, adaptive flexibility as a core mechanism underlying originality. Moreover, it demonstrates the utility of integrating drawing-based tasks with artificial intelligence to capture the dynamic, cross-modal mechanisms underpinning original thoughts.

Introduction

"There is no doubt that creativity is the most important human resource of all. Without creativity, there would be no progress, and we would be forever repeating the same patterns."

– Edward De Bono

Among the multiple strands of research exploring the content of cognition and the cognition processes that make humans unique, creativity stands out as a fascinating human capacity to formulate novel ideas, methods, and solutions (Hennessey and Amabile, 2010). While creativity can manifest as "big C" creativity, involving major breakthroughs that propel our civilization forward, it can also appear as "little c" creativity, which helps solve myriad of everyday problems through routine creative acts (Nijstad et al., 2010; Richards, 2007). Following Guilford's famous presidential address to the American Psychological Association where he pinpointed the lack of research on creativity in 1950 (De Alencar et al., 2021; Gaut, 2010), the field of creativity has witnessed burgeoning development leading to the influential *standard* definition of creativity: "creativity is usually defined as the generation of ideas, insights, or problem solutions that are new and meant to be useful" (De Dreu et al., 2008, p. 739). However, this standard definition does not overshadow the multiple dimensions of creativity, nor does it confine creativity studies to a homogeneous set of theories explaining the nature and process of creativity. Instead, creativity is increasingly recognized as a multidimensional construct that incorporates various facets, including *cognitive*, *personal*, *developmental*, and *social* factors (Kaufman and Sternberg, 2010; Plucker et al., 2004; Simonton, 2000). Notably, theories of cognitive psychology illuminate that creativity is not merely an isolated trait of exceptionally gifted people, but rather a fundamental cognitive ability inherent in all individuals, characterized by complex cognitive processes such as the generation of novel ideas, the recombination of existing information, and the redefinition of problems from new perspectives (Finke et al., 1996; Ward et al., 1997).

An essential component of these cognitive processes is the influence of mood. As diffuse affective states that are not targeted at any particular object (Desmet, 2008), mood pervades our entire framework of meaning and shapes our perception of the possibilities that the world offers (Ratcliffe, 2013). Unlike emotions, which are acute and directed responses, moods are diffuse and enduring affective states that subtly color our psychological landscape (Lischetzke and Könen, 2022). Importantly, mood significantly affects cognition by influencing what we think and the efficiency of our cognitive processes, which is supported by overlapping neural networks between mood and cognition, as identified in functional neuroanatomy studies (Chepenik et al., 2007;Dolcos et al., 2011; Storbeck and Clore, 2007). These studies reveal that both cortical and subcortical brain regions are involved, suggesting a deeply integrated system where mood can influence various cognitive functions, including perception, attention, and memory. Evidence from both functional neuroimaging and behavioral studies underscores that the substrates of cognition are not only shared with but also significantly influenced by mood states. This includes direct effects observed in studies involving individuals with psychiatric disorders and experimental studies in which mood states are induced in healthy participants to assess cognitive impacts (e.g., Cabeza and Nyberg, 2000; Iosifescu, 2012; Phan et al., 2004). These findings collectively suggest a powerful interplay between mood and cognition that can either facilitate or hinder cognitive processes depending on the nature of mood involved.

The broaden-and-build theory proposed by Fredrickson (2001) complements this understanding by suggesting that positive emotions specifically *broaden* an individual's thought-action repertoire, including an expanded locus of attention and increased focus on the big picture of the situation. Relating it back to creativity, which involves similar components of allocating attention resources and adjusting processing styles, the broadened cognitive scope could reasonably enable individuals to form more novel combinations and see connections between disparate ideas. This cognitive flexibility is essential for creative thinking, as it allows for more complex, abstract, and innovative thinking processes (Isen et al., 1987). Meanwhile, it is also worth considering whether different *activation* levels of positive mood states unequivocally facilitate creative thinking. Together, this leads us to the pivotal question: How would positive moods influence creativity? This inquiry not only probes the capacity (and perhaps boundary conditions) of positive mood states to enhance creative output, but also explores the mechanisms through which mood may dynamically interact with the cognitive processes essential for creative thinking.

To answer this question, this study refers to the dual pathway to creativity model (De Dreu et al., 2008), which proposes that creativity can arise through two distinct cognitive processes: cognitive flexibility, characterized by broad associative thinking and switching between ideas, and cognitive persistence, involving sustained, effortful focus within a narrow conceptual space. Specifically, it integrates the Incomplete Shape Drawing Task—a visual creativity task where participants complete abstract, open-ended shapes to form novel drawings—with state-of-the-art deep learning and natural language processing (NLP) techniques to quantitatively assess the flexibility and originality aspects of creativity, enabling the empirical falsification of the flexibility pathway in the dual pathway to creativity model.

Literature Review

The Psychology of Moods

Psychologists often consider state-level mood experiences to be multidimensional. Notably, Yik et al. (1999) successfully integrated four two-dimensional mood models (each based on the bipolar dimensions of *pleasant-unpleasant* and *activated-deactivated*) into a unified framework, demonstrating substantial overlap among these models when controlling for measurement errors. This two-dimensional model, visually illustrated by Feldman (1995)'s circumplex model of mood adapted from Russell (1980)'s model[1] (see Figure 1), has since been widely adopted in empirical research to explore the unique and joint effects of valence and activation. For example, Balch et al. (1999) examined how these mood dimensions influence word recall under different mood conditions, and Nealis et al. (2016) studied the role of affective valence and activation in replenishing self-control resources within an ego-depletion framework. Further challenging the traditional view of activation and valence as independent, the concept of *core affect* integrates these dimensions, underscoring how activation levels can influence perceived pleasantness or unpleasantness of stimuli (Petrolini and Viola, 2020; Russell and Barrett, 1999).

A unified mood classification framework has advanced the understanding of the cognitive and behavioral consequences of mood states (Lischetzke and Könen, 2022). For instance, research on mood congruency illustrates how pleasant moods tend to bias actions towards positive content, while unpleasant moods do the opposite, influencing mood regulation strategies as described in Larsen (2000)'s control theory model. Furthermore, mood affects both the content and the process of cognition (Forgas, 2017). Positive moods improve the recall of positive information and

[1]Note: here *arousal* can be considered as a similar construct as *activation*.

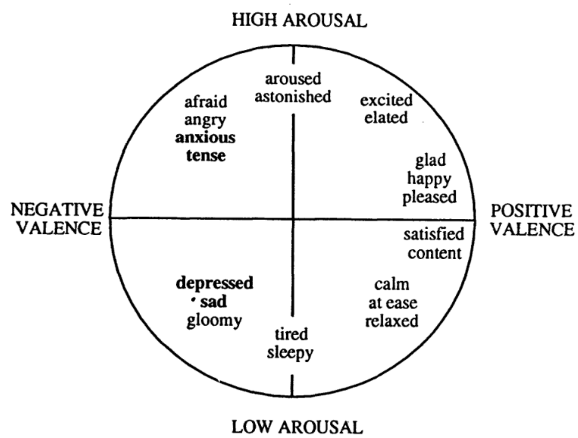

Figure 1: Valence/Arousal Circumplex Model of Mood (Feldman, 1995)

broaden attention spans, facilitating creative and broad-concept learning. In contrast, negative moods promote detailed-oriented thinking, enhancing recall of negative information and learning that requires meticulous attention. Positive moods also lead to more generous social judgments, affecting interpersonal evaluations and interactions (Forgas, 1995). This body of research illustrates how mood influences cognitive processes, including memory, attention, learning, and social judgments, emphasizing the dynamic interplay between mood and cognitive function.

Demystifying creativity

Psychological and cognitive theories on creativity have shifted from mystical views of creativity to scientific explorations based on observable and measurable cognitive functions (Finke et al., 1996). An important milestone is the growing appreciation that, while creativity is often seen as a trait belonging only to exceptionally gifted individuals, it actually forms a fundamental aspect of human cognitive abilities, demonstrated by our versatile application of language, ability to form and apply new mental categories to organize our experiences, and skill in mentally handling objects (Ward et al., 1999). This evolution is supported by theoretical and empirical advancements that elucidate specific cognitive processes that lead to creative insights (Finke et al., 1996).

Amid this background, the field has witnessed the evolution of theoretical accounts to illuminate the cognitive systems that underlie creative thinking (Johnson et al., 2022). One enduring theory is Mednick (1962)'s associative theory, which suggests that creativity stems from the ability to form associations between disparate concepts in memory, where more creative individuals form equally strong connections between common and uncommon concepts, enabling novel associations. Advancements in cognitive neuroscience have further refined this view, with Dietrich (2004) emphasizing that creativity relies on cognitive abilities such as attention, working memory, and cognitive flexibility, pinpointing specific brain circuits that underlie various creative processes. These insights have helped distinguish between deliberate and spontaneous modes of creativity, showing how these modes affect neural activity related to cognitive and emotional functions.

Building on these insights, the Creative Cognition Approach (Kaufman and Sternberg, 2010) details how basic cognitive operations—attention, perception, memory, reasoning—are utilized to generate innovative ideas. This framework extends Dietrich (2004)'s findings by emphasizing the role of an individual's knowledge depth and breadth in enhancing creative potential. It advocates for specific cognitive mechanisms such as analogical thinking and problem-solving that leverage this knowledge to foster creative outcomes.

Over the years, various theories have highlighted the stage-like nature of creative processes, commonly dividing them into two primary phases: 1) generating ideas and assessing their usefulness and 2) modifying them to meet specific creative goals (Johnson et al., 2022). A notable example is the Geneplore model (Finke et al., 1996). This model posits that creative tasks begin with the generation of preliminary ideas, termed "preinventive" because they are not yet fully developed but possess potential for originality and applicability. The process involves alternating between generating and exploring these ideas, continuously refining them to conform to the specific requirements or constraints of the task (F. Patterson, 2004).

Nijstad et al. (2010)'s dual pathway to creativity model is another influential theory that focuses on the creative ideation process. It conceptualizes creativity as a constrained stochastic process characterized by random variation and selective retention (Simonton, 2000). This model integrates aspects of the Geneplore model, which views creativity as a cognitive process that involves problem solving and memory retrieval, and also recognizes the importance of remote associations in creative thinking (Mednick, 1962). Specifically, it identifies two primary pathways: *cognitive flexibility* and *cognitive persistence*. Cognitive flexibility, often enhanced by positive mood states, allows easy switching between thoughts, aiding the exploration and connection of diverse ideas. This pathway is supported by neurophysiological features, such as the presence of dopamine in certain brain areas and reduced levels of latent inhibition, which allow more distant associations to enter working memory, thereby fostering originality. In contrast, cognitive persistence focuses on a deep, systematic exploration of fewer ideas, enhanced by negative moods that promote detailed attention and perseverance. This process involves the prefrontal cortex, particularly the dorsolateral areas involved in executive functions such as working memory and sustained attention.

Mood-Creativity Linkage

It shall be no surprise that research on the cognitive consequences of mood has intersected with studies on creativity. Extensive psychological research has examined how different mood states influence creativity. De Dreu et al. (2008) note that mood is one of the most studied and reliable predictors of creativity. While many studies suggest that positive moods elicit more creative responses than neutral moods, the comparison between positive and negative moods is less conclusive (De Dreu et al., 2008). Some research indicates that positive moods enhance creativity more than negative moods (Grawitch et al., 2003), while others find similar levels of creativity in moods (Bartolic et al., 1999), or even greater creativity in negative moods (Madjar and Oldham, 2002).

Given the bipartite dimensions of mood states (i.e., valence and activation; Yik et al., 1999), these inconsistencies may arise from a focus primarily on valence. Different cognitive processes leading to creativity (Finke et al., 1996; Nijstad et al., 2010) may also explain these contradictory results. In this sense, the dual pathway to creativity model (De Dreu et al., 2008) distinguishes itself among the various theoretical frameworks that reconcile the inconsistent findings by recognizing the dimensions of valence and activation of mood and proposing *flexibility* and *persistence* pathways as distinct yet interrelated cognitive processes behind creative thinking. Specifically, this model posits that positive hedonic tones increase openness and receptiveness, enhancing cognitive flexibility, while negative tones narrow focus, boosting cognitive persistence. Activating moods, regardless of hedonic tone, generally lead to higher levels of creativity compared to deactivating moods due to increased mental and physical energy.

Moreover, the dual pathway to creativity model delineates how mood states enhance or hinder creative output in various ideation tasks (e.g., divergent thinking tasks) by integrating broader psychological theories. It highlights that creative fluency and originality emerge from enhanced cognitive flexibility, increased persistence, or a combination of both (Nijstad et al., 2010). Research from stress performance studies, psychophysiology, and neuroimaging suggests that activating moods significantly bolster creative fluency and originality compared to deactivating moods (De Dreu et al., 2008). Furthermore, integrating the cognitive tuning model (Schwarz and Bless, 1991), the broaden-and-build theory (Fredrickson, 2001), and the insights from studies on visual and conceptual focusing (Derryberry, 1989), the dual pathway to creativity model argues that activating moods with a positive tone primarily enhance creativity through increased cognitive flexibility, whereas activating moods with a negative tone foster creativity through heightened persistence. Finally, although no significant differences are expected between positive activating moods (e.g., happiness) and negative activating moods (e.g., anger) in terms of fluency and originality, positive activating moods contribute to broader and more diverse cognitive categories, facilitating faster completion times in creative tasks. Negative activating moods tend to generate more ideas within specific cognitive categories, leading to longer completion times (De Dreu et al., 2008).

Experimental Mood Induction

One necessary condition to empirically test the link between mood and creativity is to effectively induce mood changes, allowing researchers to unravel the *unique* effects of mood states on creativity. Experimental mood induction has been shown to be effective in altering mood (Westermann et al., 1996) and thus offers stronger evidence of the causal effects of mood states on creativity. Providing a more controlled and quantifiable approach, experimental mood induction surpasses self-reported questionnaires, which suffer from 1) inherent biases such as response styles and memory recall issues and 2) fundamentally correlational nature that often complicate accurate assessment (Soubelet and Salthouse, 2011).

There are a myriad of experimental mood induction methods, including imagination, films, sound and music, images, reading and writing passages, embodiment, virtual reality, feedback on performance tasks, self-referent statements, social interaction, physiological manipulations, and motivated performance tasks (Lischetzke and Könen, 2022; Maryam Fakhrhosseini and Jeon, 2017). Siedlecka and Denson (2019) provides a classification framework for these techniques, categorizing them into visual stimuli, music, autobiographical recall, situational procedures, and imagery, which is crucial to understanding the effectiveness of various mood induction methods, helping researchers select the appropriate methodologies to investigate the impact of mood on behavior. Siedlecka and Denson (2019) found that images or videos are particularly effective in evoking a wide range of emotions, while music strongly elicits happiness, fear, and sadness. Autobiographical recall effectively induces anger, happiness, fear, disgust, and sadness. Creating social or physical situations elicits anger, surprise, fear, and happiness, and guided mental visualization is effective in inducing anger, happiness, disgust, sadness, and fear.

In addition to evaluating the effectiveness of various mood induction techniques, there has also been significant discussion on additional considerations for implementing mood induction experiments. For instance, implementing mood induction experiments requires precision in instructions and the choice of induction method to ensure the target mood state is effectively induced (Maryam Fakhrhosseini and Jeon, 2017; Siedlecka and Denson, 2019). Moreover, combining self-report and physiological measures can capture a more accurate picture of mood state (Quigley et al., 2014; Siedlecka and Denson, 2019). Ethical considerations are also crucial, especially when inducing negative mood states. It is essential to ensure voluntary participation and comprehensive debriefing (Maryam Fakhrhosseini and Jeon, 2017; Quigley et al., 2014; Siedlecka and Denson, 2019).

Common Methods to Measure Creativity

Apart from mood induction, another necessary condition to empirically test the mood-creativity linkage is choosing appropriate methods to measure creativity. Given the multifaceted nature of creativity (De Alencar et al., 2021), researchers have developed diverse methodologies, including psychometric tests, observational methods, self-assessment techniques, and dynamic approaches to measure creativity in real-time or natural settings (Kaufman and Sternberg, 2010). However, defining what should be measured remains challenging due to creativity's complexity involving cognitive processes, personality traits, and environmental influences.

Fortunately, creativity scholars have proposed framework/taxonomy of creativity measurement that helps identify the most appropriate creativity measures for researchers' specific needs. For example, Batey (2012) proposed a heuristic framework for measuring creativity at multiple levels, guiding researchers in selecting the appropriate methods. This framework includes three dimensions: levels of creativity assessment (individual, team, organizational, cultural), facets of creativity assessment (trait, process, press, product), and measurement approaches (objective, self-rated, other-rated). Furthermore, Weiss et al. (2021) proposed a taxonomy of creativity assessment tools, detailing attributes including the measurement approach (self-report, other-report, ability tests), construct type (e.g., creative interests, achievements, divergent thinking), the type of generated data, scoring methods, and psychometric issues.

Despite the challenges in capturing the multifaceted nature of creativity, the field of creativity has seen extensive development, including refined traditional tests, technology-based assessments, and ecologically valid measures (Kaufman and Sternberg, 2010). Methodological approaches grounded in disciplines such as network science have been used to model semantic memory and test the associative theory of creativity. For instance, studies by Kenett et al. (2014) and Beaty et al. (2021) show that greater semantic distance from a conventional idea increases the likelihood of a new idea being considered creative. Kenett et al. (2018) discuss the resilience of semantic memory networks, indicating greater flexibility in highly creative individuals. In addition, advances in computational linguistics and deep learning also contribute to creativity research. For example, Zedelius et al. (2019) use linguistic properties, rather than subjective scoring, to measure creativity in writing. Johnson et al. (2022) employ BERT-embedded representations to gauge narrative connections and J. D. Patterson, Merseal, et al. (2023) develop automatic scoring systems for divergent thinking tasks across multiple languages.

It is also worth mentioning that the field of creativity research stands on the cusp of several promising developments. As highlighted by Kaufman and Sternberg (2010), future creativity research should focus on innovative assessment methodologies that capture the dynamic nature of creative processes, such as real-time data collection techniques to digitally track creative activities and artificial intelligence techqniues to analyze patterns in creative output. Furthermore, cross-disciplinary approaches that integrate psychology, sociology, educational science, and neuroscience are essential to develop holistic and applicable measures across different cultural contexts, enriching our understanding of creativity and its manifestations.

Present Study

Building on significant advancements in affective psychology and creativity research, this study acknowledges the well-documented synergy between mood states and creative cognition. As described in the literature, frameworks categorizing mood along pleasant-unpleasant and activated-deactivated dimensions have elucidated the intricate relationships between mood induction methods and their cognitive consequences (Siedlecka and Denson, 2019). Coupled with the burgeoning exploration of creativity's multifaceted nature—encompassing definitions, underlying cognitive processes, and diverse assessment tasks (Kaufman and Sternberg, 2010)—this mutual enrichment has paved the way for both theoretical propositions and empirical validations of the mood-creativity linkage.

Echoing Kaufman and Sternberg (2010)'s call for innovative assessment techniques that more accurately capture the dynamics of creative thinking, this study advances the mood-creativity debate by introducing a novel task-measurement integration. Specifically, it combines the open-ended richness of the Incomplete Shape Drawing Task—capable of revealing nuanced cognitive processes behind drawing—with state-of-the-art artificial intelligence tools for automated analysis. Unlike previous studies that often relied on static, single-response tasks and subjective ratings, this approach enables multi-trial, process-level assessment of creativity through both visual and semantic modalities, providing a more fine-grained and ecologically valid evaluation of the flexibility pathway in creative cognition. Focusing on *domain-general*, *little-c* creativity, this study aims to capture the nuanced effects of mood on creative processes and, more specifically, the (potential) building effects of positive mood states on thought-action repertoires (Fredrickson, 2001). By distinguishing positive mood states varying on the activation dimension—happiness (high activation) and calmness (low activation), this study seeks to scrutinize the hypothesized flexibility pathway (as suggested by De Dreu et al. (2008)'s dual pathway to creativity model) in which positive activating mood states, rather than positive deactivating ones, predict cognitive flexibility, characterized by employing wide-ranging and comprehensive cognitive categories to form associations. The conducive influence of positive (activating) mood is further hypothesized to enhance the originality aspect of creativity (i.e., the uncommonness of ideas, solutions, or products). Specifically, this study is guided by the following two research questions:

1. **How do positive moods across the spectrum of activation level, including positive moods with high level of activation (e.g., happiness) and positive moods with low level of activation (e.g., calmness), affect cognitive flexibility during the creative ideation process, respectively?**

2. **How does cognitive flexibility during the creative ideation process further influence the originality aspect of creativity in the final product (i.e., whether flexibility mediates the relationship between positive mood and the originality aspect of creativity)?**

To answer these research questions, this study adopts a validated film-based mood induction protocol (Siedlecka and Denson, 2019) for mood induction. I randomly assign participants to one of three mood conditions (*High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control*) to explore the effects of positive mood states, ranging from activating to deactivating, on the flexibility pathway of creativity. To capture the flexibility and originality aspects of creativity, I utilize tasks that not only track the dynamics of creative processes, but also incorporate novel methodologies from generative sketch modeling and NLP to examine the proposed building effects of positive mood states on thought-action repertoires (Fredrickson, 2001).

Following Barbot's (2018) Multi-Trial Creative Ideation (MTCI) framework that emphasizes a multi-stimuli approach and the evolving dynamics of creative ideation, this study adopts the Incomplete Shape Drawing Task paired with post-hoc narratives. This design captures not only the final creative output but also the cognitive process underlying it. The collection of both behavioral (stroke-level drawing data) and semantic (narrative-based) data therefore captures the flexibility aspect of creativity through two complementary perspectives. First, the Compositional Stroke Embedding (CoSE) model, a generative model trained on large-scale human drawing data, was chosen for its ability to model the probabilistic space of motor decisions in drawing. Leveraging the Gaussian Mixture Model (GMM) to predict next-stroke trajectories in the Incomplete Shape Drawing Task, the CoSE model effectively captures not just what participants draw, but how they navigate the possible outcome space for each additional stroke. This probabilistic framework allows us to infer the degree of uncertainty and divergence in participants' stroke choices, making it particularly well-suited for quantifying the flexibility aspect of creativity. Specifically, flexibility is quantified via average entropy and Bhattacharyya distance (capturing sustained exploratory breadth), as well as the inflection proportions (capturing adaptive strategy switching) throughout the drawing process ((see Appendix B and Appendix C for details of their formulas)). Second, Divergent Semantic Integration (DSI) quantifies semantic flexibility by measuring the conceptual distance between elements in participants' post-drawing narratives (see Appendix D) for its formula). This metric leverages contextual word embeddings from BERT, a powerful language model trained on large corpora, to capture nuanced meanings in natural language. By computing the average pairwise distance between sentence embeddings within each narrative, DSI estimates how conceptually diverse or integrated the participant's ideas are. This approach is well-suited for creativity research because it moves beyond surface-level lexical diversity and instead captures deeper semantic divergence—a key indicator of flexible thinking in ideation. Meanwhile, the originality aspect of creativity (i.e., the originality of the final completed drawings) is evaluated using AuDrA, a deep learning model trained on human-rated drawings from the same task. This automated drawing assessment platform has demonstrated strong predictive accuracy and robust generalizability across datasets and raters (J. D. Patterson, Barbot, et al., 2023). Mediation analyses are conducted to test whether flexibility mediates the effect of mood condition on originality. Mood condition is treated as a multicategorical independent variable, with the neutral group serving as the reference category. Dummy coding is used to create two binary contrasts: one comparing the high-arousal positive mood group to the neutral control (D1), and another comparing the low-arousal positive mood group to the neutral control (D2). Each flexibility metric is tested as a separate mediator in a parallel mediation framework.

The primary contribution of this study is its integration of drawing tasks with deep learning and natural language processing techniques to quantitatively assess both the flexibility and originality aspects of creativity. This method offers a more comprehensive analysis than previous studies that relied solely on verbal tasks such as the alternative use task and the remote association task (e.g., Kenett et al., 2014; Kenett et al., 2018) to quantify the flexibility aspect of creativity. Complementing the predominance of verbal creativity assessments with visual creativity (a canonical form of creative expression; Morriss-Kay, 2010) allows for a holistic understanding of creative processes. Verbal and visual creativity engage different cognitive and neural pathways; verbal creativity often relies on language-based processes and abstract thinking (Benedek et al., 2014), while visual creativity engages spatial reasoning and visual-motor coordination (Schlegel et al., 2015). By studying both aspects, this proposed study could uncover complementary insights into the cognitive mechanisms underlying the flexibility aspect of creativity. This integrative approach enhances the validity of the measurements by capturing a broader range of creative expression and providing a more nuanced understanding of the dynamics of creative thinking. Meanwhile, when it comes to assessing the originality aspect of creativity (especially visual creativity), using automated scoring methods effectively addresses several practical limitations in creativity research. These include the high labor costs associated with manual evaluations and the inherent subjectivity that can bias expert ratings (J. D. Patterson, Barbot, et al., 2023). Automated methods provide a scalable and consistent way to evaluate originality, ensuring that the assessments are objective and replicable across different studies.

Methods

Participants

Participants were recruited through Amazon Mechanical Turk (MTurk) and compensated $2.00 for the online experiment that takes around 15 to 20 minutes (at an approximate rate of $7.50 per hour).

An *a priori* power analysis was conducted using G*Power version 3.1.9.6 (Faul et al., 2007) to determine the minimum required sample size for detecting differences in arousal levels between mood conditions. Based on data from Sugawara and Sugie (2021), which compared high-arousal and low-arousal positive emotions in a thought–action repertoire task using film clips for mood induction, the reported effect size was d = 1.42 for arousal ratings, a large effect according to Cohen (1992)'s criteria. Given a significance threshold of $\alpha = .05$ and power = .95, the minimum required sample size for a two-tailed independent samples t-test is N = 12 per group.

This power analysis was conducted to ensure that the mood induction procedure effectively differentiates high-arousal and low-arousal states and that any observed effects on creativity are attributable to mood rather than sample size limitations. The final sample size for the online experiment was N = 90 (30 per group), exceeding the required minimum and providing sufficient statistical power to detect mood-related differences in arousal and subsequent cognitive perfor-

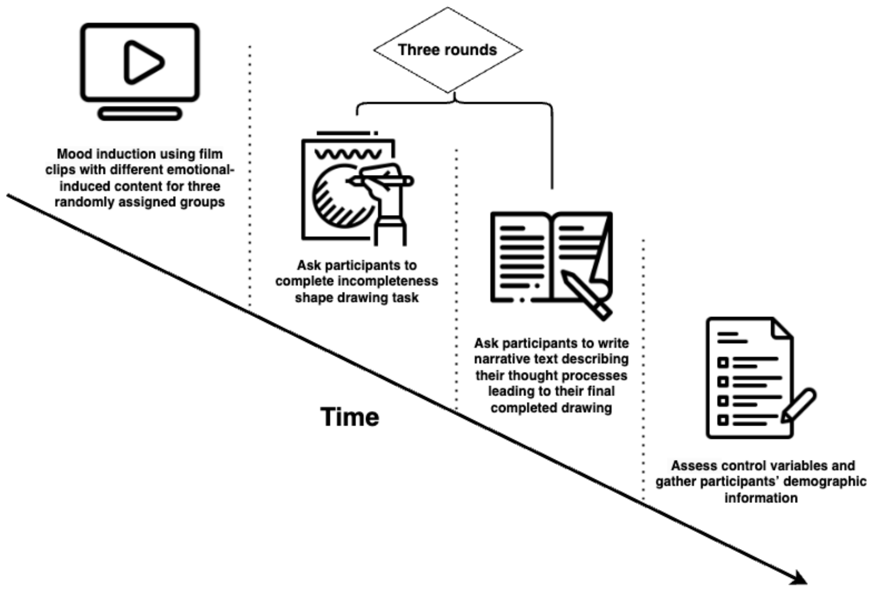

Figure 2: Experiment Web Page Design

mance. Participants were required to be physically present in the United States, as verified by their IP address.

This study was approved by the Institutional Review Board (IRB) of the University of Chicago, and all participants provided their informed consent before beginning the experiment.

Experiment Design

To test the proposed flexibility pathway linking positive activating mood with the originality aspect of creativity, this study employed a between-subjects design with three experimental conditions for mood induction: *High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control* conditions. Then I used the Incomplete Shape Drawing task (Barbot, 2018) to capture the flexibility and originality aspects of creativity. By integrating these methodological approaches, the study aimed to empirically validate the hypothesized mediating role of flexibility in the relationship between mood and creative output.

My online experiment was implemented using jsPsych (Leeuw et al., 2023), a JavaScript framework designed to conduct behavioral experiments on web browsers. The website was structured into three main sections (see Figure 2 for the overall structure of the experiment): (1) mood induction, (2) three rounds of the Incomplete Shape Drawing Task, and (3) survey data collection.

Mood Induction

After providing informed consent, participants underwent mood induction by watching film clips, which has been shown to be an effective mood induction technique to engage visual and auditory modalities and simulate real-life emotional situations (Coan and Allen, 2007; Fernández-Aguilar et al., 2019; Siedlecka and Denson, 2019). Participants were randomly assigned to one of the three mood induction conditions (*High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control*).

To induce positive high-arousal and low-arousal mood states, I used two film clips validated by Wensveen et al. (2002) that tap into positive valence mood at the polar ends of the arousal continuum within the Circumplex Model of Mood (Feldman, 1995). These film clips were validated through the Mood Induction Procedure (MIP; Lench et al., 2011), where participants rated their valence and arousal levels using the Self-Assessment Manikin (SAM; Bradley et al., 1999), a graphic scale representing the orthogonal valence and arousal elements of mood states. Specifically, for high-arousal positive mood, I used a 2:55-minute clip from *Blues Brothers* as in Wensveen et al., 2002's study. This scene features an energetic gospel performance, with James Brown and the Rev. James Cleveland Choir singing *The Old Landmark*. The combination of lively music, dynamic movement, and expressive enthusiasm evokes an elevated state of excitement and joy, which are representative of high-arousal positive affect. Meanwhile, for low-arousal positive mood, I chose a 2:38-minute clip from *Easy Rider*. This scene depicts the protagonists riding motorcycles along a tranquil desert highway at sunset, accompanied by *The Weight* by The Band. Smooth pacing, warm visual tones, and a soothing soundtrack induce a relaxed and peaceful emotional state, which are representative of low-arousal positive affect. Finally, for the neutral control group, I followed Maryam Fakhrhosseini and Jeon (2017)'s and Siedlecka and Denson (2019)'s approach, in which neutral affect is typically induced using low-arousal, emotionally neutral visual stimuli (e.g., nature documentaries and weather forecast). In this study, I chose a 1:56-minute UK morning weather forecast from Met Office[2].

Before viewing the video clips, participants received the instruction to immerse themselves in the clip as they would when watching a movie in a cinema, without needing to memorize any

[2] Link to mood induction clips.

details from the clips they would be watching. This way, the framing effects on induced moods could be minimized, as opposed to using more directive prompts like "Let yourself experience your emotions fully." To assess the effectiveness of mood induction, participants rated their valence and arousal levels using SAM (Bradley et al., 1999). Valence ranged from -4 (very negative) to +4 (very positive), and arousal ranged from 1 (low) to 9 (high), though only the visual representations of those point values, and not the point values themselves, were visible to the participant.

Incomplete Shape Drawing Tasks

After mood induction, participants completed three rounds of the Incomplete Shape Drawing Task (Barbot, 2018), where participants encountered an incomplete shape and were encouraged to fully engage their imagination, take their time, and produce a drawing that was as creative as possible. Each participant was presented with three qualitatively distinct incomplete shapes, selected from three different stimulus groups and presented in a randomized order. This multi-trial approach aligns with Barbot (2018), facilitating an in-depth exploration of the dynamics of creative thinking and allowing researchers to examine within-subject variation in flexibility and originality (see Appendix A for sample completed drawings of the Incomplete Shape Drawing Task).

The task was implemented using the built-in sketchpad plugin provided by jsPsych (Leeuw et al., 2023), an open-source JavaScript library for running behavioral experiments in a web browser. This interactive interface provided participants with essential drawing tools, including options for undoing, redoing, and clearing strokes, ensuring an intuitive user experience. In addition to capturing the final drawing, the system recorded x, y coordinates and the timing of mouse movements throughout the drawing process. These data were stored in a JSON-like structure using base64 encoding for subsequent computational analysis (Bainbridge, 2022).

Following each drawing session, participants were prompted to give a label for each completed drawing. They were then asked to provide a detailed narrative describing their step-by-step thought process behind their completed drawing. Specifically, they reflected on their initial impressions of the incomplete shape—what first came to mind upon seeing it and whether it reminded them of anything specific. They were encouraged to discuss whether multiple ideas were considered before settling on a final concept and to elaborate on how their idea evolved during the drawing process, including any triggers for conceptual shifts. Meanwhile, they were also encouraged to identify the theme or category their drawing fit into, such as nature, technology, people, animals, or abstract concepts, and discussed whether any new themes emerged as they worked. This narrative was designed to capture participants' forming of associative connections between different semantic categories, tapping into the flexibility aspect of creativity.

Survey Data Collection

Once participants completed the mood induction and incomplete shape drawing task phases, they completed several surveys that allowed me to measure participant-level control variables and obtain demographic information. Including these control measures was crucial to improving causal inference by accounting for individual differences that could otherwise confound the relationship between mood and creativity.

Participants first completed several questionnaires that assessed control variables, including trait affect (measured by the Positive and Negative Affect Schedule; Watson et al., 1988) to control for baseline emotional tendencies that could impact mood-induction effects. Furthermore, openness to experiences (measured by the Ten Item Personality Measure; Gosling et al., 2003) was included, as prior research suggests that individuals high in openness are more likely to have higher intrinsic motivation and creative process engagement, both of which enhance creativity (Tan et al., 2019). To further account for variations in cognitive adaptability, participants completed the Cognitive Flexibility Scale (Martin and Rubin, 1995), which assessed one's trait-level ability to change perspectives and adapt to new information, both critical for creative ideation (Lin et al., 2014; Müller et al., 2016). Additionally, self-rated artistic skill was included to examine whether prior artistic experience influenced task performance, ensuring that creativity differences are not solely attributable to skill level. After completing these control measures, participants provided demographic information, including age, gender, race, and education level.

Creativity Assessment

Measuring the Flexibility Aspect of Creativity

According to Nijstad et al. (2010)'s dual pathway to creativity model, the flexibility aspect of creativity centers on employing wide-ranging and comprehensive cognitive categories to form associations. In the context of the Incomplete Shape Drawing Task, flexibility specifically refers to the ability of participants to explore a wide range of qualitatively distinct creative solutions through two complementary operationalizations: 1) real-time, observable stroke decisions during the drawing process and 2) post-hoc reflective narratives about their thought processes.

The real-time, observable stroke decisions focused on participants' ability to dynamically generate diverse and innovative strokes as they navigated the spatial and conceptual possibilities of the incomplete shape. Each stroke reflected an immediate decision, offering insights into how participants engaged with qualitatively distinct creative solutions (both in terms of starting position and trajectory) for each stroke and made creative choices in real-time. On the other hand, the post-hoc narrative aspect emphasized how participants recollected and articulated their cognitive processes, including their ability to connect disparate ideas, integrate themes, and explain their conceptual shifts. These narratives captured the depth and diversity of associative thinking, offering a window into how participants structured and evaluated their creative decisions retrospectively.

Together, these operationalizations provided a nuanced understanding of flexibility, capturing both the dynamic, moment-to-moment exploration of ideas and the reflective integration of conceptual categories.

Real-Time Stroke Decisions To gain insight into the flexibility aspect of creativity via real-time stroke decisions during the drawing process, I used the Compositional Stroke Embedding (CoSE) model (Aksan et al. (2021)) that predicted the starting position and trajectory of the next stroke using the Gaussian Mixture Model (GMM). That GMM's forecast strokes with varying degrees of uncertainty in both prediction and between-component (potential stroke) distances matched the operational definition of flexibility. Specifically, I hypothesized that a more creatively flexible individual will not only consider a broader array of potential next strokes, but will also remain open to choosing other paths that are qualitatively distinct from each other in their choice space during their creative processes.

To quantify these characteristics, I utilized two key measures derived from the GMM: entropy and Bhattacharyya distance (see Appendix B and Appendix C for details of their formulas). Entropy captures the degree of uncertainty in the GMM predictions, reflecting the breadth of possible next strokes available to participants at a given moment. A higher entropy value indicates a wider range of creative possibilities, reflecting an individual's ability to explore diverse options. On the other hand, Bhattacharyya distance is a metric of similarity that ranges from 0 to ∞, where a smaller value indicates a higher degree of similarity (or overlap) between the two distributions, and a higher value suggests greater divergence. It is particularly useful in the context of GMM for assessing overlap and separation between different clusters (Alangari et al., 2023). In the context of the Incomplete Shape Drawing Task, Bhattacharyya distance measures the divergence between potential next strokes (GMM components), providing insight into the distinctiveness of the paths being considered. A greater distance between components suggests a more varied and inclusive exploration of qualitatively distinct possibilities.

To map the dynamic changes in these two measures throughout the drawing process to the flexibility pathway of creativity, I selected two summary metrics that capture distinct facets of creative exploration: the average values of the measures and the proportion of inflection points. These metrics reflect the ability to not only consider a broader array of potential next strokes but also remain open to exploring alternative paths that are qualitatively distinct within the possibility space. Together, they provide insight into how participants navigated and engaged with the total space of possible next strokes during the creative process. The average values and proportion of inflection points highlight both the sustained breadth of exploration and the dynamic shifts in strategy that characterize flexible creative behavior.

The average values of entropy and Bhattacharyya distance across all strokes serve as cumulative indicators of a participant's overall creative breadth and divergence across the entire drawing task. High average entropy reflects a consistent ability to maintain a wide range of potential next strokes, indicating that the participant explores a large portion of the space of possibilities throughout the task. This measure captures the participant's sustained openness to generating diverse options and avoiding early fixation on a single creative trajectory. Similarly, a high average Bhattacharyya distance suggests that participants consistently consider strokes that are qualitatively distinct from each other, emphasizing their ability to incorporate varied and unconventional approaches into their creative process. By summarizing the overall level of exploration and divergence, the average values provide a bird's-eye view of a participant's capacity to engage with the task's inherent creative possibilities and remain broadly flexible over time.

The proportion of inflection points, in contrast, delves deeper into the moments of dynamic change within the creative process. Inflection points—defined as significant shifts in the trends of entropy or Bhattacharyya distance—represent critical junctures where participants reconsider their trajectory or diverge from their current path. A higher proportion of inflection points suggests that participants frequently engage in deliberate transitions between different creative strategies, reflecting their ability to pivot dynamically within the space of possibilities. These moments of change are particularly important in understanding flexibility because they indicate a willingness to disrupt the status quo, reframe the problem, and explore new directions. This adaptability, captured through the proportion of inflection points, complements the broader patterns revealed by the average values and provides a richer understanding of how participants dynamically engage with alternative possibilities throughout their creative process. In this study, I used the Pruned Exact Linear Time (PELT) algorithm (Dorcas Wambui, 2015) that utilizes *ruptures* Python library (Truong et al., 2020) to identify the inflection point(s).

Post-Hoc Narrative Complementing real-time, observable stroke decisions throughout the incomplete drawing task, this study also relied on the verbal description of the participants about their thought processes behind their completed drawings to examine the diversity of ideas/concepts they connect during creative ideation processes. As one type of observation offering data on individuals' cognitive processes (Ericsson and Simon, 2003), verbal report could serve as a window into people's thought processes and the dynamics of creative thinking by requiring the organization and expression of ideas, reflecting the cognitive processes involved in structuring and connecting these ideas. As individuals construct stories, they engage in memory retrieval, association, and synthesis, which are key components of creative thinking. Narratives unfold over time, mirroring the dynamic nature of creative thought, allowing researchers to observe how ideas evolve, merge, and diverge.

Specifically, this study will utilize Divergent Semantic Integration (DSI; see Appendix D) for its formula) to measure the diversity of concepts participants connected to complete incomplete shapes, inferred through their narrative about how they have approached and completed the drawings (Johnson et al., 2022). DSI echoes Kaufman and Sternberg (2010)'s call for interdisciplinary approaches to measure creativity by integrating Mednick (1962)'s associative theory with distributional semantics theory in the linguistics field to assess how narratives integrate divergent ideas. On the one hand, DSI captures the essence of creativity while individuals form associations between disparate concepts in memory. On the other hand, DSI capitalizes on the theory of distributional semantics, which allows a computational understanding of semantics (word meanings) in a scalable manner. Specifically, distributional semantics is based on the Distributional Hypothesis, which posits that words with similar meanings occur in similar contexts (Lenci, 2008). By analyzing word co-occurrence in large text corpora, this approach creates vector-based representations of words in a high-dimensional space, and the proximity of these vectors reflects semantic similarity, allowing distributional semantics to capture word meanings based on usage patterns (Boleda, 2020). Together, individuals with higher flexibility in their creativity would navigate further in his/her concept space to connect more distinct concepts, reflected in a higher DSI.

Measuring the Originality Aspect of Creativity

To measure the *originality* aspect of creatvity, I referred to the pre-trained AuDrA model and implementation code provided on J. D. Patterson, Barbot, et al. (2023)'s open-access repository. In an attempt to overcome the limitations of subjective creativity scoring, including labor cost and subjectivity, these authors joined the movement to capitalize on machine learning to automatically assess creativity (e.g., Acar et al., 2023; Beaty and Johnson, 2021). Targeting the tablet-based drawing task under Barbot (2018)'s MTCI framework, AuDrA extends the (mere) fluency measurement via reaction time data in the original task by developing an automated method to assess the originality of the sketches.

As a modified ResNet architecture that allows continuous prediction of creativity scores, the AuDra model was trained using over 13,000 sketches rated for creativity by nearly 60 human raters across four datasets. It used a supervised learning approach, utilizing the human-provided ratings as feedback to optimize its predictive accuracy for the specific task of visual creativity assessment. AuDrA demonstrated a high correlation with human creativity ratings in new drawings on the same task. In addition, AuDrA's performance predicting creativity scores surpassed the correlations between level of elaboration (ink on the page) in drawings and human creativity ratings, suggesting that AuDrA is sensitive to features of drawings beyond simple complexity or elaboration.

Adopting AuDrA is suitable for the current research for three reasons. First, the Incomplete Shape Drawing task adopted here is the same as the one AuDrA was trained on. Second, the model allows automated originality assessment (with evidence of good model performance), contituting significant time and cost savings over collecting humans ratings. Third, AuDrA measures the *originality* aspect of creativity, which complements the adoption of CoSE that captures the *flexibility* aspect of creativity. Together, these two models enable an examination of the complete (hypothetical) flexibility pathway from positive activating mood to the originality aspect of creativity.

Statistical Analysis

To examine the hypothesized flexibility pathway linking positive activating mood to originality in creativity, I employed mediation analysis (MacKinnon et al., 2007) within the framework of the dual pathway to creativity model (De Dreu et al., 2008). Specifically, I tested whether the effect of mood induction (independent variable, IV) on the originality aspect of creativity (dependent variable, DV) was mediated by the flexibility aspect of creativity (mediator, M), as assessed through multiple quantitative measures.

Mediation analysis is well-suited for this study as it allows for a systematic examination of whether the flexibility aspect of creativity serves as a cognitive mechanism linking mood induction to originality. First, it enables an empirical test of the dual pathway to creativity model, which posits that mood influences originality through cognitive flexibility, by assessing whether flexibility statistically mediates this relationship. Second, mediation analysis allows for the decomposition of total effects into direct and indirect effects, distinguishing whether positive activating mood enhances originality directly or indirectly via flexibility. This distinction is crucial in determining whether flexibility is a necessary cognitive pathway in mood-induced creative enhancement.

Following best practices in mediation analysis (Koschate-Fischer and Schwille, 2022), I leveraged randomized experimental design to strengthen causal inference. The random assignment of participants to mood conditions helps prevent any observed relationships between mood and creativity from being confounded by pre-existing differences in cognitive abilities. Furthermore, I controlled for state-level affect, openness to experiences, trait-level cognitive flexibility, and self-rated artistic skill, reducing potential alternative explanations for observed effects.

Mediation Model Specification

The independent variable (IV) comprises three mood conditions: *High-Arousal Positive Mood* ($D1$), *Low-Arousal Positive Mood* ($D2$), and *Neutral Control* (reference category). Following recommendations for categorical predictors in mediation models Hayes and Preacher, 2014, I dummy-coded the mood conditions to compare each experimental group against the neutral condition. The dependent variable (Y)—originality in creativity—was measured using the AuDrA model, which predicts creativity ratings based on visual output.

The mediator (M)—cognitive flexibility—was operationalized through multiple quantitative measures reflecting different facets of the flexibility pathway. Specifically, entropy of GMM predictions capture uncertainty in stroke selection, Bhattacharyya distance between GMM components reflects the divergence among predicted strokes, and Divergent Semantic Integration (DSI) measures conceptual flexibility in narrative descriptions. For entropy and Bhattacharyya distance, they are further decomposed into two components: the average value, which represents the overall level of exploration across the drawing process, and the proportion of inflection points, which captures fluctuations in flexibility, indicating shifts between exploratory and convergent thinking. Given that these mediators may independently contribute to originality, I estimate separate mediation models for each.

For each mediator (M_k), I estimate the following mediator model:

$$M_k = \alpha_0 + \alpha_1 D1 + \alpha_2 D2 + \alpha_3 X + \varepsilon_{M_k}$$

where M_k represents each mediator: M_1a = Average entropy, M_1b = Proportion of entropy inflection points, M_2a = Average Bhattacharyya distance, M_2b = Proportion of Bhattacharyya distance inflection points, M_3 = DSI; α_0 is the intercept; α_1 and α_2 are coefficients for the mood conditions; X is the vector of control variables; ε_{M_k} is the error term.

Meanwhile, for each mediator, the outcome model is similarly expressed as:

$$Y = \beta_0 + \beta_1 D1 + \beta_2 D2 + \beta_3^k M_k + \beta_4 X + \varepsilon_Y$$

where Y is originality in creativity; β_0 is the intercept; β_1 and β_2 capture the direct effects of mood condition; β_3^k represents the effect of each mediator on originality; $\beta_4 X$ accounts for control variables; ε_Y is the error term.

Testing Direct, Indirect, and Total Effects

To evaluate the hypothesized flexibility pathway, I systematically tested direct effects, indirect effects, and total effects in the aforementioned mediation model, offering insights into which aspects of flexibility serve as potential mechanisms for creative originality.

The direct effects, captured by β_1 (*High-Arousal Positive Mood*) and β_2 (*Low-Arousal Positive Mood*), measure the extent to which mood conditions influence originality (Y) independently of cognitive flexibility. A significant direct effect suggests that mood itself contributes to originality beyond its impact on flexibility. If these coefficients remain significant while mediation is present, it indicates partial mediation, meaning mood enhances originality both directly and through flexibility.

The key test of mediation involves the indirect effects, quantified as:

$$\alpha_k \times \beta_3^k$$

for each mediator (M_k), where α_k represents the effect of mood on the flexibility measure, and β_3^k represents the effect of the flexibility measure on originality. A significant indirect effect suggests that cognitive flexibility partially or fully explains the link between mood and creativity. Following Preacher and Hayes (2008)'s approach, I used bootstrapping with 5,000 resamples to estimate the confidence interval (CI) for indirect effects, providing a more robust inference of mediation pathways. A mediation effect is significant if the bootstrap CI does not include zero.

The total effect captures the overall impact of mood on originality, combining both direct and indirect pathways:

$$\beta_1 + (\alpha_k \times \beta_3^k) \quad \text{(for } \textit{High-Arousal Positive Mood}\text{)}$$

$$\beta_2 + (\alpha_k \times \beta_3^k) \quad \text{(for } \textit{Low-Arousal Positive Mood}\text{)}$$

where each term represents the contribution of a single mediator tested in separate models.

A significant total effect confirms that mood induction influences originality, regardless of whether the effect is primarily direct, indirect, or a combination of both. If the direct effect is insignificant while the indirect effect remains significant, it suggests full mediation, suggesting that cognitive flexibility fully accounts for mood-induced changes in originality.

Results

Participant Demographics

Of the final sample (N = 90), participants ranged in age from 19 to 65 years ($M = 33.5$, $SD = 10.4$). The sample included 43 females (47.8%), 44 males (48.9%), and 3 participants identifying as non-binary or other (3.3%). 47.8% identified as White, 13.3% as Black or African American, 13.3% as Asian, 12.2% as Hispanic or Latino, and 13.3% as multiracial or other. Educational attainment was relatively high: 42.2% of participants held a bachelor's degree, and 24.4% had completed a graduate degree. All participants were physically located in the United States.

Manipulation Check: Mood Induction

To verify that the mood induction procedure successfully manipulated participants' mood states along both the arousal and valence dimensions, I conducted one-way ANOVAs with mood group (*High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control*) as the between-subjects factor.

For arousal ratings, a one-way ANOVA revealed a significant effect of induced mood condition, $F(2,87) = 6.86$, $p = .0017$, with a moderate effect size ($\eta^2 = .14$). Furthermore, post-hoc Tukey tests showed that participants in the *High-Arousal Positive Mood* group ($M = 6.70$, $SD = 1.02$) reported significantly higher arousal than those in the *Neutral Control* group ($M = 4.05$, $SD = 1.12$; $p = .0021$) and the *Low-Arousal Positive Mood* group ($M = 4.53$, $SD = 1.09$; $p = .0171$). No significant difference was observed between the *Neutral Control* and *Low-Arousal Positive Mood* groups ($p = .7641$; see Figure 3).

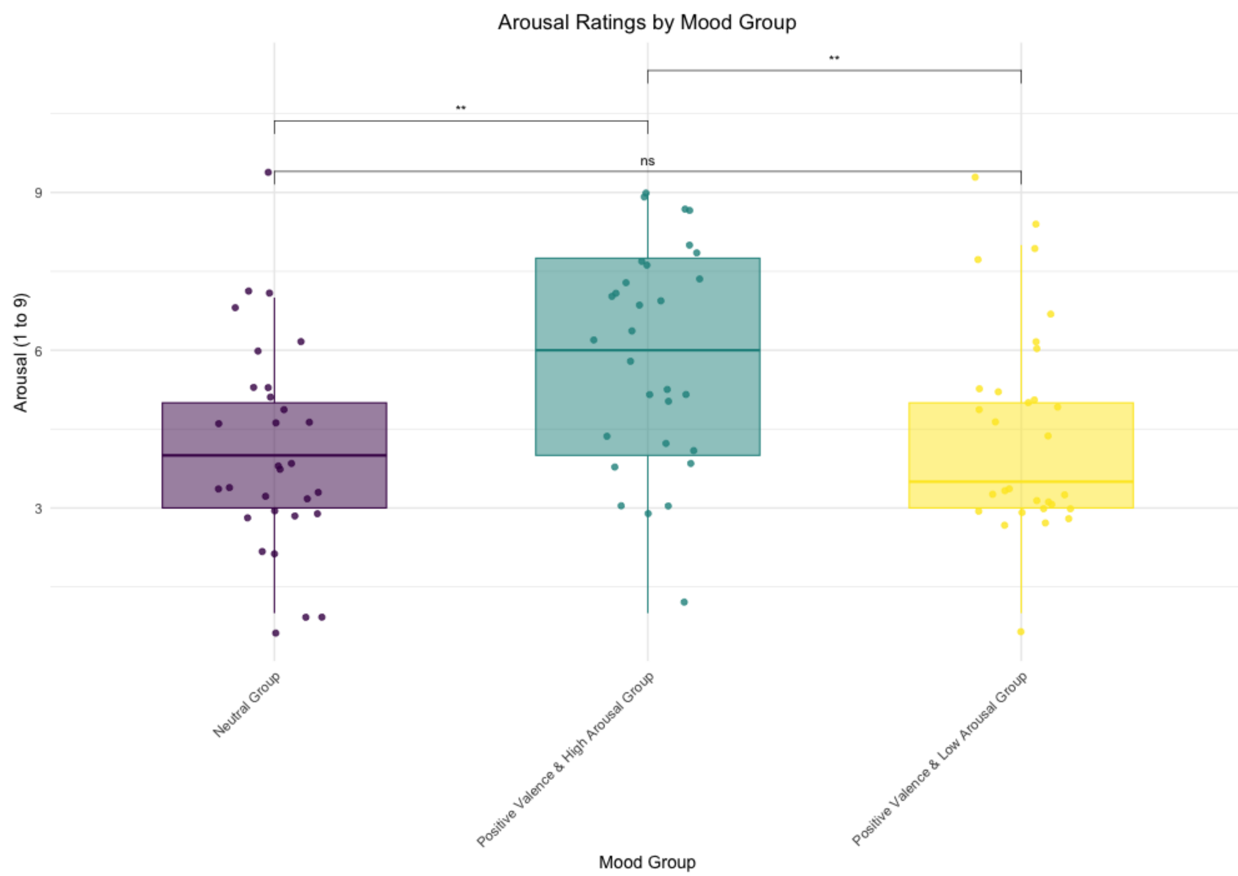

Figure 3: Boxplot of Arousal Ratings by Mood Group. Boxes represent the interquartile range (IQR), with horizontal lines indicating the median. Jittered points show individual participant ratings. Horizontal bars above the boxes denote pairwise group comparisons, with associated significance levels based on t-tests.

Valence was significantly different between groups, $F(2,87) = 4.44$, $p = .0146$, revealing a moderate effect size ($\eta^2 = .09$). Post-hoc Tukey tests revealed that the *High-Arousal Positive Mood* group ($M = 2.91$, $SD = 0.96$) reported significantly higher valence than the *Neutral Control* group ($M = 1.24$, $SD = 1.24$; $p = .0167$), whereas the *Low-Arousal Positive Mood* group ($M = 2.16$, $SD = 1.10$) did not significantly differ from either group ($ps > .05$; see Figure 4).

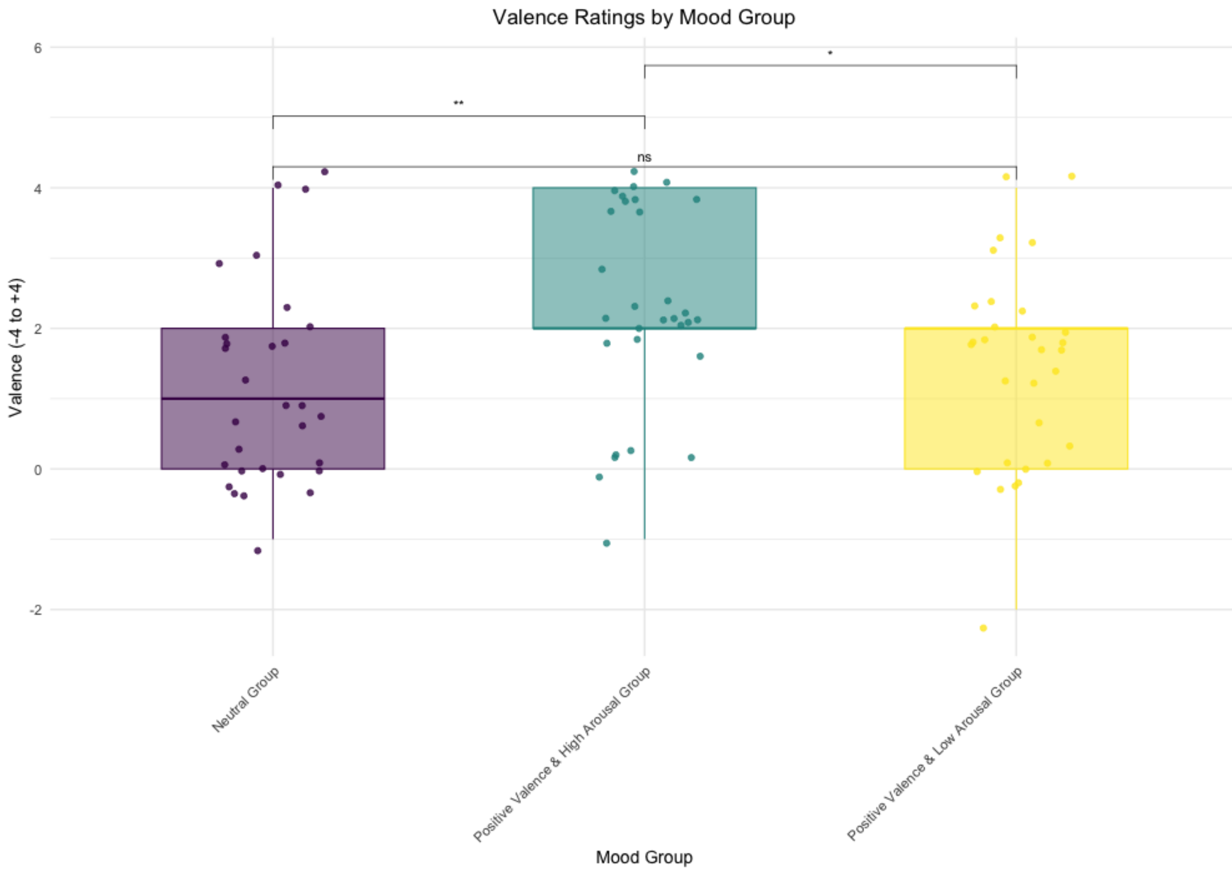

Figure 4: Boxplot of valence ratings by mood group. Boxes represent the interquartile range (IQR), with horizontal lines indicating the median. Jittered points show individual participant ratings. Horizontal bars above the boxes denote pairwise group comparisons, with associated significance levels based on t-tests.

Overall, the experimental mood induction procedure using three validated film clips achieved the anticipated mood manipulation results. For the two positive valence groups, there was a significant difference in arousal ratings, whereas the valence ratings did not significantly differ. This pattern supports the intended orthogonal manipulation of arousal while holding valence constant, allowing for a more focused investigation of arousal's unique effects on subsequent creative processes. Meanwhile, the significant differences in both arousal and valence ratings between the *High-Arousal Positive Mood* and *Neutral Control* groups confirm the successful induction of a distinctly activated positive affective state in the high-arousal condition.

Descriptive Statistics of Flexibility and Originality Measures

The descriptive statistics for all the measures of flexibility and originality across mood conditions are presented in Table 1. Overall, the flexibility metrics demonstrated subtle group differences. Average entropy and Bhattacharyya distance were highest in *High-Arousal Positive* group and lowest in *Low-Arousal Positive* group, though these differences were small. Inflection proportions of entropy and Bhattacharyya distance were slightly elevated in *Low-Arousal Positive* group, suggesting greater within-trial shifts in drawing strategy. DSI scores were highest in *High-Arousal Positive* group, indicating more semantically diverse narrative content, with *Neutral Control* and *Low-Arousal Positive* groups showing similar levels. Originality, as measured by the AuDrA model, remained stable under all conditions, with means ranging narrowly from 0.36 to 0.37 and no apparent variation across groups.

Table 1: Descriptive Statistics by Mood Condition (Mean (SD))

Measure	**Neutral Group**	**High Arousal Group**	**Low Arousal Group**
Avg. Entropy	1.77 (0.09)	1.78 (0.07)	1.74 (0.10)
Avg. Bhatt. Dist.	2.51 (0.29)	2.50 (0.25)	2.45 (0.28)
Inflect. Prop. Entropy	0.41 (0.18)	0.42 (0.17)	0.45 (0.17)
Inflect. Prop. Bhatt	0.42 (0.18)	0.43 (0.16)	0.44 (0.20)
DSI	0.59 (0.28)	0.66 (0.22)	0.58 (0.30)
AuDrA	0.37 (0.10)	0.36 (0.10)	0.37 (0.11)

Note. Avg. Entropy = Average Entropy; Avg. Bhatt. Dist. = Average Bhattacharyya Distance; Inflect. Prop. Entropy = Inflection Proportion of Entropy; Inflect. Prop. Bhatt = Inflection Proportion of Bhattacharyya Distance; DSI = Divergent Semantic Integration; AuDrA = Automated Drawing Assessment (Originality Score).

To further statistically assess group differences across the three induced mood conditions, a series of one-way ANOVAs were performed for each flexibility measure and originality. As shown in Table 2, none of the ANOVAs reached significance and all effect sizes were small ($\eta^2 < .03$). This suggests that mood induction did not lead to significant differences in cognitive flexibility or originality. In other words, mood induction, despite being shown to alter the arousal and valence ratings, did not affect the originality aspect of creativity or any of the process measures, as mentioned in previous studies.

Table 2: One-way ANOVA Results for Group Comparisons

Measure	$F(2,87)$	p	η^2
Avg. Entropy	1.30	.2784	.029
Avg. Bhatt. Dist.	0.44	.6456	.010
Inflect. Prop. Entropy	0.41	.6620	.009
Inflect. Prop. Bhatt	0.12	.8850	.003
DSI	0.63	.5375	.014
AuDrA	0.18	.8357	.004

Note. Avg. Entropy = Average Entropy; Avg. Bhatt. Dist. = Average Bhattacharyya Distance; Inflect. Prop. Entropy = Inflection Proportion of Entropy; Inflect. Prop. Bhatt = Inflection Proportion of Bhattacharyya Distance; DSI = Divergent Semantic Integration; AuDrA = Automated Drawing Assessment (Originality Score).

Correlational Analyses of Flexibility and Originality Measures

When it comes to the relationship between the process measures of creativity and the originality aspect of creativity, correlation analyses revealed a notable divergence between two modes of cognitive flexibility. As shown in Figure 5, average entropy and average Bhattacharyya distance were strongly positively correlated with each other ($r = .83$), but both showed insignificantly weak correlations with their respective inflection metrics and with DSI (rs between –.12 and –.18). These trends suggest that participants who sustained a broad space of exploratory stroke options throughout the drawing process tended to make fewer within-trial shifts in drawing strategy and produced less semantically divergent narratives.

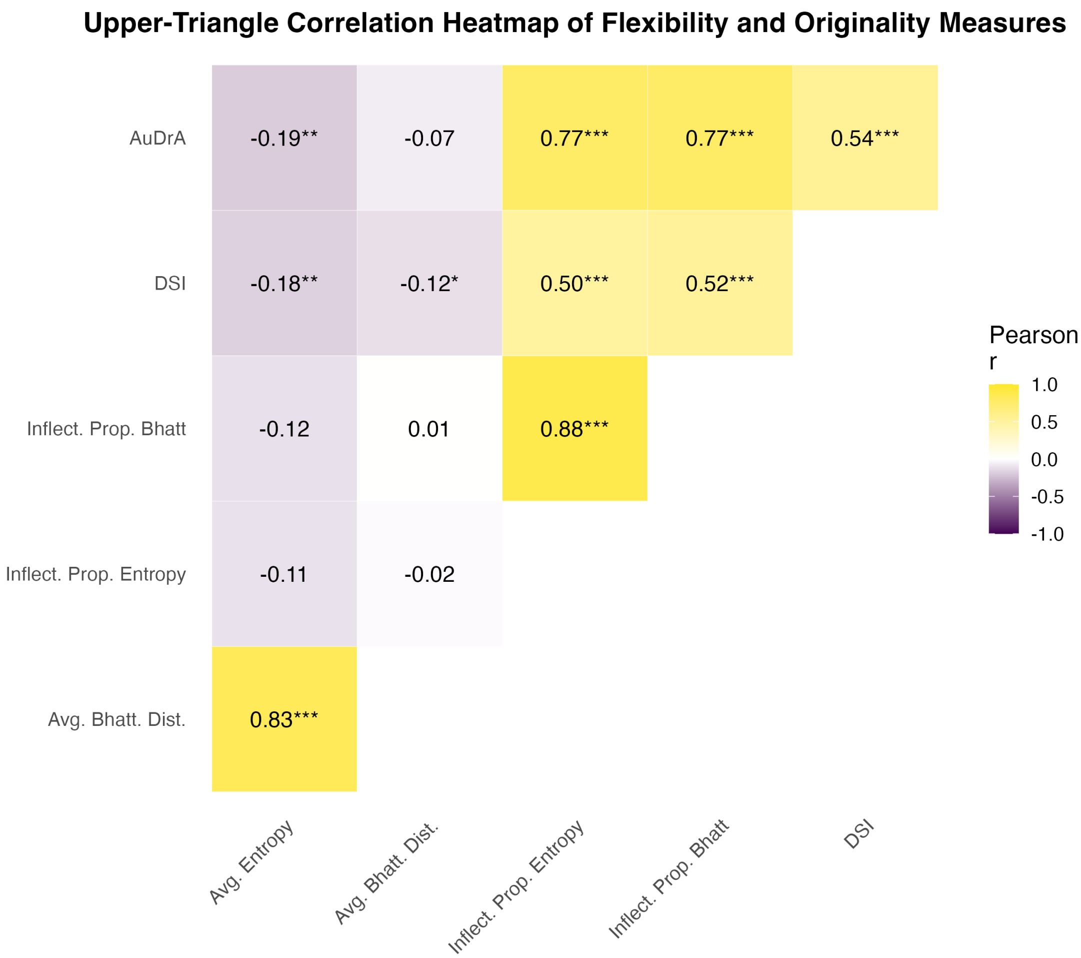

Figure 5: Pearson Correlation Heatmap of Flexbility and Originality Measures. Avg. Entropy = Average Entropy; Avg. Bhatt. Dist. = Average Bhattacharyya Distance; Inflect. Prop. Entropy = Inflection Proportion of Entropy; Inflect. Prop. Bhatt = Inflection Proportion of Bhattacharyya Distance; DSI = Divergent Semantic Integration; AuDrA = Automated Drawing Assessment (Originality Score).

In contrast, the two inflection-based measures were strongly positively correlated with each other ($r = .88$), and both were moderately positively associated with DSI ($r > .50$), indicating a shared flexibility dynamic rooted in frequent strategic switching and a wider conceptual integration. These switching-based flexibility metrics demonstrated a modest positive relationship with originality (AuDrA), while the average metrics (entropy and Bhattacharyya distance) showed little to no association with originality.

Taken together, these results suggest that real-time flexibility may manifest through two distinct behavioral strategies: one characterized by persistent exploratory breadth (high average entropy and Bhattacharyya distance) and another characterized by dynamic switching between ideas (high inflection proportions and DSI). Importantly, only the latter appears to be meaningfully connected to originality in this task context.

Multilevel Regression Analysis: Predicting Originality From Flexibility Measures

Given that mood induction did not significantly influence originality or any flexibility process measures (as established through the series of one-way ANOVAs above), one of the necessary conditions for the mediation analysis (i.e., the significance of both the indirect and direct effects) was not met. Hence, I chose not to perform the planned mediation analysis (see the full mediation model output in Appendix E that confirms the insignificance of indirect and direct effects of positive, activating mood states on originality). Although the present study did not replicate prior findings suggesting that positive activating mood enhances originality via cognitive flexibility, subsequent correlation analyses revealed significant associations between specific flexibility measures and originality. These findings highlight the importance of examining process-level predictors of the originality aspect of creativity, independent of mood effects.

Hence, to directly assess the unique predictive contribution of each flexibility measure to creative originality, I implemented a multilevel regression model that accounted for the nested structure of the data, in which each participant completed three drawing trials. This modeling framework offered two key advantages: (1) it allowed me to partition both between- and within-participant variability, and (2) it appropriately leveraged the repeated-measures design to improve statistical power while accounting for dependency among observations. The model specified random intercepts for participants and treated originality scores, as assessed by the AuDrA model, as the dependent variable. All five flexibility measures—average entropy, average Bhattacharyya distance, inflection proportion of entropy, inflection proportion of Bhattacharyya distance, and DSI—were included as fixed-effect predictors. In addition, several covariates were entered to control for potential confounding factors: positive and negative affectivity (trait affect), openness to experiences, trait-level cognitive flexibility, and self-rated artistic skill.

Table 3: Multilevel Regression Predicting Originality from Flexibility Measures and Covariates

Predictor	**Estimate (β)**	**95% CI**	**p-value**
(Intercept)	0.30	[0.16, 0.43]	$< .001$
Avg. Entropy	−0.07	[−0.17, 0.02]	.105
Avg. Bhatt. Dist.	0.00	[−0.02, 0.03]	.772
Inflect. Prop. Entropy	0.18	[0.11, 0.25]	$< .001$
Inflect. Prop. Bhatt	0.16	[0.09, 0.23]	$< .001$
DSI	0.06	[0.02, 0.09]	.004
Positive Affectivity	−0.00	[−0.00, −0.00]	$< .001$
Negative Affectivity	0.00	[−0.00, 0.00]	.083
Openness to Experiences	0.00	[−0.00, 0.01]	.129
Cognitive Flexibility	0.00	[−0.00, 0.00]	.104
Self-Rated Artistic Skill	−0.00	[−0.01, 0.01]	.531
Random Effects			
Residual Variance (σ^2)	0.00		
Intercept Variance (Participant) (τ_{00})	0.00		
ICC	0.07		
N (Participants)	90		
Observations	270		
Marginal R^2 / Conditional R^2	0.725 / 0.745		

Note. CI = confidence interval; ICC = intraclass correlation coefficient. Estimates reflect fixed effects from a multilevel model with random intercepts for participants. Avg. Entropy = Average Entropy; Avg. Bhatt. Dist. = Average Bhattacharyya Distance; Inflect. Prop. Entropy = Inflection Proportion of Entropy; Inflect. Prop. Bhatt = Inflection Proportion of Bhattacharyya Distance; DSI = Divergent Semantic Integration; AuDrA = Automated Drawing Assessment (Originality Score).

As shown in Table 3, the multilevel regression model demonstrated strong explanatory power, with a marginal R^2 of .725 and a conditional R^2 of .745. These values indicate that the fixed effects alone explained approximately 73% of the variance in originality scores and that including random intercepts for participants provided a small additional improvement in the fit of the model. This high level of explained variance is further supported by the predicted versus observed plot shown in Figure 6. The strong alignment of data points along the diagonal reference line suggests that the model accurately captures the underlying variability in originality ratings across trials and participants.

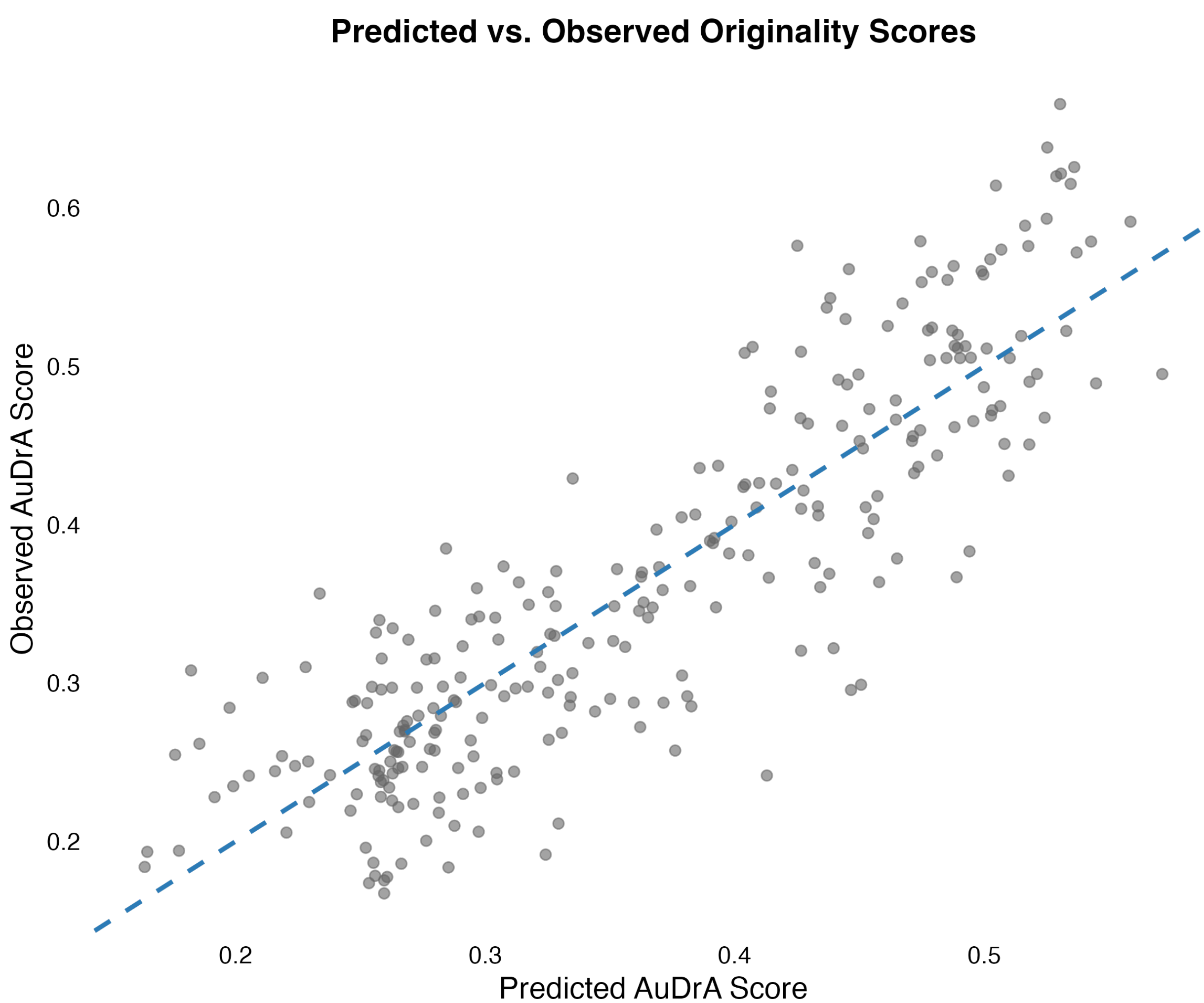

Figure 6: Predicted vs. observed originality scores from the multilevel regression model. The dashed line represents the identity line ($y = x$). AuDrA = Automated Drawing Assessment (Originality Score).

When it comes to how each flexibility measure predicted originality, three flexibility measures emerged as statistically significant predictors of originality in the multilevel regression model (see both Table 3 and Figure 7): inflection proportion of entropy ($\beta = 0.18$, $p < .001$), inflection proportion of Bhattacharyya distance ($\beta = 0.16$, $p < .001$), and DSI ($\beta = 0.06$, $p = .004$). These effects remained significant after controlling for trait affectivity, openness, cognitive flexibility, and self-rated artistic skill. These relationships are further illustrated in Figure 8, which shows the marginal effects of each significant predictor on originality. All three predictors exhibit a clear linear trend, with higher inflection proportions and DSI scores associated with increased model-predicted originality.

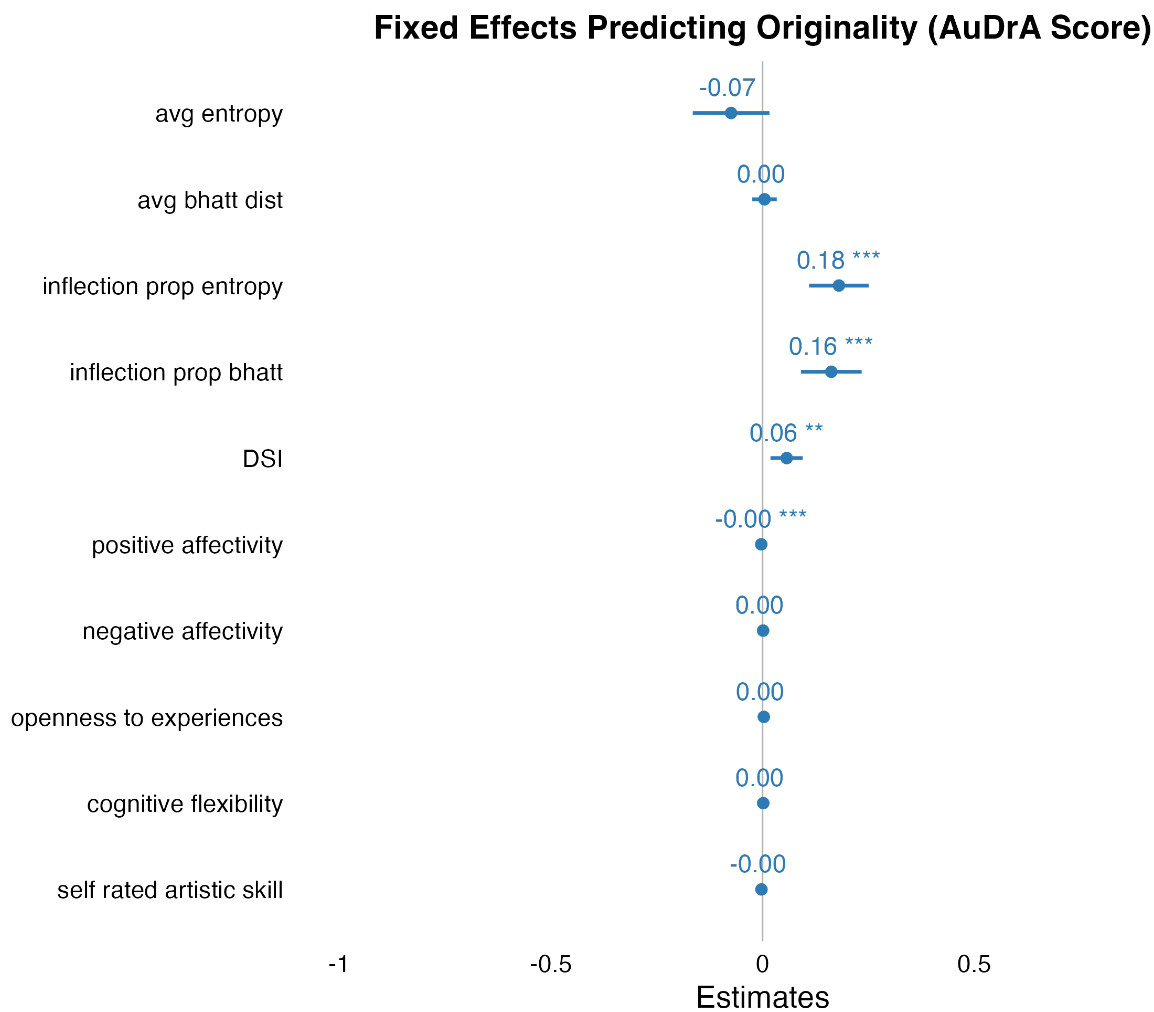

Figure 7: Fixed effects estimates from the multilevel regression model. Error bars indicate 95% confidence intervals. avg entropy = Average Entropy; avg bhatt dist = Average Bhattacharyya Distance; inflection prop entropy = Inflection Proportion of Entropy; inflection prop bhatt = Inflection Proportion of Bhattacharyya Distance; DSI = Divergent Semantic Integration.

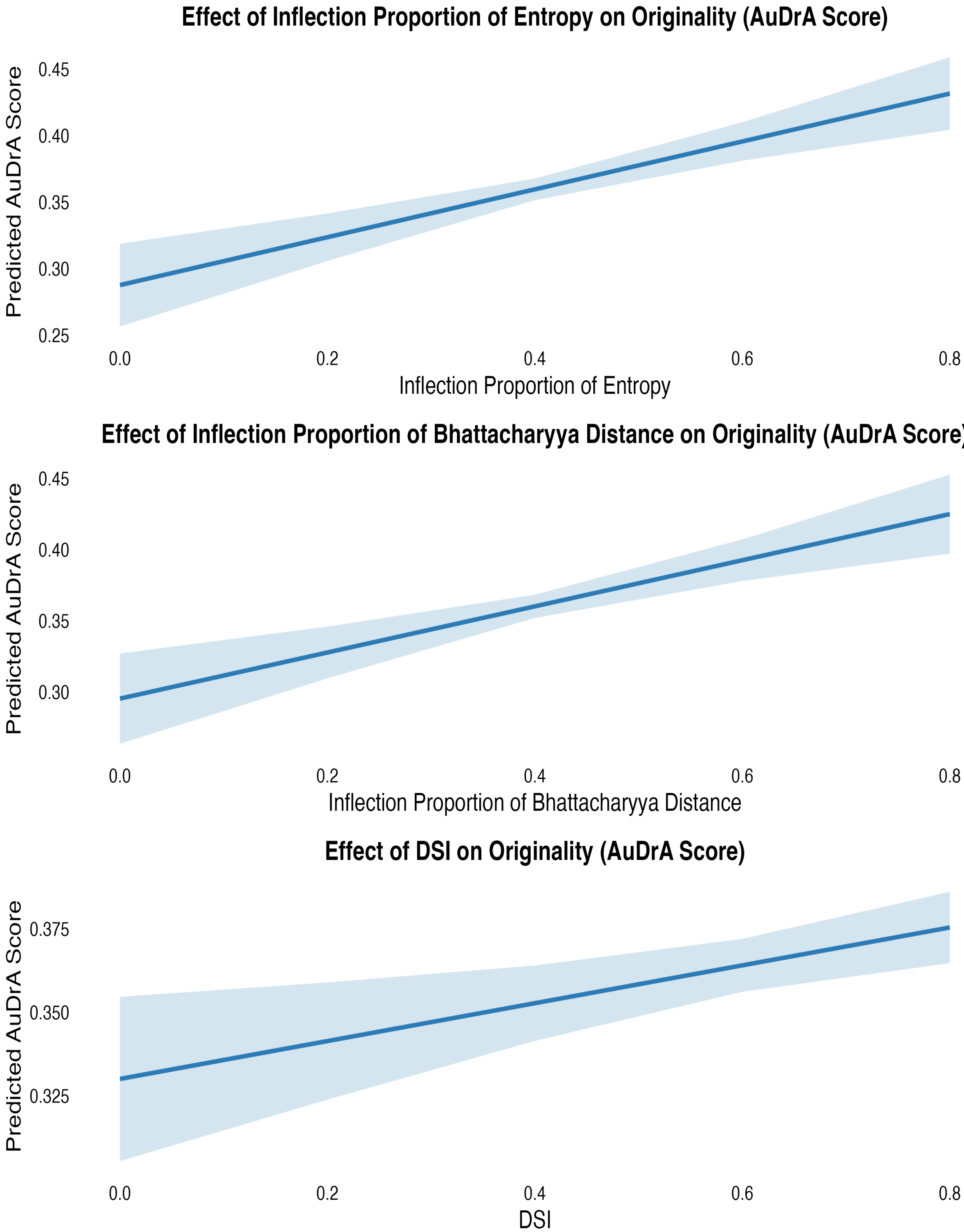

Figure 8: Marginal effects of the three significant predictors on originality. Shaded areas represent 95% confidence intervals.

By contrast, neither average entropy ($\beta = -0.07$, $p = .105$) nor average Bhattacharyya distance ($\beta = 0.00$, $p = .772$) significantly predicted originality. These null findings reinforce and extend the distinction observed in the earlier correlational analysis (see Figure 5 above) between two qualitatively different modes of flexibility: persistent exploratory breadth and dynamic switching. Average entropy and average Bhattacharyya distance—strongly correlated with each other but uncorrelated with inflection-based metrics or DSI—did not significantly predict originality in the multilevel model. In contrast, the inflection-based measures and DSI, which were positively correlated and previously shown to relate more closely to originality, emerged as significant predictors here as well. Taken together, both the correlational and multilevel findings converge to suggest that originality is more strongly associated with dynamic switching between ideas—captured by inflection proportions and conceptual integration—than with global exploratory breadth alone. That is, originality appears to benefit more from flexible transitions and semantic diversity than from consistently high uncertainty or divergence throughout the task.

Discussion

Aiming to join the debate on mood-creativity linkage, this study combined visual creative tasks (specifically, the Incomplete Shape Drawing Task) with state-of-the-art computer vision and NLP techniques to capture both the creative processes that demonstrate the flexibility aspect of creativity and the final products of drawings that show the originality aspect of creativity. By successfully manipulating participants' mood states (particularly along the arousal dimension) into *High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control* groups using three validated film clips, the current study examined the flexibility pathway in the dual pathway to creativity model, where positive activation moods enhance cognitive flexibility, thereby increasing originality in creative output.

Despite successful mood manipulation-particularly along the arousal dimension-there were no significant group differences in CoSE-based flexibility measures, semantic integration (DSI), and originality (AuDrA) scores across induced mood conditions. As such, a core precondition for conducting mediation analysis (i.e., a significant relationship between the independent variable and the mediator and/or dependent variable) was not met. Therefore, I decided not to perform the planned mediation analysis and instead shift the focus to evaluate the process-level relationship between flexibility and originality (i.e., the flexibility pathway to creativity according to the dual pathway to creativity model).

Both correlation and multilevel regression analyses revealed a consistent dissociation between two types of flexibility. Average entropy and average Bhattacharyya distance were highly correlated with one another, suggesting a shared representation of persistent exploratory breadth, but they showed weak associations with originality. In contrast, inflection-based metrics and DSI—indicators of dynamic switching and semantic richness—were positively correlated with one another and significantly predicted originality. These effects were confirmed in a multilevel regression model that accounted for the nested structure of the data and controlled for trait affectivity, openness to experience, cognitive flexibility, and self-rated artistic skill. Three predictors—inflection proportion of entropy, inflection proportion of Bhattacharyya distance, and DSI—emerged as significant contributors to originality, while the average-based measures did not.

The Elusive Role of Positive Mood in Creativity

The present study aimed to test a core prediction of the dual pathway to creativity model (Nijstad et al., 2010), where positive activating moods enhance cognitive flexibility and thus increase creative originality. While the manipulation check confirmed that the mood induction procedure successfully altered both arousal and valence—particularly distinguishing the *High-Arousal Positive Mood* group from the *Neutral Control*—its downstream impact on creative performance was unexpectedly limited. Across all creativity-related measures (i.e., average entropy, average Bhattacharyya distance, inflection proportion of entropy, inflection proportion of Bhattacharyya distance, DSI, and AuDrA), none showed significant between-group differences in one-way ANOVAs across the three induced mood conditions.

These findings appear to diverge from the general trend reported in previous meta-analyses, which suggest that positive mood enhances creativity by broadening cognitive categories and fostering associative thinking (e.g., Davis, 2009; Fredrickson, 2001). However, a growing body of research has also documented small or nonsignificant effects of positive mood on creativity, pointing to a more complex and context-sensitive relationship. For example, Baas et al. (2008) conducted a meta-analysis spanning 25 years of research and found only a modest average effect size of $r = .15$ for the link between positive mood and creativity, with substantial variability between studies. Similarly, Zenasni and Lubart (2002) reported that positive mood does not reliably enhance creativity across all contexts, especially when tasks involve higher cognitive demands or when participant characteristics (e.g., openness to experience, emotion regulation) vary widely. These findings suggest that positive mood may not consistently yield measurable gains in creative output, particularly under certain experimental conditions.

In the current study, several aspects of the design may have attenuated the influence of mood on creativity. The limited effect of mood on process-based flexibility may be due to the transient nature of the induced affective states. Prior research has shown that mood manipulations involving brief film clips can quickly fade, especially in online experimental environments where participant engagement and environmental control are inherently limited (Fong, 2006). Additionally, a mismatch in the time scale between mood induction and the drawing task may have further diluted the intended effect. The delay between the end of the film clip and the execution of the creative task could have limited the extent to which the induced mood persisted through the peak period of cognitive demand (Monno et al., 2024). Future studies could address this issue by borrowing strategies from mental health research, such as incorporating real-time mood sampling, repeated mood inductions, or task paradigms that tightly integrate affective and cognitive processes. Approaches such as gamified interfaces or feedback-sensitive interactive environments, which have been shown to enhance emotional engagement and sustain affective states in mental health interventions (e.g., Balaskas et al., 2021), may help preserve induced mood throughout periods of peak creative demand and lead to more robust effects on creative performance.

Two Modes of Creative Flexibility: Persistent vs. Adaptive

Both the correlation and multilevel regression results revealed a notable divergence among the flexibility measures, pointing to two distinct behavioral profiles. Average-based metrics—including average entropy and Bhattacharyya distance—were highly correlated with each other but showed weak or no associations with originality. In contrast, inflection-based metrics and DSI were moderately correlated with each other and significantly predicted originality. This dissociation suggests that the flexibility metrics captured qualitatively different modes of behavior, motivating a closer theoretical examination of what these modes may represent in the context of creative performance.

The first mode, indexed by average entropy and average Bhattacharyya distance, may reflect a persistent exploratory approach, where participants maintained a broad search space throughout the drawing process without frequent shifts in strategy. The second mode, captured by inflection-based metrics and DSI, reflects adaptive flexibility, characterized by frequent changes in drawing direction and greater conceptual integration across narrative elements.

Importantly, while both modes may reflect distinct cognitive strategies, only adaptive flexibility—not persistent exploratory breadth—was reliably associated with higher originality. Inflection-based metrics and DSI showed significant positive relationships with originality (all $p < .001$), whereas average-based metrics did not. This divergence supports a growing literature emphasizing that moment-to-moment switching between ideas, rather than merely sustaining a wide exploratory range, may be more critical to creative performance.

This distinction mirrors dual-process models in creativity and executive function research. For example, Sowden et al. (2015) described creativity as involving a flexible interplay between generative and evaluative modes, which may require shifting between cognitive sets. Similarly, Nusbaum, Emily C. and Silvia, Paul J. (2019) argued that executive control plays a critical role in enabling idea switching and overcoming cognitive fixation. The present findings align with these accounts, as participants who frequently switched strategies—captured by drawing inflections—also produced more semantically diverse narratives, as measured by DSI.

The observed pattern also resonates with the work on the exploration-exploitation tradeoff in idea generation. Hills et al. (2015) proposed that successful creative thinkers must balance the exploration of new conceptual territories with the exploitation of promising ideas. In this framework, persistent flexibility may reflect broad but undirected exploration, while adaptive flexibility—marked by targeted switching—may be more efficient for generating novel combinations. Notably, the task design in this study (incomplete drawing with open-ended narrative elaboration) may have favored participants who could dynamically adapt to shifting constraints and integrate visual and conceptual modes of ideation.

This distinction can also be mapped to separate brain systems involved in creative thought. Beaty et al. (2016) suggested that spontaneous and controlled creativity involves distinct but interacting networks: the default mode network supports associative generation, while executive control networks facilitate goal-directed idea evaluation and refinement. Participants who demonstrated adaptive switching may have engaged this interplay more effectively, translating flexibility into higher originality.

Taken together, these findings provide converging support for the idea that not all forms of flexibility are equally predictive of creativity. While persistent exploration may signal openness or fluency, it is the capacity to adaptively shift strategies and integrate across representational modes that appears to drive original output in this task. Future research might examine whether this distinction holds across other creative domains, and whether training interventions can selectively enhance adaptive flexibility as a means of boosting creative performance.

Linking Drawing Dynamics, Semantic Integration, and Originality

Beyond exploring the effects of (positive) mood states, this study provides important insights into the cognitive pathways linking flexibility and creative originality. Across both drawing-based and narrative-based measures, consistent associations emerged between process-level flexibility and originality, as measured by the AuDrA model. Specifically, the inflection proportions of entropy and the inflection proportion of the Bhattacharyya distance (stroke-level metrics that capture moment-to-moment shifts in drawing behavior) were significant predictors of originality. Similarly, DSI (a semantic measure of narrative flexibility) showed a robust positive association with originality. In contrast, average entropy and average Bhattacharyya distance, which index the sustained breadth of exploration, were not significantly related to originality.

Although the present study did not replicate the hypothesized effect of positive activating mood on creativity, the findings nevertheless lend support to the flexibility pathway within the dual pathway to creativity model, which posits that creative ideation can arise through adaptive switching between categories or perspectives (Nijstad et al., 2010). The observed associations between inflection-based metrics and originality support the notion that adaptive shifts in strategy, whether visual or conceptual, are predictive of original creative output. This interpretation is consistent with long-standing theoretical accounts that position ideational flexibility as a core component of creativity. For example, Guilford (1967) emphasized flexibility as distinct from fluency and originality, highlighting its role in allowing individuals to shift between conceptual categories. Similarly, Johnson-Laird (1988) described creativity as arising from the generation and transformation of mental models, a process that inherently requires the ability to abandon habitual associations. More recent empirical studies have corroborated this view, showing that flexibility, especially when measured as the ability to switch between semantic fields or representational frames, predicts performance on divergent thinking tasks (Benedek et al., 2012; Kenett et al., 2016). There is also converging neuroimaging evidence supporting this flexibility–originality pathway. Building on behavioral findings, research by Beaty et al. (2016) demonstrates that cognitive flexibility engages dynamic interactions between large-scale brain networks, particularly the default mode network (DMN)—which facilitates associative and spontaneous thought—and the executive control network (ECN)—which enables goal-directed regulation and cognitive control. The inflection-based stroke metrics used in the present study may reflect these underlying neural dynamics, capturing real-time behavioral expressions of transitions between exploratory and evaluative modes of thinking. That DSI, a measure grounded in semantic processing and entirely distinct from motor behavior, also significantly predicted originality further reinforces the idea that adaptive switching, whether expressed visually or conceptually, is a core process underlying creative output.

Furthermore, from a methodological standpoint, the convergence of flexibility-originality pathway across the two modalities (i.e., drawing and narrative) provides empirical support for the validity of the measures employed. Specifically, CoSE-derived inflection metrics successfully captured behavioral flexibility at the stroke level, while DSI effectively indexed semantic flexibility in participants' post-task narratives. Additionally, the positive association between stroke-based and narrative flexibility measures and the automated rating of drawing originality (i.e., AuDrA) supports the theoretical claim that adaptive, real-time flexibility underlies creative output. Inflection-based metrics captured shifts in visual strategy during the drawing task, while DSI reflected semantic divergence in narrative responses. Their shared ability to predict originality demonstrates convergent validity with AuDrA—a model trained on human ratings—suggesting that both measures capture core aspects of creativity recognized in human evaluations. Meanwhile, the lack of association between average-based metrics and originality, meanwhile, highlights the specificity of the inflection-based measures in capturing meaningful creative dynamics. Taken together, these findings validate the use of automated, quantitative approaches for assessing creativity, particularly in the visual domain where human scoring is traditionally labor-intensive and subjective.

These findings also align with a broader methodological shift in the cognitive sciences: the increasing use of cross-modal and machine learning approaches to investigate higher-order cognitive processes such as attention, memory, and executive function. By integrating data across sensory modalities and leveraging computational models to decode brain or behavioral signals, these approaches allow researchers to capture the complexity and dynamism of cognition with greater granularity than traditional methods (e.g., Ye et al., 2024; Vessel et al., 2019). This paradigm has also begun to influence creativity research, where the need to assess process-level dynamics in multiple representational domains—such as vision, semantics, and motor—has grown. In particular, drawing-based tasks, once primarily assessed through subjective scoring, are increasingly being paired with computational tools to extract features such as semantic divergence or stroke dynamics. These developments enable more scalable and interpretable models of creativity, and the present study contributes to this growing framework by demonstrating how both visual and narrative flexibility can be quantitatively linked to model-assessed originality. Recent advances in sketch-to-image translation (e.g., Ghosh et al., 2019; Wang et al., 2023) demonstrate how neural networks can interpret sparse visual input and generate semantically rich visual outputs, reflecting the generative potential of sketch-based expression. Meanwhile, work at the intersection of text and drawing has explored how multimodal inputs, such as hand-drawn sketches combined with textual prompts, can guide complex generative systems (Chen et al., 2023), offering new possibilities for modeling creativity in naturalistic and user-directed settings. The present study contributes to this growing body of research by showing that stroke-based and semantic flexibility measures, both derived from a drawing-based task, meaningfully predict originality as assessed by a computational model (AuDrA). These results suggest that drawing, when paired with principled computational methods, is a powerful and underutilized modality for assessing creative processes across cognitive and representational domains.

Strengths, Limitations and Future Directions

Aiming to investigate the mood-creativity linkage (particularly the flexibility pathway) as proposed in the dual pathway to creativity model, this study offers several key contributions to creativity research. First, it provides empirical evidence for two distinct modes of creative flexibility: (1) a persistent exploratory approach, characterized by sustained entropy and broad stroke divergence, and (2) an adaptive flexibility, marked by real-time shifts in drawing strategy and semantic integration. Crucially, only the adaptive mode of flexibility—captured through inflection-based stroke dynamics and DSI—predicted originality, supporting the theoretical claim that the ability to shift between ideas, rather than simply maintaining a broad search space, underlies creative ideation. Second, by combining stroke-based metrics derived from drawing behavior and language-based metrics extracted from narrative responses, the study demonstrates a cross-modal approach to measuring cognitive flexibility. This integration captures flexibility at both the sensorimotor level (via shifts in visual-motor execution) and the conceptual level (via semantic divergence in language), offering converging evidence for the underlying cognitive processes that contribute to originality. Third, the study employs an ecologically valid low-instruction drawing task that allows participants to generate creative responses with minimal constraints. Unlike traditional divergent thinking tasks, which often rely on highly structured prompts and focus predominately on the verbal domain, this approach supports spontaneous and context-sensitive creative expression. By embedding creativity assessment in a simple open-ended visual completion task, the study captures creativity as it unfolds more naturally, aligning more closely with real-world creative behavior and reducing cultural or linguistic bias that may affect verbal tasks. Finally, this study introduces a scalable and automated framework for creative assessment that significantly reduces the dependency on labor-intensive human scoring. By leveraging machine learning and natural language processing techniques—including the CoSE model for drawing analysis, DSI for narrative analysis, and AuDrA for originality evaluation—the framework supports efficient, reproducible, and interpretable assessments of creativity across multiple modalities.

Despite boasting these strengths, this study is not without limitations, which point toward promising directions for future research. First, although the sample size ($N = 90$) was sufficient to detect medium-to-large effects, it may have been underpowered to capture the subtler effects of mood on flexibility and originality, which are often modest in size. Meta-analytic evidence suggests that mood influence on creativity tends to be small and highly context dependent (Baas et al., 2008), and detecting such effects may require larger samples, especially when examining indirect pathways or interactions. Moreover, the transient nature of mood states induced through brief film clips raises questions about the duration and depth of emotional engagement during the task. Future research could use repeated or sustained mood manipulations, mood tracking across the task, or immersive delivery methods (e.g., virtual reality) to better capture the dynamic relationship between affect and creative processing. Second, despite improving accessibility and ecological reach, the online experiment in this study also introduces uncontrolled variability in participant environments. Factors such as external distractions and reduced engagement may have weakened the effects of mood or interfered with task performance. Although basic quality control procedures were used, future studies could incorporate richer behavioral indicators of engagement—such as drawing latency, cursor dynamics, or time-on-task measures—to assess and filter data quality more systematically. Third, the study focused solely on behavioral and narrative data without probing the neurocognitive mechanisms underling flexibility and originality. Previous research has emphasized the importance of dynamic interactions between the default mode network (DMN) and the executive control network (ECN) in supporting creative thought (e.g., Beaty et al., 2016). To more directly examine the neural correlates of adaptive flexibility, future studies could incorporate neurophysiological measures such as EEG or fMRI. For instance, EEG-based time-frequency analyses could be used to track changes in frontal midline theta activity, which has been linked to cognitive control and set shifting. Similarly, event-related potentials (ERPs) could isolate neural responses to inflection points in the drawing task, marking moments of strategic switching. Furthermore, using fMRI, researchers could apply functional connectivity analyses or dynamic causal modeling (DCM) to examine how activation and communication between DMN and ECN evolve throughout the creative process. Combining these neural indices with stroke- or narrative-level flexibility metrics would allow for a more integrated, multimodal understanding of how brain dynamics support creative behavior in real time. Fourth, the analysis pipeline relied on summary-level metrics (e.g., entropy, inflection proportion), which, while interpretable and efficient, may oversimplify the temporal structure of the creative process. Drawing is inherently sequential and dynamic, offering opportunities to model ideation and strategy shifts over time. Future work could adopt more process-sensitive modeling approaches, such as Hidden Markov Models (HMMs), Bayesian switching models, or dynamic time warping, to identify latent cognitive states or transitions in creative behavior. These methods would allow researchers to move beyond static indicators and toward a more process-oriented account of flexibility. Finally, although the AuDrA model provides a scalable, automated measure of originality, the current study did not include human ratings of creativity for comparison. Incorporating dual evaluation methods (i.e., combining human ratings with algorithmic scores) could improve the validity of machine-based creativity assessments and may reveal meaningful divergences between human and computational perspectives on originality.

Conclusion

This study examined the mood-creativity linkage proposed by the dual pathway to creativity model: Positive activating moods enhance cognitive flexibility, thereby increasing originality in creative output. Specifically, it leveraged the Incomplete Shape Drawing Task coupled with state-of-the-art NLP and computer vision techniques to derive flexibility measures from the stoke dynamics and post-drawing narratives and originality measures from the final completed drawings. Although mood induction successfully manipulated the arousal and valence scores of *High-Arousal Positive Mood*, *Low-Arousal Positive Mood*, and *Neutral Control* groups, it surprisingly did not yield significant differences in flexibility or originality measures across groups, which could be attributed to a statistically underpowered sample size to capture the subtler effects of mood on flexibility and originality or the transient nature of mood states induced through brief film clips. Nonetheless, the findings revealed two distinct modes of cognitive flexibility: persistent exploratory breadth, reflected by higher average entropy and Bhattacharyya distance in stroke predictions, and adaptive switching, captured by the proportion of inflection points in the time series of entropy and Bhattacharyya distance, as well as semantic integration in narratives. Crucially, only adaptive flexibility was significantly associated with originality, supporting the idea that the capacity to change strategies and integrate distinct concepts in real time is central to creative performance. These findings not only highlight the caveats of experimental mood induction for creativity research but also underscore the value of combining visual creativity tasks with computational modeling to unpack the cognitive processes underlying originality. By capturing both stroke-based and narrative expressions of flexibility, this study offers a cross-modal, process-oriented framework for understanding creative performance beyond traditional verbal tasks.

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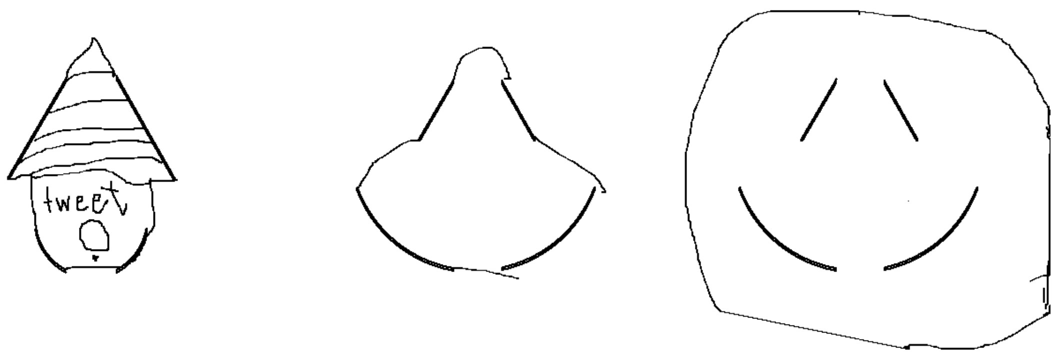
Appendices

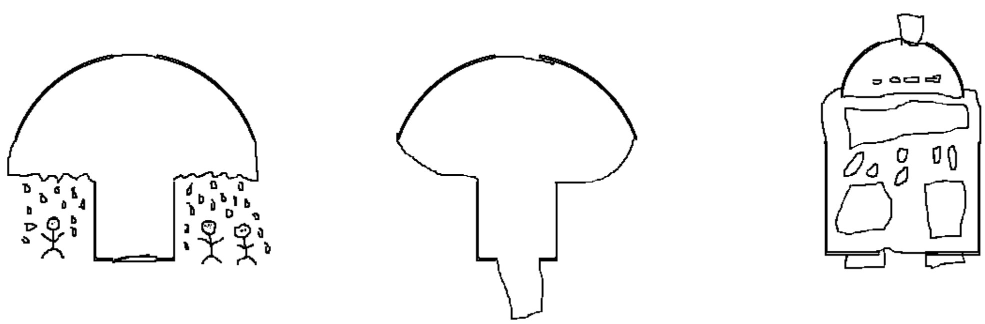
A Sample Completed Drawings

This section presents sample completed drawings from three different stimulus groups (A, B, and C) in the Incomplete Shape Drawing Task.

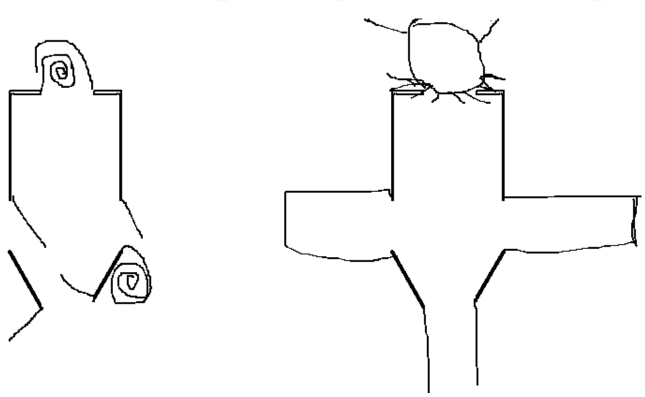
Sample Completions from Group A Stimuli



Sample Completions from Group B Stimuli



Sample Completions from Group C Stimuli



B Formula for Calculating Entropy of the Gaussian Mixture Model

This study adopts the approach proposed by Huber et al. (2008) to approximate the entropy of a GMM by incorporating the Kullback-Leibler (KL) divergence between each pair of components within the mixture, as suggested by Hershey and Olsen (2007):

$$H(GMM) \approx -\sum_{i=1}^{N} \pi_i \log\left(\sum_{j=1}^{N} \pi_j \exp\left(-\frac{1}{2} D_{KL}(N_i||N_j)\right)\right),$$

$$D_{KL}(N_i||N_j) = \frac{1}{2}\left(\mathrm{tr}(\Sigma_j^{-1}\Sigma_i) + (\mu_j - \mu_i)^T \Sigma_j^{-1}(\mu_j - \mu_i) - k + \ln\left(\frac{|\Sigma_j|}{|\Sigma_i|}\right)\right),$$

where:

- N represents the number of components in the GMM.
- π_i and π_j are the mixing coefficients for components i and j, respectively, indicating the weight of each component in the mixture.
- $D_{KL}(N_i||N_j)$ measures the divergence between the i-th and j-th components of the GMM, quantifying the difference between these two probability distributions.
- Σ_i and Σ_j are the covariance matrices of components N_i and N_j, respectively.
- μ_i and μ_j are the mean vectors of components N_i and N_j, respectively.
- $\mathrm{tr}(\cdot)$ denotes the trace of a matrix, the sum of its diagonal elements.
- k is the dimensionality of the data or the number of features in the dataset.
- $|\Sigma|$ denotes the determinant of the covariance matrix Σ.

C Formula for Calculating Aggregated Bhattacharyya Distance

Given a Gaussian Mixture Model (GMM) with N components, each defined by a mean vector μ_i and a covariance matrix Σ_i, the Bhattacharyya distance (D_B) between any two components i and j can be calculated as:

$$BC[\mu_i, \Sigma_i, \mu_j, \Sigma_j] = \left|\frac{\Sigma_i + \Sigma_j}{2}\right|^{-\frac{1}{2}} \cdot |\Sigma_i|^{\frac{1}{4}} \cdot \left|\Sigma_j\right|^{\frac{1}{4}} \cdot \exp\left(-\frac{1}{8}\Delta\mu_{ij}^T \left(\frac{\Sigma_i + \Sigma_j}{2}\right)^{-1} \Delta\mu_{ij}\right)$$

where $\Delta\mu_{ij} = \mu_j - \mu_i$ is the difference between the mean vectors of components i and j. To compute the aggregated Bhattacharyya distance (D_{AB}) across all unique pairs of components in the GMM, one option would be averaging the distances calculated using the formula above:

$$D_{AB} = \frac{1}{\binom{2}{N}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} BC[\mu_i, \Sigma_i, \mu_j, \Sigma_j].$$

D Formula for Calculating Divergent Semantic Integration

After converting narrative texts into BERT word embeddings, pairwise semantic distances are calculated, which are further used to derive DSI scores using the following formula (Johnson et al., 2022):

$$DSI = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{k=i+1}^{n} D_{\cos}(\omega_i, \omega_k)$$

$$D_{\cos}(\omega, k) = 1 - \frac{\omega \cdot k}{\|\omega\| \|k\|}$$

where:

- ω_i, ω_k are the embeddings for words i and k.
- $D_{\cos}$ measures the cosine distance, which is 1 minus the cosine similarity, between the embeddings.
- n is the number of unique word pairs considered.

E Mediation Analysis

To evaluate whether mood condition influenced creative originality through different aspects of cognitive flexibility, a series of mediation models were conducted, testing each flexibility measure individually as a mediator. Mood conditions were dummy-coded using the Neutral Control group as the reference category. The outcome variable in all models was originality, measured via AuDrA (see Table 4 for detailed mediation results).

Average Entropy. Mood condition had no significant effect on average entropy (D1: $\beta = -0.010$, $p = .646$; D2: $\beta = -0.046$, $p = .039$), and average entropy did not significantly predict originality ($\beta = -0.255$, $p = .010$). While the path b effect was statistically significant, the indirect effects were not: indirect$_{D1}$ = 0.003 ($p = .672$), indirect$_{D2}$ = 0.012 ($p = .106$). Direct effects of mood on originality were non-significant, and total effects were close to zero.

Average Bhattacharyya Distance. Neither mood condition (D1: $\beta = -0.042$, $p = .552$; D2: $\beta = -0.107$, $p = .113$) nor average Bhattacharyya distance ($\beta = -0.037$, $p = .239$) significantly predicted originality. Indirect effects were also non-significant (indirect$_{D1}$ = 0.002, $p = .658$; indirect$_{D2}$ = 0.004, $p = .359$), and direct effects remained negligible.

Inflection Proportion of Entropy. Mood condition had no significant effect on inflection proportion (D1: $\beta = 0.018$, $p = .649$; D2: $\beta = 0.042$, $p = .268$), but inflection proportion strongly predicted originality ($\beta = 0.447$, $p < .001$). Indirect effects were not significant (indirect$_{D1}$ = 0.008, $p = .652$; indirect$_{D2}$ = 0.019, $p = .266$), but the strength of the b-path suggests this mediator may still play a functional role. Direct effects remained non-significant.

Inflection Proportion of Bhattacharyya Distance. Patterns were similar: no significant effect of mood condition on the mediator (D1: $\beta = 0.024$, $p = .540$; D2: $\beta = 0.027$, $p = .510$), but a strong effect of inflection proportion on originality ($\beta = 0.446$, $p < .001$). Indirect effects again were non-significant (indirect$_{D1}$ = 0.011, $p = .542$; indirect$_{D2}$ = 0.012, $p = .511$).

Divergent Semantic Integration (DSI). DSI was weakly predicted by mood condition (D1: $\beta = 0.078$, $p = .163$; D2: $\beta = 0.008$, $p = .897$), but it significantly predicted originality ($\beta = 0.219$, $p < .001$). Although the indirect effects were not statistically significant (indirect$_{D1}$ = 0.017, $p = .177$; indirect$_{D2}$ = 0.002, $p = .898$), the direct effects of mood on originality were also non-significant, suggesting a partial mediation.

Overall, while mood induction did not significantly influence most flexibility measures, originality was reliably predicted by DSI and inflection-based flexibility. These findings support the notion that originality may depend more on dynamic, adaptive shifts and conceptual integration rather than on sustained exploratory breadth alone.

Table 4: Mediation Model Summary: Flexibility Measures as Mediators of Mood on Originality

Mediator	**Path a** (β)	**Path b** (β)	**Indirect Effect**	**Direct Effect**
Avg. Entropy	D1: –0.010 ($p = .646$)	–0.255*** ($p = .010$)	D1: 0.003 [–.010, .015] ($p = .672$)	D1: –0.006 ($p = .759$)
	D2: –0.046* ($p = .039$)		D2: 0.012 [–.000, .028] ($p = .106$)	D2: –0.005 ($p = .821$)
Avg. Bhatt. Dist.	D1: –0.042 ($p = .552$)	–0.037 ($p = .239$)	D1: 0.002 [–.005, .009] ($p = .658$)	D1: –0.005 ($p = .803$)
	D2: –0.107 ($p = .113$)		D2: 0.004 [–.003, .015] ($p = .359$)	D2: 0.003 ($p = .899$)
Inflect. Prop. Entropy	D1: 0.018 ($p = .649$)	0.447*** ($p < .001$)	D1: 0.008 [–.027, .043] ($p = .652$)	D1: –0.011 ($p = .326$)
	D2: 0.042 ($p = .268$)		D2: 0.019 [–.015, .052] ($p = .266$)	D2: –0.012 ($p = .285$)
Inflect. Prop. Bhatt	D1: 0.024 ($p = .540$)	0.446*** ($p < .001$)	D1: 0.011 [–.024, .046] ($p = .542$)	D1: –0.014 ($p = .162$)
	D2: 0.027 ($p = .510$)		D2: 0.012 [–.025, .047] ($p = .511$)	D2: –0.005 ($p = .609$)
DSI	D1: 0.078 ($p = .163$)	0.219*** ($p < .001$)	D1: 0.017 [–.006, .045] ($p = .177$)	D1: –0.021 ($p = .213$)
	D2: 0.008 ($p = .897$)		D2: 0.002 [–.023, .028] ($p = .898$)	D2: 0.005 ($p = .749$)

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Path a = Mood group $\rightarrow$ Flexibility; Path b = Flexibility $\rightarrow$ Originality (AuDrA); Indirect effect = a $\times$ b; D1 = High Arousal vs. Neutral; D2 = Low Arousal vs. Neutral. Confidence intervals based on 5,000 bootstrapped samples.