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 proposed study aims to join the debate on mood-creativity linkage by integrating visual creative tasks with state-of-the-art computational techniques. In line with the flexibility pathway in the dual pathway to creativity model, this study hypothesizes that positive activating moods enhance cognitive flexibility, thereby increasing originality in creative output. Diverging from the predominance of verbal tasks to measure creativity, this study employs an incompleteness drawing task within the Multi-Trial Creative Ideation (MTCI) framework to track the dynamics of the creative process. A custom-built website will be built to induce mood states, administer drawing tasks, and gather narrative accounts of the creative process from approximately 300 participants sourced through Amazon Mechanical Turk.

The main contribution of this study lies in its integration of drawing tasks with deep learning and natural language processing techniques to quantitatively assess the flexibility and originality aspects of creativity, which allows for rigorous testing of the hypothesized flexibility pathway linking positive mood states to creativity. Specifically, this study will measure flexibility using the Compositional Stroke Embedding (CoSE) model, which utilizes a Gaussian Mixture Model (GMM) to predict potential strokes in the incompleteness shape drawing task. This approach assesses the uncertainty and variability between possible strokes, employing metrics such as entropy and Bhattacharyya distance to capture the dynamic range of creative options. Complementing this, flexibility will be further evaluated through Divergent Semantic Integration (DSI), which employs BERT-generated embeddings to analyze how participants integrate divergent ideas into their narratives. Meanwhile, originality will be evaluated using the Automated Drawing Assessment (AuDrA) model trained with human ratings on the same incompleteness shape drawing task. Together, this proposed study not only aims to elucidate mood-creativity linkage, but also underscores the transformative potential of integrating artificial intelligence into the study of complex human cognitive processes.

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˙creativity˙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˙dual˙2010**; **richards˙everyday˙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˙theory˙2021**; **gaut˙philosophy˙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˙hedonic˙2008**). 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˙cambridge˙2010**; **plucker˙why˙2004**; **simonton˙creativity˙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˙creative˙1996**; **ward˙conceptual˙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˙15˙2008**), mood pervades our entire framework of meaning and shapes our perception of the possibilities that the world offers (**ratcliffe˙why˙2013**). Unlike emotions, which are acute and directed responses, moods are diffuse and enduring affective states that subtly color our psychological landscape (**lischetzke˙mood˙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˙influence˙2007**;**dolcos˙neural˙2011**; **storbeck˙interdependence˙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˙imaging˙2000**; **iosifescu˙relation˙2012**; **phan˙functional˙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˙role˙2001<empty citation>** 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˙positive˙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, the study refers to the dual pathway to creativity model (**de˙dreu˙hedonic˙2008**) to examine the link between positive mood and creativity. Specifically, it integrates the incompleteness drawing task 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˙structure˙1999<empty citation>** 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˙variations˙1995<empty citati** circumplex model of mood adapted from **russell˙circumplex˙1980<empty citation>**'s model[1] (see Figure **??**), has since been widely adopted in empirical research to explore the unique and joint effects of valence and activation. For example, **balch˙dimensions˙1999<empty citation>** examined how these mood dimensions influence word recall under different mood conditions, and **nealis˙positive˙2016<empty citation>** 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˙core˙2020**; **russell˙core˙1999**).

A unified mood classification framework has advanced the understanding of the cognitive and behavioral consequences of mood states (**lischetzke˙mood˙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˙toward˙2000<empty citation>**'s control theory model. Furthermore, mood affects both the content and the process of cognition (**forgas˙chapter˙2017**). Positive moods improve the recall of positive information and broaden attention spans, facilitating creative and broad-concept learning. In contrast, negative moods promote detailed-oriented thinking, enhancing recall of negative

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

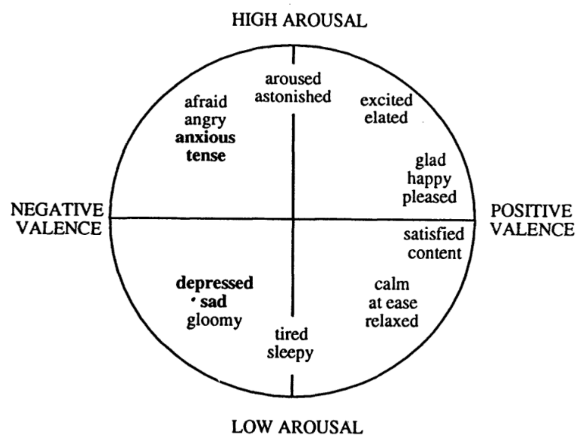


Figure 1: Valence/Arousal Circumplex Model of Mood (**feldman˙variations˙1995**)

information and learning that requires meticulous attention. Positive moods also lead to more generous social judgments, affecting interpersonal evaluations and interactions (**forgas˙mood˙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˙creative˙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˙creative˙1999**). This evolution is supported by theoretical and empirical advancements that elucidate specific cognitive processes that lead to creative insights (**finke˙creative˙1996**).

Amid this background, the field has witnessed the evolution of theoretical accounts to illuminate the cognitive systems that underlie creative thinking (**johnson˙divergent˙2022**). One enduring theory is **mednick˙associative˙1962<empty citation>**'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˙cognitive˙2004<empty citation>** 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˙cambridge˙2010**) details how basic cognitive operations—attention, perception, memory, reasoning—are utilized to generate innovative ideas. This framework extends **dietrich˙cognitive˙2004<empty citation>**'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˙divergent˙2022**). A notable example is the Geneplore model (**finke˙creative˙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 (**patterson˙personal˙2004**).

nijstad˙dual˙2010<empty citation>'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˙creativity˙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˙associative˙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˙hedonic˙2008<empty citation>** 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˙hedonic˙2008**). Some research indicates that positive moods enhance creativity more than negative moods (**grawitch˙effects˙2003**), while others find similar levels of creativity in moods (**bartolic˙effects˙1999**), or even greater creativity in negative moods (**madjar˙preliminary˙2002**).

Given the bipartite dimensions of mood states (i.e., valence and activation; **yik˙structure˙1999**), these inconsistencies may arise from a focus primarily on valence. Different cognitive processes leading to creativity (**finke˙creative˙1996**; **nijstad˙dual˙2010**) may also explain these contradictory results. In this sense, the dual pathway to creativity model (**de˙dreu˙hedonic˙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˙dual˙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˙hedonic˙2008**). Furthermore, integrating the cognitive tuning model (**schwarz˙happy˙1991**), the broaden-and-build theory (**fredrickson˙role˙2001**), and the insights from studies on visual and conceptual focusing (**derryberry˙hemispheric˙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˙hedonic˙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˙relative˙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˙influence˙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˙mood˙2022**; **maryam˙fakhrhosseini˙affectemotion˙2017**). **siedlecka˙experimental˙2019<empty citation>** 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˙experimental˙2019<empty citation>** 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˙affectemotion˙2017**; **siedlecka˙experimental˙2019**). Moreover, combining self-report and physiological measures can capture a more accurate picture of mood state (**quigley˙inducing˙2014**; **siedlecka˙experimental˙2019**). Ethical considerations are also crucial, especially when inducing negative mood states. It is essential to ensure voluntary participation and comprehensive debriefing (**maryam˙fakhrhosseini˙affectemotion˙2017**; **quigley˙inducing˙2014**; **siedlecka˙experimental˙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˙theory˙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˙cambridge˙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˙measurement˙2012<empty citation>** 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˙improved˙2021<empty citation>** 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˙cambridge˙2010**). Computational approaches, such as network science, model semantic memory to test the associative theory of creativity. For instance, studies by **kenett˙investigating˙2014<empty citation>** and **beaty˙forward˙2021<empty citation>** show that greater semantic distance from a conventional idea increases the likelihood of a new idea being considered creative. **kenett˙flexibility˙2018<empty citation>** 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˙beyond˙2019<empty citation>** use linguistic properties to measure creativity in writing, bypassing subjective scoring. **johnson˙divergent˙2022<empty citation>** employ BERT-embedded representations to gauge narrative connections and **patterson˙multilingual˙2023<empty citati** 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˙cambridge˙2010<empty citation>**, 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.

Data and Methods

Overview of Research Design

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˙experimental˙2019**). Coupled with the burgeoning exploration of creativity's multifaceted nature—encompassing definitions, underlying cognitive processes, and diverse assessment tasks (**kaufman˙cambridge˙2010**)—this mutual enrichment has paved the way for both theoretical propositions and empirical validations of the mood-creativity linkage.

Echoing **kaufman˙cambridge˙2010<empty citation>**'s call for innovative assessment techniques that more accurately reflect the dynamics of creative thinking, this proposed study aims to advance the debate on the mood-creativity connection by introducing a novel *task-measurement* combination, which leverages both the versatility of drawing tasks to uncover the cognitive underpinnings of creativity and employing state-of-the-art artificial intelligence techniques. Focusing on *domain-general*, *little-c* creativity, our 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˙role˙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˙hedonic˙2008<empty citation>**'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, by adopting validated experimental mood induction methods (**siedlecka˙experimental˙2019**), this study will explore the effects of positive mood states—ranging from activating to deactivating—on the flexibility pathway of creativity. This research will 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˙role˙2001**). The following research questions will guide the investigation:

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)?

Following **barbot˙dynamics˙2018<empty citation>**'s Multi-Trial Creative Ideation (MTCI) framework (featuring multi-stimuli approach & dynamics of ideation process), this proposed study will adopt drawing tasks (particularly the incomplete shape drawing task) and narrative about creative ideation processes to not only record the final creative output, but also track the dynamics of creative thinking that leads to the final completed drawings. 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˙investigating˙2014**; **kenett˙flexibility˙2018**) to quantify the flexibility aspect of creativity. Complementing the predominance of verbal creativity assessments with visual creativity (a canonical form of creative expression; **morrisskay˙evolution˙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˙create˙2014**), while visual creativity engages spatial reasoning and visual-motor coordination (**schlegel˙artist˙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 (**patterson˙audra˙2023**). Automated methods provide a scalable and consistent way to evaluate originality, ensuring that the assessments are objective and replicable across different studies.

Specifically, this study will measure flexibility using the Compositional Stroke Embedding (CoSE) model, which utilizes a Gaussian Mixture Model (GMM) to predict potential strokes in the incompleteness shape drawing task. This approach assesses the uncertainty and variability between possible strokes, employing metrics such as entropy and Bhattacharyya distance to capture the dynamic range of creative options. Complementing this, flexibility will be further evaluated through Divergent Semantic Integration (DSI), which employs BERT-generated embeddings to analyze how participants integrate divergent ideas into their narratives. Meanwhile, originality will be evaluated using the Automated Drawing Assessment (AuDrA) model trained with human ratings on the same incompleteness shape drawing task. Together, this proposed study not only aims to elucidate mood-creativity linkage, but also underscores the transformative potential of integrating artificial intelligence into the study of complex human cognitive processes. Together, the overall research design is illustrated in Figure **??**.

Experiment Implementation

The proposed study will design a website to facilitate an online experiment to collect data to test the proposed flexibility pathway linking positive activating mood with the originality aspect of creativity. As shown in Figure **??**, this proposed study will first design the experiment using jsPsych (**leeuw˙jspsych˙2023**), a JavaScript framework to design behavioral experiments running on a web browser. The website will then be pretested among a sample of approximately 30 University of Chicago participants (in exchange for course credit) and ask for feedback on areas of

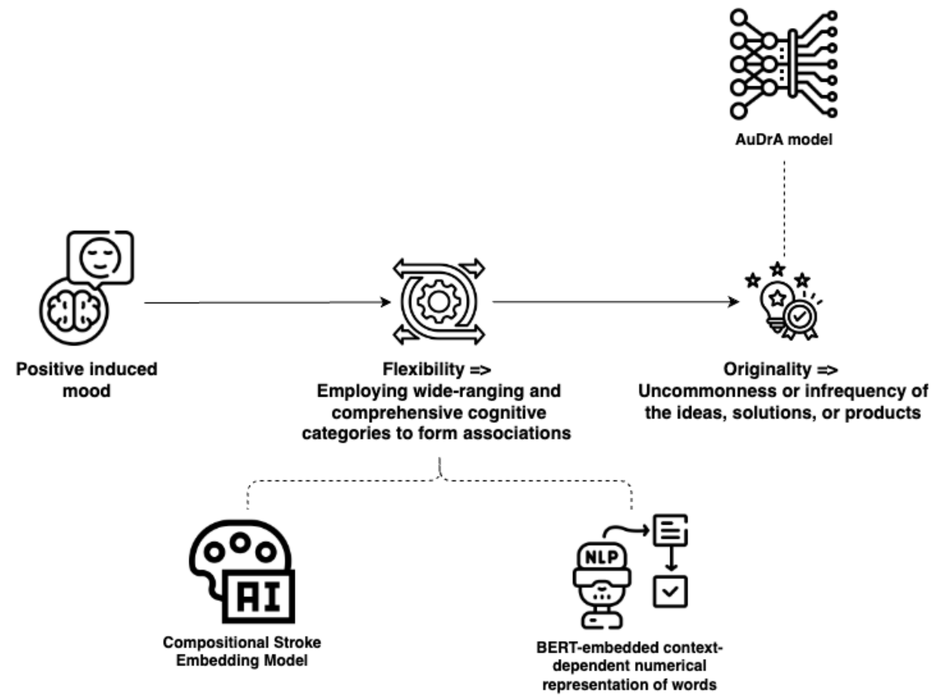


Figure 2: Overview of Research Design

improvement regarding the website and research design. This study plans to recruit approximately 300 participants recruited from Amazon Mechanical Turk (MTurk) to participate in this online experiment hosted on the improved version of the experiment website, which also allows me to download data for later data analysis.

When it comes to the design of the web page in particular, this experiment website will consist of four main blocks: survey data collection, mood induction, incompleteness drawing tasks, and narrative on thought processes behind completing the drawings (see Figure **??**). Specifically, after completing informed consent, participants will complete survey questions related to

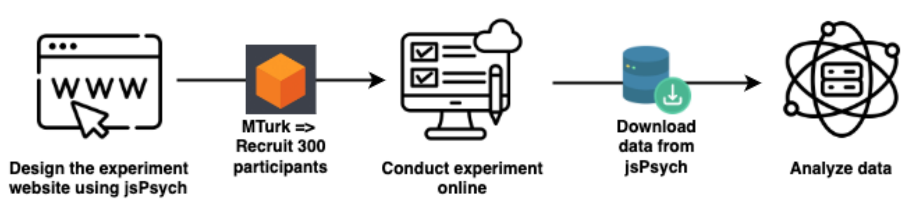


Figure 3: Workflow of Online Experiment

demographic information, as well as questionnaires that measure cognitive abilities (intelligence, working memory, metacognitive ability) and self-rated artistic expertise as control variables in this study. Subsequently, mood induction will be performed by streaming film clips, which has been proven to be an effective mood induction technique to engage visual and auditory modalities and simulate real-life emotional situations (**siedlecka˙experimental˙2019**). After controlling display size and film duration and prescreening participants who have viewed the films, this proposed study will play video clips that target different induced mood states for the three randomly assigned groups. Specifically, amusing and engaging clips from validated sets (e.g., Sister Act; **maryam˙fakhrhosseini˙affectemotion˙2017**) will be used to induce happiness, while calmness will be elicited using stimuli suggested by **kimura˙emotional˙2019<empty citation>**. For the control group, neutral clips such as nature documentaries and weather news will be chosen (**siedlecka˙experimental˙2019**). Before viewing the video clips, participants will receive the instruction 'Please watch the film carefully' to minimize the framing effects on induced moods, rather than more directive prompts like 'Let yourself experience your emotions fully.' Furthermore, to check the effectiveness of mood induction, participants will be asked to 1) rate the degree to which they are in a joyful, calm, or neural mood state when they watch the video and 2) rate the levels of valence (from unpleasant to pleasant) and arousal (from sleepy to highly aroused) of induce mood states (**kucera˙using˙2012**).

The next section of the experiment website is the creative task of incompleteness shape drawing task, where participants will be presented with an abstract or concrete shape and asked to creatively integrate this initial shape into their drawings at their own pace (see Figure **??**; **patterson˙audra˙2023**). To implement this drawing task, this study will develop a web-based drawing interface using *sketchpad* plugin of jsPsych (**leeuw˙jspsych˙2023**). This plugin includes options for undoing, redoing, and clearing strokes. In addition, it records the position (x, y coordinates) and the timing of mouse movements during drawing and saves images as text (json-like structure) using base64 encoding for later data analysis (**bainbridge˙tutorial˙2022**). After each drawing session, participants write a narrative detailing their thought processes and the creative choices made during the drawing task, providing insights into the cognitive mechanisms influencing their creativity. There will be in total three rounds of incompleteness drawing task (different starting incomplete shapes) and narrative on thought processes, echoing **barbot˙dynamics˙2018<empty citation>**'s multi-

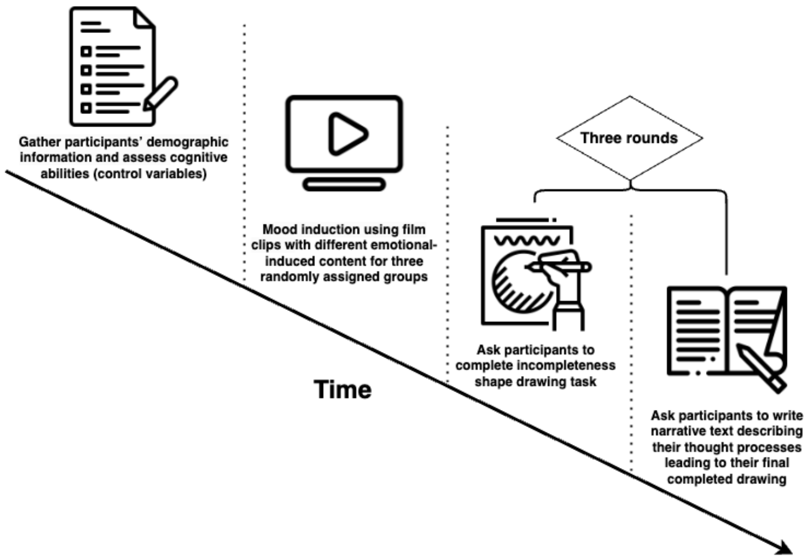


Figure 4: Experiment Web Page Design

Weekly_assignments/Example of Incompleteness Shape Task.png

Figure 5: Example of Incompleteness Shape Task

stimuli approach to uncover the (variation of) the dynamics behind creative thinking.

Methods

Measuring the Flexibility Aspect of Creativity

This proposed study will investigate the flexibility pathway leading to creativity using the incompleteness shape drawing task. The flexibility pathway refers to the process of employing wide-ranging and comprehensive cognitive categories to form associations, according to **nijstad˙dual˙2010<empty cit** dual pathway to creativity model. In the context of the incompleteness shape drawing task, flexibil-

ity specifically refers to the ability of participants to explore a wide range of qualitatively distinct creative solutions (both in terms of starting position and trajectory) for each stroke they add to an incomplete shape. This operational definition of flexibility hinges on the premise that a more creatively flexible individual will not only consider a broader array of potential next strokes, but also open to the possibility of choosing other paths that are qualitatively distinct from each other in their choice space during their creative processes.

Compositional Stroke Embedding Model The use of a generative model, specifically the Compositional Stroke Embedding (CoSE) model in this proposed study, allows for a novel examination of the flexibility aspect of creativity by taking advantage of the ability of the model to predict the next stroke using the Gaussian mix model (GMM). Specifically, the model's ability to forecast these strokes with both varying degrees of uncertainty (in its prediction) and between-component (potential stroke) distances offers a tangible metric to assess both the expansiveness and dynamic narrowing of creative possibilities of an individual's creative thought process. Initially, with the canvas largely blank and minimal constraints imposed by previous strokes, the GMM's forecasts encompass a broad spectrum of potential directions. This high degree of uncertainty and between-component distances in the model's predictions mirror an expansive field of creative potential, where participants are poised at the brink of numerous possible creative trajectories. Such a scenario exemplifies the task's capacity to engage a participant's broad and inclusive cognitive categories. As participants engage in the task, each decision—each stroke added to the canvas—serves not just as an act of creation but as a sieve, gradually filtering the boundless array of potential futures into a converging path toward a specific creative outcome. This process is hypothetically reflected in the gradual decrease in degree of uncertainty and between-component distances.

In order to capture the degree of uncertainty and between-components distances in GMM's prediction that are pertinent to the flexibility aspect of the creative ideation process, this proposed study will use the following two measures (see Appendix **??** and Appendix **??** for details in formula):

1. **Entropy of the Gaussian Mixture Model (GMM)**. Entropy quantifies the uncertainty or variability in the model predictions for the next stroke. High entropy indicates a state of high creative flexibility, where the participant is free to explore (and potentially follow) a wide

range of directions for their next stroke at a given number of completed strokes. This study adopts the approach proposed by **huber˙entropy˙2008<empty citation>** 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˙approximating˙2007<empty citation>**. This formulation provides a method for approximating the entropy of a GMM by considering the diversity and weight of each component in the mixture, thus reflecting the variability and uncertainty in the model predictions for the next stroke in the drawing task.

2. **Bhattacharyya Distance for Measuring Component Divergence**. Another measure to capture the flexibility aspect of creativity in this study is the Bhattacharyya distance, a measure of divergence between two probability distributions. 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 a greater divergence. It is particularly useful in the context of GMM for assessing overlap and separation between different clusters (**alangari˙intrinsically˙2023**). This measure is instrumental in global interpretation, helping to discern the distinctiveness and similarities between clusters by quantifying the degree of overlap between their corresponding Gaussian components. Taking a step further, the aggregated Bhattacharyya distance in the context of GMM, where multiple Gaussian components represent different aspects of the data (creative possibilities in the context of my study), can be conceptualized as a measure of overall divergence or dissimilarity between all pairs of components within the model. This aggregated measure provides a holistic view of the diversity and separation inherent in the model's representation of the data. In the case of the incompleteness shape drawing task, the aggregated Bhattacharyya distance across all component pairs in the GMM provides a quantitative measure of the dynamic narrowing process of possibilities of next stroke (positions and trajectories). A decrease in aggregated Bhattacharyya distance over time would indicate a gradual focusing of creative possibilities, reflecting the participant's transition from exploring a wide array of potential ideas to honing in on a more defined set of creative directions.

The interplay between the entropy and the Bhattacharyya measure as quantitative tools offers a nuanced view of the creative journey in the drawing task. Initially, one might expect both high entropy (indicating many possible next strokes) and significant distances between GMM components (suggesting diverse creative paths). Initially, high values in these measures reflect a phase of creative exploration, where participants are most open to employing a wide array of cognitive categories and making remote associations. As the task progresses, both measures are likely to decrease, reflecting the natural progression of creative work from exploration to execution. This progression from a broad, unbounded exploration of ideas towards a more focused and refined output is at the heart of cognitive flexibility. By quantifying this transition, the proposed measures not only capture the essence of the flexibility aspect of creativity, but also provide a structured means to examine how individuals navigate the complex landscape of potential ideas. For instance, the rate at which the possibility space narrows (as captured by these measures) mirrors the cognitive shifts that occur as a creative work evolves, offering a direct link between the theoretical underpinnings of cognitive flexibility and its practical, observable manifestations in creative tasks.

As such, investigating both the overall characteristics and the dynamic trend of the entropy of GMM and aggregated Bhattacharyya distance enables a nuanced view of the creative journey in the incompleteness shape drawing task for each participant. This is not limited to overall aggregated measure of the entropy of GMM and aggregated Bhattacharyya distance but also the steepness of the trend and the frequency and timing of significant rate of change (inflection point) of these measures over time. Here are three measures that I believe effectively distinguish the flexibility pathway during one's creative ideation process (i.e., higher flexibility versus lower flexibility aspect of creativity):

1. **Average Entropy of GMM and Aggregated Bhattacharyya Distance Across Trials**. Since the entropy of GMM indicates the level of uncertainty in the model's prediction of the participants' next move(s), a higher average entropy signifies a broader and meanwhile unpredictable exploration within the creative process, a hallmark of heightened cognitive flexibility. This is complemented by a larger aggregated Bhattacharyya distance, which underscores the extent of divergence in the exploration of creative possibilities, reflecting an engagement with a broad spectrum of cognitive categories. Hence, calculating these aggregated measures for each participant enables us to distinguish the overall breadth of creative exploration and levels of creative flexibility.

2. **Aggregated Rate of Change in Entropy of GMM and Aggregated Bhattacharyya Distance**. Extending from the average of entropy of GMM and aggregated bhattacharyya distance, the aggregated rate of change in these measures becomes pivotal. Specifically, individuals endowed with a high degree of creative flexibility tend to engage in a more extended period of ideational exploration, evidenced by a slower rate of convergence (a gradual decrease in both entropy and Bhattacharyya distance). This phenomenon is quantified by computing the first derivative of these measures over time, which offers a glimpse into the dynamic interplay between divergent and convergent thinking phases. The direction of this derivative, whether positive or negative, eloquently speaks to the prevailing mode of thought, be it expansive exploration (divergence) or focused refinement (convergence).

3. **Number and Timing of Inflection Points**. The algorithmic identification of inflection points (significant shifts in the rate of change) within the creative process, especially when analyzing the entropy of GMM or aggregated Bhattacharyya distance over GMM components in a time series, provides a nuanced view of the level of flexibility in the creative ideation process. First, it is hypothesized that people with high cognitive flexibility might exhibit a greater *number of inflection points*. This pattern suggests a more dynamic process that involves frequent shifts between exploration and refinement, reflecting their comfort with navigating diverse cognitive spaces and their readiness to adapt their creative strategies in response to new insights. Second, when it comes to the *timing of inflection points*, it is posited that the first major inflection point, marking the shift from initial exploration to more focused convergence, might occur later for individuals with high flexibility, suggesting a prolonged engagement with a broad range of possibilities before narrowing down to specific ideas. For this proposed study, I will adopt the Pruned Exact Linear Time (PELT) algorithm (**dorcas˙wambui˙power˙2015**) using *ruptures* Python library (**truong˙selective˙2020**) to identify the inflection point(s) in the time series of entropy of the GMM and Bhattacharyya distance.

Narrative about Creative Ideation Processes Apart from capturing the flexibility aspect of creativity using generative stroke models, this study relies on participants' verbal description on their thought processes (behind their completed drawings) as a complementary measure 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˙verbal˙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; **johnson˙divergent˙2022**) 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. As an original measurement of creativity in narratives, DSI echos **kaufman˙cambridge˙2010<empty citation>**'s call for interdisciplinary approaches to measure creativity by integrating **mednick˙associative˙1962<empty citat** 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 featuring forming 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 salable manner. Specifically, distributional semantics is based on the Distributional Hypothesis, which posits that words with similar meanings occur in similar contexts (**lenci˙distributional˙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˙distributional˙2020**).

Together, DSI is arguably an effective measure to characterize the flexibility pathway of creativity. By combining associative theory with distributional semantics, DSI captures the association and integration of connections between disparate ideas and concepts—a hallmark of creative flexibility. Furthermore, it employs the BERT model (**devlin˙bert˙2019**) to generate context-dependent embedding of words to capture nuanced semantic relationships that reflect creative integration (see Appendix **??** for details in formula). This approach provides a precise measurement of the semantic distance of concepts within the concept space that are involved in completing the drawings.

Specifically, a more flexible individual would navigate further in his/her concept space to connect more distinct concepts, which predicts a higher DSI.

Measuring the Originality Aspect of Creativity

To measure *originality* aspect of creatvity, this study will refer to the pre-trained AuDrA model and implementation code provided on **patterson˙audra˙2023<empty citation>**'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˙applying˙2023**; **beaty˙automating˙2021**). Targeting at the tablet-based drawing task under **barbot˙dynamics˙2018<empty citation>**'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, 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 performance in 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 my proposed research for three reasons. First, the drawing task I plan to implement is the same as the one AuDrA was trained on. Second, it allows automated originality assessment (with evidence of good model performance), which counts as a more feasible option in terms of my dispensable resources. Third, that AuDrA measures the *originality* aspect of creativity complements the adoption of CoSE that captures the *flexibility* aspect of creativity. Together, these two models enable me to examine the complete (hypothetical) flexibility pathway from positive activating mood to the originality aspect of creativity.

Mediation Analysis to Test Flexibility Pathway

To test the proposed relationship in which positive activating mood influences the originality aspect of creativity through the cognitive flexibility pathway, following the dual pathway to creativity model (**de˙dreu˙hedonic˙2008**), this proposed study will utilize mediation analysis to examine the hypothesized flexibility pathway. Causal claims in mediation analysis can be significantly strengthened through experimental methods (**homburg˙mediation˙2022**) Specifically, randomizing the independent variable (IV) enhances causal inference for the effect of IV on the mediator (M), and on the total effect of IV on the dependent variable (DV). This enhancement comes from the clear precedence of IV over M and DV if IV is successfully manipulated and through controlling potential confounding variables via random assignment of participants to different levels of IV. Consequently, with experimental manipulation of induced mood conditions, alongside controlling for cognitive abilities (specifically, intelligence, working memory, metacognitive ability) and self-rated artistic expertise, the mediation analysis in this study helps establish a stronger causal claim that positive activating mood influences the originality aspect of creativity through the cognitive flexibility pathway.

The independent variable (IV) in the mediation model comprises multicategorical mood conditions, which are dummy-coded as suggested by **hayes˙statistical˙2014<empty citation>**. For mediation analysis in experimental research, each experimental group G_i is compared to a reference group G_R (**homburg˙mediation˙2022**). Accordingly, the regression coefficients associated with dummy coded indicator variables denote the mean difference between a group G_i and G_R, respectively. For this analysis, the dummy-coded mood conditions include Happiness (D1), Calmness (D2), with Neutral serving as the reference. Each dummy variable D_i (where $i = 1, \ldots, k-1$) is set to 1 for cases in group i, and 0 otherwise, with the unrepresented group serving as the reference category. The mediator (M) is the flexibility in creativity, assessed using entropy and Bhattacharyya distance from drawing tasks, along with Divergent Semantic Integration (DSI) from after-drawing narratives. The dependent variable (DV) is the originality of output, evaluated using the Automated Drawing Assessment (AuDrA) model. Additionally, the model includes control variables such as cognitive abilities (intelligence, working memory, metacognitive ability) and self-rated artistic expertise, which help isolate the specific effects of mood on creativity.

As such, the **mediator model** is defined as follows:

$$M = \alpha_0 + \alpha_1 D1 + \alpha_2 D2 + \alpha_3 X + \varepsilon_M$$

where M represents the mediator, flexibility in creativity; α_0 is the intercept; α_1 and α_2 are the coefficients for the effects of happiness (D1) and calmness (D2), respectively; α_3 is the vector of coefficients for control variables X; and ε_M is the error term for the mediator model.

Meanwhile, the **outcome model** is similarly expressed as:

$$Y = \beta_0 + \beta_1 D1 + \beta_2 D2 + \beta_3 M + \beta_4 X + \varepsilon_Y$$

where Y denotes the dependent variable, originality in creativity; β_0 is the intercept; β_1 and β_2 reflect the direct effects of the dummy-coded mood conditions on originality; β_3 represents the effect of the mediator on the dependent variable; β_4 covers the vector of coefficients for control variables; and ε_Y is the error term for the outcome model.

Understanding the mediation effects articulated in these models is pivotal in confirming the hypothesized flexibility pathway. The indirect effects, specifically $\alpha_1 \times \beta_3$ for happiness and $\alpha_2 \times \beta_3$ for calmness, highlight how mood conditions foster creativity through enhanced cognitive flexibility. The direct effects, captured by β_1 for happiness and β_2 for calmness, reflect the immediate influence of each mood condition on the originality aspect of creativity. The total effects, $\beta_1 + (\alpha_1 \times \beta_3)$ for happiness and $\beta_2 + (\alpha_2 \times \beta_3)$ for calmness, encompass the aggregate impact, integrating both direct and mediated pathways, illustrating the comprehensive influence of mood on creativity through the flexibility pathway.

Preliminary Work

This section is organized into four parts. The first part involves simulating the data collection process for my online experiment by submitting a sample response on the experiment website. The second part focuses on deriving two measures of creativity flexibility from a sample drawing, utilizing the CoSE model (**aksan˙cose˙2021**). The third part is to simulate the process of calculating DSI (**johnson˙divergent˙2022**) from sample narratives. The fourth part aims to automate the originality assessment of a sample of incompleteness shape task drawings using the AuDrA model (**patterson˙audra˙2023**).

Building the website

Since I plan to recruit participants from MTurk, coupled with the inclusion of drawing tasks in my experiment (which is different from simply collecting survey responses in traditional psychology studies), building a website that fulfills my experimental design and collects data in the format I want becomes critical. Utilizing jsPsych (**leeuw˙jspsych˙2023**) to run my experiment in web browsers, I designed the website to include four main blocks: survey data collection, mood induction, incompleteness shape drawing tasks, and narrative on thought processes [2].

This gif file records how I completed the website as a participant would[3]. A point of note here is that the website now has the same block structure as my final, anticipated experiment website, but that does not mean that the content will be exactly the same because I need additional time to determine the final materials used in the experiment (based on the feedback from my pretest result). I first completed informed consent and then filled out some survey questions. Then, I watched a film clip for mood induction, before completing the incompleteness shape drawing task. After I finished drawing, I was asked to provide a label for my drawing, as well as a narrative on my thought processes leading to my final output. After completing the whole experiment, I could also see the result in json format, encompassing survey answers, completed drawings (including base64 encoding and coorindates), and narratives on thought processes.

Testing the CoSE Model

In my proposed research, deriving the flexibility measures (that is, the entropy of the Gaussian Mixture Model and Bhattacharyya distance) from the CoSE model is crucial. To simulate the calculation of these measures, I generated a sample image (see Figure **??**) and followed a systematic data pre-processing pipeline (see Appendix **??**for more details). This included splitting and padding strokes to ensure uniform stroke length, size normalization to focus on shape and sequence rather than absolute dimensions, resampling strokes for consistent temporal spacing, and calculating statistics for zero-mean and unit-variance normalization. These steps prepare the drawing data for effective input into the CoSE model.

[2] See my github repository for details on code behind the experiment web page.

[3] Note: gif stands for Graphics Interchange Format. This gif file is also available on my github repository.

Weekly_assignments/Figures for mocked-up results/my_sample_drawing.p

Figure 6: My Sample Drawing

Subsequently, the preprocessed drawings were processed through the CoSE model's core functions: encoding strokes into a latent space, predicting the position of the next stroke, computing the latent representation for the upcoming stroke, and reconstructing the predicted stroke on the canvas (see Appendix **??** for more details). This iterative process allows the CoSE model to generate complex structures based on individual stroke characteristics and their interrelations.

Finally, I calculated the entropy of the Gaussian mixture model and the Bhattacharyya distance for each stroke in the sample drawing (see Appendix **??** and Appendix **??** for more details). The resulting arrays of flexibility measures were visualized using line charts (see Figure **??**, which revealed valuable insights into the evolving creative process. The high entropy values indicated broad exploration, while the Bhattacharyya distances highlighted significant diversity between the next potential strokes. The high correlation between these two measures is visually corroborated by the line chart, which indicates a similar trend of changes.

Weekly_assignments/Figures for mocked-up results/Entr

Figure 7: Line Charts of Flexibility Measures for My Sample Drawing

However, one thing to notice from the two line charts is that they both do not follow a simple linear decrease in (flexibility) measures, as I hypothesized earlier. This could be due to an outlier effect of my random drawing, which could be overcome by my (relatively) large sample of participants for my experiment. In addition, by tracking changes in flexibility measures starting from a given number of strokes (compared to all strokes), which is the case in incompleteness shape drawing task where a specific number of strokes are already given, the trend may align closer to my hypothesized trend.

Nevertheless, by plotting these metrics, the line charts illustrate not just static values but also the dynamic shift from high to low, effectively mapping out the cognitive journey from open-ended exploration to specific execution. This graphical representation improves understanding by providing a visual narrative of the cognitive shifts occurring as a function of input strokes (number of strokes drawn). It allows for a direct observation of the inflection points where significant changes in creativity metrics occur, offering empirical support to the theoretical framework posited about cognitive flexibility in creative tasks. The time series of these two flexibility measures, therefore, not only validate the use of the CoSE model in capturing the nuances of creative thought processes but also enrich our understanding of how individuals navigate the complex landscape of creativity.

Testing the Calculation of DSI

I also simulated the process of calculating another measure of flexibility from participants' verbal description of their creative thought processes: DSI. Specifically, I used the sample narrative text from **johnson˙divergent˙2022<empty citation>**'s Open Science Framework (OSF) repository (which contains 179 observations) and calculated DSI scores for each verbal description (see my github repository containing output csv file). Table **??**, which shows the narratives with the highest and lowest 2 DSI scores, offers a glimpse into the valid assessment of DSI of participants' narratives. Specifically, the low DSI scores of narratives 3 and 4 are evident given their straightforward and simplistic content. These narratives consist of short, factual sentences with minimal descriptive detail and lack of complex, divergent ideas. By comparison, narratives 1 and 2, which have high DSI scores, exhibit more unique and imaginative elements. These narratives are characterized by rich descriptive language, emotional depth, and the integration of multiple ideas and themes.

Narratives	DSI
His mother woke up, distressed and unsettled. She only had one more stamp left. Had she really sent that many letters already? Her son left for bootcamp only three weeks ago, and the two books of stamps went much faster than the long days she spent without him, wondering what he could possibly be doing.	0.823803246
She had spent her whole life writing this letter. Every little detail she poured her heart into, making sure it was clear and her voice was loud. She stuck in in the envelop, carefully placed the bright red stamp, and sealed it shut. She got in her car, hands trembling, ready to give her life away in this tiny rectangular package. Sending the letter away was sending apart of her away. And send it she did.	0.822249174
I wrote a letter to my aunt. I went to the post office and bought a stamp. I put the stamp on the letter and gave it to the mailman to send.	0.735599697
I wrote a letter to my mom. I am going to send it today. I need to find a stamp first. After I find one, I will send it.	0.734623551

Table 1: Narratives with Top and Bottom Two DSI Scores

Testing the AuDrA Model

Finally, I used the pre-trained AuDrA model to simulate the process of assessing the originality of four sample drawings from **patterson˙audra˙2023<empty citation>**'s Open Science Framework (OSF) repository (see Figure **??**). In my opinion, the originality ratings (see Table **??**) on these sample drawings boast a valid assessment of originality. Specifically, the low originality ratings of drawings 2 and 3 are evident given the lack of distinctive or creative features in these drawings, such as simple shapes and repetitive patterns. By comparison, drawings 1 and 4 exhibit more unique and imaginative elements, including complex shapes, innovative patterns, and creative use of space, which are reflected in their higher originality ratings. This suggests that the AuDrA model effectively captures the nuanced aspects of creativity and originality that align with my expectations and previous assessments.

ID	Originality Rating
1	0.502454519
2	0.273976982
3	0.25074771
4	0.589645386

Table 2: AuDrA Originality Ratings on Four Sample Drawings

Proposed Timeline and Feasibility Assessment

IRB Approval

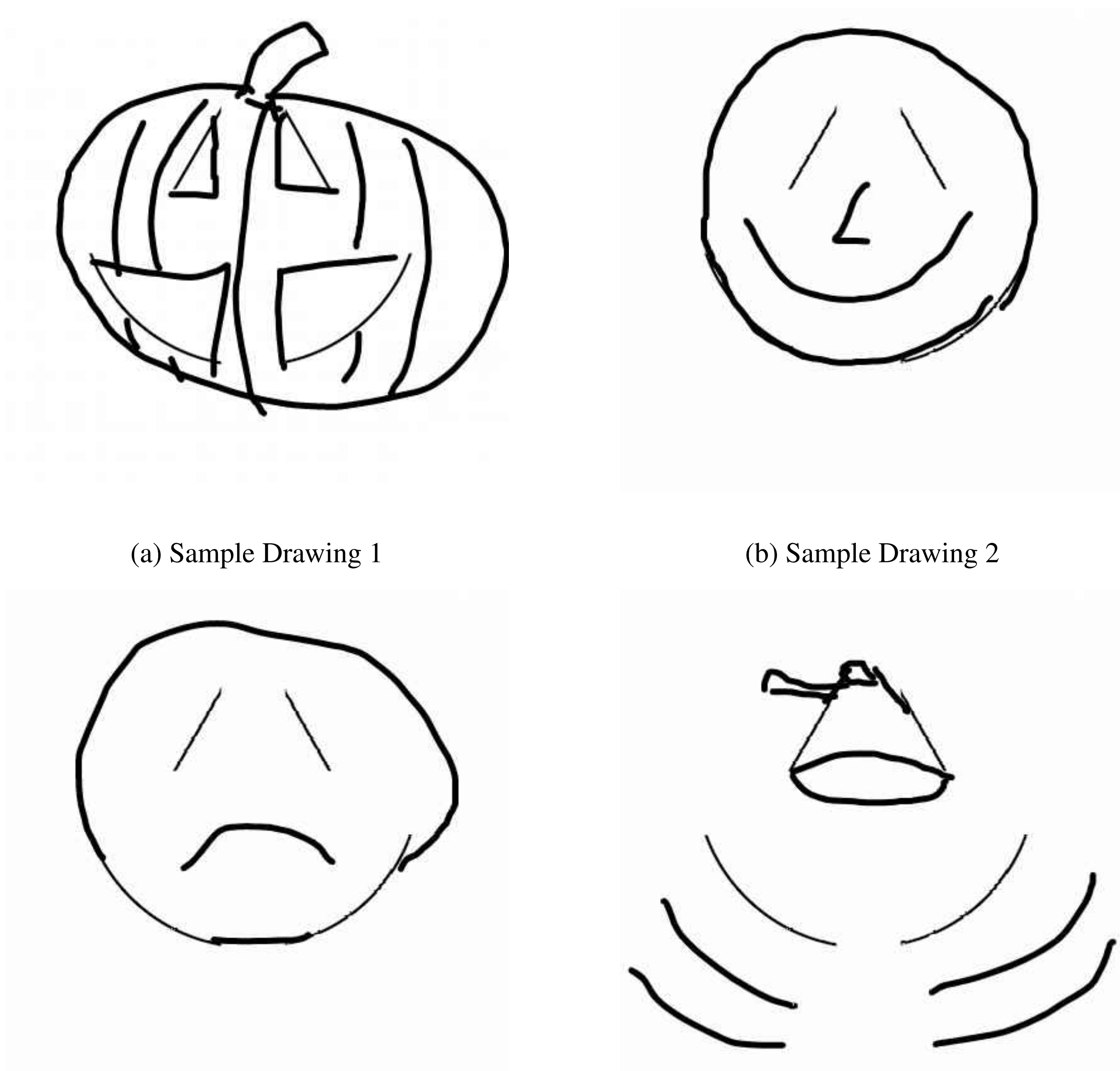
This proposed study is expected to receive IRB approval as it adheres to the four ethical principles (**salganik˙bit˙2019**). First, it respects the honor of participants by providing them with informed consent before the experiment. Second, it maximizes potential benefits while minimizing potential harm to participants, as it does not induce negative mood states. Third, it treats every participant equally so that the benefits and risks are allocated fairly. Fourth, it complies with legal and public interest standards.

Timeline

The proposed timeline for this study is described in Table **??**.

Cost

Based on the pricing information provided in Amazon Mechanical Turk website, the total cost for each participant will be \$1.00 (base pay) + \$0.20 (MTurk fees) = \$1.20. For 300 participants, the total cost will be $\$1.20 \times 300 = \$360$.



(a) Sample Drawing 1

(b) Sample Drawing 2

(c) Sample Drawing 3

(d) Sample Drawing 4

Figure 8: Four Sample Drawings for AuDrA Originality Assessment

Quarter	Activities
Summer	Implement pilot study for pretesting.
Next autumn	1) Refine experiment website and research design based on feedback from pilot study; 2) Publish research design online and begin participant recruitment through MTurk.
Next winter	1) Conduct data analysis; 2) Complete the draft of the final thesis.
Next spring	Finalize and submit the thesis paper.

Table 3: Proposed Timeline

Deep Learning Models and Computing Power

As an integral part of this proposed study, deep learning models require considerable time and resources for both training and implementation. Fortunately, the pre-trained models and the running code for the two deep learning models that I plan to use (i.e., AuDrA and CoSE models) are publicly available online. Moreover, this proposed study will utilize university high-performance computing clusters (specifically, Midway 3) for potential deep learning model fine-tuning.

Potential Supervisors

The following is my list of potential supervisors[4]:

1. **Akram Bakkour**[5]. I have been working at Dr. Bakkour's lab upon joining the MACSS program, and he has been quite familiar with my research project and also provided me with constructive feedback while I was improving this proposed project. I will benefit from Dr. Bakkour's expertise in cognitive psychologist in terms of the overarching research design and also the proposal/paper drafting later.

2. **Michael Maire**[6]. Since my proposed project involves utilizing the generative stroke em-

[4]I have secured Dr. Bakkour as my advisor. I am also asking Dr. Maire and Dr. Beaty to be potential advisors.
[5]School Website for Akram Bakkour
[6]School Website for Michael Maire

bedding model to infer participants' creative ideation process for the drawing task, I would definitely benefit from an expert in the field of computer vision. Upon viewing the faculty profiles on the Department of Computer Science website, I think Dr. Maire's rich experience in deep learning models for perceptual organization and object recognition would provide me with new insights into interpreting and utilizing the model parameters.

3. **Roger Beaty**[7]. This would be an external professor from PennState, who I contacted while I was searching for a summer research assistant job. During my chat with Dr. Beaty, he expressed some interest in my proposed research project and asked me if I am interested in potential collaboration (though we have not reached the final decision for now). The main reason I would like to invite Dr. Beaty as my supervisor is that he has done a great amount of research in the field of creativity and, more importantly, explored many computational methods to better understand human creativity over the past few years. With his supervision, I am confident that I can formulate a better research design and methodology.

[7] School Website for Roger Beaty

References

Appendices

A Formula for Calculating Entropy of the Gaussian Mixture Model

This study adopts **huber˙entropy˙2008<empty citation>**'s approach to approximate the entropy of a GMM by incorporating the Kullback-Leibler (KL) divergence between each pair of components within the mixture:

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

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

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.

B 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:

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

C 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˙divergent˙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.

D Data Preprocessing for Testing CoSE Model

To use the CoSE model for stroke prediction, several data preprocessing steps were performed:

Splitting and Padding Strokes: This step ensures that all strokes in a drawing have the same length, which is critical for feeding the data into neural networks that require fixed-size inputs. Strokes are padded with zeros where necessary, and a binary flag indicates the end of a stroke. This uniformity is crucial for the model to correctly interpret stroke sequences.

```
def split_and_pad_strokes(stroke_list):
    max_len = np.array([len(stroke[0]) for stroke in stroke_list]).max()
    strokes = []
    for stroke in stroke_list:
        padded_stroke = np.zeros([max_len, 4], dtype=np.float32)
        for i, point in enumerate(stroke):
            padded_stroke[i, :len(point)] = point
        strokes.append(padded_stroke)
    return np.array(strokes)
```

Listing 1: Splitting and Padding Strokes

Size Normalization: Drawings are normalized to a consistent scale by adjusting their dimensions relative to a common bounding box. This normalization aids the model in focusing on the shape and sequence of strokes rather than their absolute size or position, which enhances the model's ability to generalize across various drawing styles.

```
def size_normalization(drawing):
    min_x, max_x = min([p[0] for stroke in drawing for p in stroke]), max([p[0] for stroke in drawing for p in stroke])
    min_y, max_y = min([p[1] for stroke in drawing for p in stroke]), max([p[1] for stroke in drawing for p in stroke])
    scale = max(max_x - min_x, max_y - min_y)
    normalized_drawing = [[[p[0] / scale, p[1] / scale] for p in stroke] for stroke in drawing]
    return normalized_drawing
```

Listing 2: Size Normalization

Resampling: Strokes are resampled at uniform intervals to ensure that the model receives input with consistent temporal spacing. This step prevents the model from misinterpreting quick or slow strokes as different from one another.

```
def resample_stroke(stroke, step=5):
    resampled = []
    for i in range(0, len(stroke), step):
        resampled.append(stroke[i])
    return resampled
```

Listing 3: Resampling

Statistics Calculation for Normalization: Statistical measures such as mean and standard deviation are calculated for further normalization of coordinates. This normalization (zero-mean and unit-variance) is crucial for machine learning models to avoid biases associated with the scale of the data and to improve convergence during training.

```
def calculate_statistics(drawings):
    all_x = [p[0] for drawing in drawings for stroke in drawing for p in
        stroke]
    mean_x, std_x = np.mean(all_x), np.std(all_x)
    return mean_x, std_x
```

Listing 4: Statistics Calculation

In sum, the preprocessing of drawing data follows a systematic order, which is vital for preparing the data in a manner that enhances the performance and accuracy of the CoSE model. The preprocessing pipeline starts with the process of splitting and padding strokes, which helps standardizes the length of all strokes as consistent input to be handled by the CoSE model. Next, all strokes are scaled to fit within a standardized bounding box, focusing the model's attention on the shape and sequence of strokes rather than their absolute size or position. Resampling are then performed to adjust the temporal spacing between points in each stroke to be uniform, ensuring consistent temporal data across various drawing speeds. Finally, overall mean and standard deviation of x and y coordinates for all drawings in the sample is calculated for further normalization to zero-mean and unit-variance.

E Passing Through the Model Signatures for Testing CoSE Model

The preprocessed drawings are further processed through the core functions of the CoSE model (as shown in Listing **??** below), implemented as a sequence of method calls. First, the *encode_stroke* signature transforms each stroke into a fixed-dimensional latent space, capturing essential local features like shape and size while abstracting from global context. Next, the *predict_position* signature uses the encoded strokes to anticipate the starting position of the next stroke, integrating relational aspects of the drawing layout. Subsequently, the *predict_embedding* signature computes the latent representation for the forthcoming stroke, ensuring that the new stroke aligns with the drawing's compositional structure. Finally, the *decode_stroke* signature reconstructs the predicted stroke from its latent code, converting it back into a visible stroke on the canvas. This sequential processing allows the CoSE model to generate complex structures by iteratively predicting and rendering strokes based on both individual characteristics and their inter-relations.

```python
# Load pre-trained CoSE model
model_signature_directory = '../thesis/model_architecture.csv'
model = tf.saved_model.load("../pretrained_model/
    saved_model_with_signatures")

# Load signatures of pre-trained models
encode_stroke = model.signatures["encode_stroke"]
predict_position = model.signatures["predict_position"]
predict_embedding = model.signatures["predict_embedding"]
decode_stroke = model.signatures["decode_stroke"]
```

Listing 5: CoSE Model Signatures

The preprocessed drawings are further processed through the core functions of the CoSE model, implemented as a sequence of method calls. First, the *encode_stroke* function transforms each stroke into a fixed-dimensional latent space, capturing essential local features like shape and size while abstracting from global context. Next, *predict_position* uses the encoded strokes to anticipate the starting position of the next stroke, integrating relational aspects of the drawing layout. Subsequently, *predict_embedding* computes the latent representation for the forthcoming stroke, ensuring that the new stroke aligns with the drawing's compositional structure. Finally, the *de-*

code_stroke function reconstructs the predicted stroke from its latent code, converting it back into a visible stroke on the canvas. This sequential processing allows the CoSE model to generate complex structures by iteratively predicting and rendering strokes based on both individual characteristics and their inter-relations.

F Python Code to Calculate Entropy of the Gaussian Mixture Model

```python
def entropy_gmm(predict_result):
    pi = predict_result['pi'].numpy().flatten()
    mus = predict_result['mu'].numpy().squeeze()
    sigmas = [np.diag(sigma) for sigma in predict_result['sigma'].numpy().
        squeeze()]

    N = len(pi)
    kl_matrix = np.zeros((N, N))

    for i in range(N):
        for j in range(N):
            diff_mu = mus[j] - mus[i]
            inv_sigma_j = inv(sigmas[j])
            kl_matrix[i, j] = 0.5 * (np.trace(inv_sigma_j @ sigmas[i]) +
                diff_mu.T @ inv_sigma_j @ diff_mu - mus.shape[1] + np.log(
                det(sigmas[j]) / det(sigmas[i])))

    log_terms = -0.5 * kl_matrix  # -1/2 factor from the exponent in the
        entropy formula
    log_sum_exp = logsumexp(log_terms, b=pi, axis=1)
    entropy = -np.sum(pi * log_sum_exp)
    return entropy
```

Listing 6: Code for Entropy Calculation

G Python Code to Calculate Bhattacharyya Distance

```python
def bhattacharyya_distance(predict_result):
    pi = predict_result['pi'].numpy().flatten()
    mus = predict_result['mu'].numpy().squeeze()
    sigmas = [np.diag(sigma) for sigma in predict_result['sigma'].numpy().
        squeeze()]

    N = len(pi)
    bc_values = []

    for i in range(N):
        for j in range(i+1, N):
            sigma_i = sigmas[i]
            sigma_j = sigmas[j]
            sigma_avg = 0.5 * (sigma_i + sigma_j)
            delta_mu = mus[j] - mus[i]
            term = 0.25 * delta_mu.T @ inv(sigma_avg) @ delta_mu
            bc = np.sqrt(det(sigma_i)**0.25 * det(sigma_j)**0.25 / det(
                sigma_avg)**0.5) * np.exp(-term)
            bc_values.append(-np.log(bc))  # Convert BC to a distance

    return np.mean(bc_values)
```

Listing 7: Code for Calculating the Bhattacharyya Distance