Art, Agency, and Computers: Human Perceptions of Creativity in Artistic Processes That Use Computational Agents

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Abstract

This study investigates human perceptions of creativity within computational artistic processes, examining the effects of delegating various stages (modes of creativity) to computational or non-computational entities. The research takes particular interest in how perceptions of AI-based artistic processes are situated within the existing landscape of computational processes. An online survey was used to gauge participants' anthropomorphization tendencies, experience levels in computer science and the visual arts, and the extent to which they attributed creativity to a set of nine different artistic processes. Each computational process ceded control of a different combination of stages to computational agents. Findings revealed that there was a gradual decrease in perceived creativity as more modes were delegated, removing them from the full control of the artist. The use of AI in itself did not drastically exaggerate this broader trend. The weightings that participants attributed to different modes provided further insights on how AI-based artistic processes can be adapted to better foster creativity. Trends across mode weights consistently varied between computational and non-computational processes, with implementation taking precedence for non-computational processes while higher-level modes such as design and composition took precedence in computational processes. Human-controlled design was shown to have a particularly high capacity to increase perceptions of creativity. While evaluation was not weighted highly in most computational processes, its importance to respondents was multiplied 2-3x when this mode was delegated to an AI system, suggesting that it is a crucial though subtle factor of creativity. In conjunction, these findings underscore a nuanced relationship between creativity and human agency. The study overall implies an exciting potential for developers to enhance AI-based artistic processes by building pipelines that engage human artists alongside computational agents, particularly at pivotal design and evaluation junctures.

Contents

List of Acronyms

IDE Ideation.

DES Design.

COM Composition.

IMP Implementation of Formal Elements.

EVA Evaluation.

DI Digital Illustration.

WC Watercolor.

PP Pen Plotter.

GE Graphics Engine.

ED Edge Detector.

CP Classical Proportion.

FS Fractal Set.

IS Image Segmentation.

AI Artificial Intelligence.

1 Introduction

With the advent of large-scale artificial intelligence models, both developers and users of AI-based products are becoming increasingly conscious of the applicability of AI to domains once thought to be exclusively human. This applies to extremely technical tasks — including making medical diagnoses and reviewing legal contracts — in addition to tasks that require soft skills — including providing customer service and screening resumes. This new ability to deploy AI to handle daunting challenges across industries and applications is exciting, but wielding AI indiscriminately could easily waste its potential or lead to its misuse. To avoid imposing AI where it is undesirable, it is essential to articulate the application-specific conditions that make AI use genuinely constructive. Understanding this context is the only way to develop future iterations of AI tools that intelligently address particular needs on their own terms.

With regards to art, the use of successful and public text-to-image generators like OpenAI's DALL-E or Midjourney is controversial. In producing visuals that aesthetically correspond to given prompts, these tools raise questions about whether AI impedes upon individual agency within the artistic process to a transformative extent. This is a complicated question — while many would agree that fully automating the production of art to the exclusion of channels for personal expression would take the creativity out of the process, the practice of inviting external agents into parts of the artistic process to reject the notion of single authorship is not new. From the readymades exhibited by Marcel Duchamp to the automatism of the Surrealists to the drip technique of Jackson Pollock, many eminent artists have sought to use forces they cannot control (like gravity) in their art to displace their own artistic subjectivity. With increased access to computers starting in the 1950s and 1960s, this same mentality drove numerous artists' strategies to call upon computers to assume control over parts of the artistic process. In this way, artists throughout history have treated creativity as an open question rather than a static paradigm to embody.

Though specific technologies have evolved and changed over time, artistic processes have habitually leveraged them to interrogate creativity and pose new ideas about where meaning comes from. While each instance of this tradition has met critiques about the extent to which creativity is possible in a process that the artist doesn't have full control over, contemporary media tends to characterize AI as an unprecedented attack on artistic creativity. To truly understand the substance behind public hesitation to accept AI art into artistic processes, perceptions about AI art must be compared and contextualized with views on other types of computational art. This understanding can open up insights about how computational agents can be conducive to creativity, whether people see AI art as unforgivably divergent from these conditions, and how AI-based artistic tools can be changed to contribute more positively to creative artistic processes.

Overall, this paper investigates the following research questions:

1. To what extent do people attribute creativity to processes that delegate agency to computational agents during artistic production?

2. How do perceptions of creativity differ between computational artistic processes and non-computational artistic processes?

3. How do specific stages of the artistic process vary in their impact on perceived creativity when assigned to a computational agent?

To answer these questions, we developed a survey that measured perceptions of creativity within nine artistic processes. Each process was divided into five modes of creativity, which represented a standardized set of stages (modes of creativity) in artistic production — ideation, design, composition, implementation of formal elements, and evaluation. The processes were selected for the survey such that they delegated different combinations of these modes to external agents. Participants rated each process' creativity on a scale from 1 to 7, which was then followed up by a written justification for the score they provided with reference to the modes of creativity that they deemed most influential. Analyzing these results meant comparing raw numerical scores but also developing a codebook to track common themes (mostly related to the modes of creativity) across responses.

This information led to findings about perceptions of overall levels of creativity in computational processes, the importance of different modes of creativity in different processes, and differences between processes that delegated modes to computational agents versus those that did not. Raw creativity scores saw a gradual and iterative decline across all computational processes as more modes were delegated to external agents. This contextualized perceptions of creativity within the AI-based artistic process within a larger set of computational processes, rejecting the notion that AI acts as a singular, standalone affront to creativity. Participants' justifications of their raw scores shed further light upon how modes of creativity were used to inform their perceptions. While modes were weighted differently in different processes, participants consistently saw ideation to be an extremely crucial stage for the development of creativity. While implementation itself was weighted particularly highly in non-computational processes, computational processes shifted emphasis to modes which were more focused on planning execution, such as design or composition. Evaluation was also found to be perceived as significantly important; although evaluation weighted quite low across processes where it was comfortably under artist control, its weighting jumped significantly in the AI-based process, where agency over evaluation was removed. This suggested that evaluation was considered something of a base condition for creativity.

These findings have key implications for the development of future AI systems built for generating art. While, by nature, AI-based artistic processes will inevitably delegate control over certain stages of artistic production to a computational agent, this study provides insights as to which of those delegations are most damaging to overall perceptions of creativity. Ultimately high weights for the design and evaluation modes suggest that developers could realize significantly large gains in perceived creativity if artists are given greater agency over those stages. This highlights the value of attempts to change the rhetoric around AI while developing new AI systems specifically for explainability or greater human involvement earlier in the pipeline.

2 Related Works

To ground the methodology of this study, this section explores previous work on interdisciplinary attempts to define creativity, assessments of creativity in computer-generated art, and the frameworks within which people attribute responsibility to AI.

2.1 Interdisciplinary Theories of Creativity

Even excluding the complications brought on by artificial intelligence, the definition of creativity is contested amongst art historical, psychological, and philosophical experts. At a basic level, creative entities are those which embody both novel and "interestingness" (Elton, 1995; Runco and Jaeger, 2012). However, even this standard definition leads to contradictions and disputes amongst scholars.

Broadly, the criterion of novelty implies that creative artworks should be different from those that have already been seen — an idea of creativity that doesn't initially seem too contentious. However, some scholars and artists question whether pure novelty is even possible. The nature of the site where an artwork's meaning comes from has been actively unsettled, questioned, and dispersed since the 1950s. Neo-dada artists including Robert Rauschenberg and Jasper Johns created art that intentionally derives its meaning from the invisible yet pervasive traditions, symbols, and cultural norms that are tacitly understood by society. By drawing attention to how these assumed conventions bear upon a work, they rejected the idea that an artist can fully define the meaning of any work. Only a few years later, the emergence of the conceptual art movement further centered the thought processes through which artworks are eventually manifested rather than the formal physical characteristics of these manifestations themselves. In the context of this movement, planning and design were prioritized over execution, which was dismissed as a "perfunctory affair" (LeWitt, 1967, p. 822). Intellectual theorist Michel Foucault rationalizes these types of art, pointing out that originality does not exist as a trait inherent to an artwork — every artist, including those we perceive as highly creative, draws upon images and ideas that they have seen before (Foucault, 1977). The value of an artwork therein lies in this phenomenon rather than a singular object. This line of thinking has found resonance across disciplines, with literary theorist Roland Barthes writing that singular authorship is a myth, with messages and meanings coming instead from the public collective construct of language itself. In this way, originality is further characterized as impossible; all writing is instead "drawn from many cultures and entering into mutual relations of dialogue, parody, contestation" (Barthes, 1977, p. 148). It was not uncommon to attribute the value of an individual work to the broader societal milieu in which it was created, asserting that neither the object nor the artist could claim full authorship, credit or originality over it.

However, this full rejection of novelty has met some dissent; from social theorists to practicing artists, some scholars contend that the complete erasure of individual choice in the face of societal structures destroys artist agency — there are ways for artists to be creative even as they surrender to certain aspects of society (Habermas, 1987; Freedman, 2010). Regardless, art is never created in a vacuum and always is produced as a result of a synthesis of individual inspirations and social conventions. In challenging the existence of pure novelty itself, the absence of synthesis becomes irrelevant and perhaps even impossible. Instead, looking for novelty prompts an examination of the methods of synthesis itself and how these methods blend artist agency with uncontrolled elements of the external world. Thus, creativity is situated within the inner workings of synthesis, opening the possibility for it to be interpreted as a process-based metric.

Although the term's vagueness cannot be escaped, "interestingness" — the second component of the standard definition of creativity — can be considered in a new light in the context of process-based creativity. Interestingness refers to the idea that creative entities must be purposeful, compelling, and of value. This precludes the affiliation of creativity with ideas that are merely random yet uncommon (Barron, 1955). However, in different domains, the notion of value looks very different, meaning that while interestingness is acknowledged as a necessary aspect of creativity, it does not translate into any kind of robust measure. From a purely product-based lens, interestingness is difficult to disentangle from artistic talent, perhaps due to prevalent "art bias" — the implicit association of creativity with art as compared to other disciplines (Glăveanu, 2014). However, when interestingness is applied to processes, particularly the synthesis of external influences with individual ideas, interestingness takes on new meaning. Philosopher Vincent Tomas, an early supporter of a process-based conception of creativity, suggests that a work cannot be interesting or compelling when an artist lacks control over the "activity to which the work owes its origin" (Tomas, 1958, p. 5). This echoes Habermas, asserting a relationship between artist agency and creativity while questioning whether they persist when the artist surrenders to external frameworks for the creation of art.

Other theorists adopt and extend this approach. Educational psychologist and creativity researcher Mel Rhodes theorizes the Four Ps of Creativity model, where creativity is said to lie at the intersection of person, process, product, and press/environment. (Rhodes, 1961). A group of Rhodes' contemporaries in educational psychology rearticulate this idea in combination with the standard definition discussed earlier, saying that "creativity is the interaction among aptitude, process, and environment by which an individual or group produces a perceptible product that is both novel and useful as defined within a social context" (Plucker et al., 2004, p. 90). This model reinforces the idea that process and environment give shape to the social, cultural, and historical conditions within which interestingness or novelty are interpreted. Exclusively product-based assessments of creativity are thus limited; shifts in context can entirely change how interestingness, novelty, and thus creativity are interpreted within a work even if its aesthetic and physical properties remain the same. While artist individualism is important, a full picture of creativity can only be apprehended by balancing considerations of product individualism alongside the nature of an artist's "engagement with the unfamiliar" in the context of their process (Glăveanu and Beghetto, 2020, p. 76).

These threads of similarity have converged in interesting ways throughout the twentieth century, but academics still remain divided on their definitions of creativity. Thus, these ideas function not as rigorous theories of creativity but rather as landmarks and frameworks for future creativity research to contextualize itself within.

2.2 Assessments of Computational Creativity

In their current form, most creativity theory is indeterminate, not specific or measurable enough to ground contemporary efforts to develop AI models that create art. As such, a different class of definitions for creativity have emerged in the field of AI. Computer scientists have largely drawn upon the same concepts of novelty and interestingness that define creativity across disciplines. However, as they are used to train AI models, measures of novelty, interestingness, and creativity are product-based rather than process-based. The majority of these measures are learned from large image datasets by a combination of deep learning and statistical analysis.

In one project, researchers developed a dataset with crowdsourced scores for a range of desirable but subjective qualities including "aesthetic quality," "beauty," and "composition" (Amirshahi et al., 2015). Other studies have expanded on these efforts, continuing to crowdsource quantitative scores for abstract categories such as "naturalness," "emotion" — and of course, "interestingness," "novelty," and "creativity" (Redi et al., 2014; Yang et al., 2022; Soleymani, 2015). The dataset collected in the work of Redi et al. was used to train a model to learn a heuristic that could relate visual qualities of training images — including contrast, rule of thirds, symmetry, complexity and other abstract compositional characteristics — to their corresponding creativity scores. This ultimately enabled the model to make automatic creativity classifications by applying its learned heuristic to any image's extractable visual features (Redi and Merialdo, 2012; Redi et al., 2014). While this model's test accuracy was an impressive

80%, it predicted creativity as a binary, precluding the model from having to learn to associate different patterns with varying degrees of creativity. Researchers have also leveraged these datasets to develop CNNs and other deep learning models that independently formulate and learn abstract visual features to allow them to predict sentiment, emotion and interestingness (Cetinic et al., 2019; Mohammad and Kiritchenko, 2018).

This type of assessment of creativity is unique in that it benchmarks itself on public opinion rather than theory. However, when soliciting evaluations of creativity (or novelty or interestingness or sentiment), these methods do not allow respondents to consider process or environment as context; they are only given access to the resultant product artwork. As a result, the conceptions of creativity that are solicited in these studies — and thus those that AI models learn — are incomplete. Unlike many significant stakeholders in the art world, these models are unable to relate creativity with artist agency, external actors, or any features that are not formal visual metrics. Because of this, several researchers acknowledge the limitations of these frameworks; judgements about creativity and emotion are incomplete without art historical and social context (Cetinic and She, 2022).

Large-scale generative AI models follow from these established metrics for creativity, relying extensively on massive image datasets (and corresponding captions that supply information about semantic characteristics) to create and enforce creativity heuristics. Programmers behind AICAN, an AI system developed to create art, argue that the sheer size of the datasets that large AI models train on distinguish their creativity. As a result of its intensive training process, AICAN autonomously synthesizes thousands of external influences in a process similar to that of human artists. Some researchers have sought to dissect this synthesis process, running an experiment over several case study diffusion models. Each model was trained on a dataset provided by researchers and then gauged for its tendency towards data replication versus its capacity for originality using both qualitative and quantitative methods. For each model, researchers found evidence of copying when textual prompts included uncommon phrases (Somepalli et al., 2023). This method proves comprehensive, referring to process in addition to product to measure the novelty component of creativity. It only falls short when comparing creativity between AI art and human-created art —discrete external influences are not so easily identifiable in human brains.

Even so, many studies conducted on the creativity of generative AI systems are not holistic. The AICAN programmers implemented a study akin to a visual Turing test, checking participants' ability to determine the difference between unlabeled AICAN works and human-created works. Results demonstrated that in 75% of scenarios, participants thought AICAN generated images to be human made (Mazzone and Elgammal, 2019). However, this measure of creativity again failed to account for process or control. While the programmers seemed satisfied in concluding that AICAN's synthesis process is creative, information about this process was obscured from their survey population, leaving participants to infer creativity from exclusively product-based ideas and personal aesthetic preferences. This diminishes the value of synthesis as an essential determinant of creativity in an artistic process, ignoring the crucial choices that are made by the model to reconcile individual artistic choice (direction from the prompt) with pre-existing conventions (as learned in training).

Surveying previous work to assess computational creativity, it is clear that the majority of metrics for computational creativity are directly based on creativity scores and classifications collected from humans. However, these perceptions of creativity are limited given that participants typically have no insight into the processes that have been used to create various works. As numerous creativity experts discuss in Section 2.1, a picture of creativity that considers aesthetic properties without context is not only incomplete but likely subject to change over time. The assumption that a large enough dataset can implicitly represent this context during training is flawed. Given that the populations which generate creativity data are predominantly not art experts, the data itself contains limited contextual knowledge, even latently.

This comprises a critical gap in existing literature, particularly for visual arts communities. Enjoyment of art is closely related to appreciation of the process that it was created with. Without understanding public perceptions of emerging AI-based artistic processes, the reception of works that utilize them will only become more difficult to predict. Attempts to improve AI tools in this environment can only be unproductive; they are not informed by popular ideas about what makes an artistic process creative or how AI impacts artistic processes. It is increasingly important that AI developers consider this dimension of artistic communities' reaction to AI tools and adapt their tools in accordance with these views.

Thus, this study aims to discern public perceptions of creativity in AI art as they are situated not only in AI-based artistic processes themselves but also in the broader landscape of artistic processes that confront tradeoffs between artist agency and external computational actors. Furthermore, the study attempts to understand perceptions of creativity beyond a black box, prompting participants to identify specific areas within a process where creativity is particularly concentrated and/or threatened. This study will thus attempt to provide a fuller picture of public perceptions on creativity in AI art as well as new insights on the specific issues (or nonissues) that people see in computer-based artistic processes.

2.3 Frameworks for Public Views on AI

Numerous surveys have been conducted to gauge public opinion on the use of AI in various spheres, especially considering themes of AI responsibility and accountability. These studies establish interesting frameworks around perceptions of AI at large. While most large-scale AI tools are complex networks of humans, machine learning algorithms, datasets and their interactions with one another, rhetoric around AI is increasingly anthropomorphic; this is true across media channels, popular culture, commercial products, and even formal academic papers (Proudfoot, 2011). The description of AI using vocabulary that is typically reserved for human beings has been shown to lead to the attribution of human characteristics such as agency and consciousness onto AI actors (Araujo, 2018; Munnukka et al., 2022).

One study measured human participants' tendency to anthropomorphize AI as it related to their willingness to trust autonomous drivers. An initial anthropomorphization score was conducted using a short survey where participants were asked how smart the car was, how well it could understand what was happening around it, how well it could anticipate what was going to happen in the future, and how well it could plan a route (Waytz et al., 2014). The keywords "smart", "understand", "anticipate", and "plan" were anthropomorphizing in nature — the participants' willingness to ascribe these particular words onto an AI-driven car was indicative of their willingness to anthropomorphize AI at large. The study then compared these anthropomorphization scores with physically recorded (e.g. heart rate change) and self-reported metrics (e.g. trust) of participants' comfortability riding in an autonomous vehicle. Results demonstrated that participants who anthropomorphized AI to greater extents also recorded higher levels of trust (both self-reported and measured) in the vehicle.

The effects of this increased tendency to consider AI as an agent rather than a tool has especially important implications in the field of AI art. Another study drew upon the work of Waytz et al. to measure the relationship between tendencies to anthropomorphize and tendencies to attribute responsibility to AI in the production of art (Epstein et al., 2020). The study asks participants to fairly distribute the profits from an AI-generated artwork amongst several stakeholders of the production process, including the technologist who tuned the AI system, the artist who provided the prompt, the crowd who sourced the dataset, and the AI itself. This line of questioning essentially served as a proxy for the more difficult question of the agency (and thus credit deserved) that was realized by various actors in the process. Results suggested that participants who viewed AI as an agent were indeed willing to attribute more credit to the technologist/AI system and less credit to the artist.

These findings exhibit anthropomorphism-based divisions amongst participants regarding where the credit, agency, and responsibility are concentrated in the production process of AI art. It is possible that these same divisions could apply to the same or a lesser extent within production processes of other forms of computer art, though there is no literature yet that definitively substantiates this. Regardless, while measuring participants' willingness to attribute creativity to computer-generated art in the context of process-based tradeoffs between human artists and computational entities, it is important that these divisions — in addition to the broader dichotomy between AI as a tool versus AI as an agent — are considered. These frameworks of creativity, agency, and anthropomorphism are central to the methodology of this study.

3 Survey Design

The survey was divided into three distinct parts. Part 0 asked about participant backgrounds in computer science and the visual arts, while Part 1 gauged participants' tendencies towards anthropomorphization and Part 2 prompted them to assign creativity scores to nine artistic processes along with an explanation of each score. Part 2 was most relevant to the research questions outlined above — raw creativity scores provided information about participants' overall perceptions of creativity in computational (and non-computational) processes, and qualitative explanations provided information about how the level of agency within specific stages of these processes influenced their raw scores. Part 0 and Part 1 addressed sub-questions related to the main research questions, allowing for later analysis to test whether certain participant characteristics (background in computer science/visual arts and tendencies towards anthropomorphization, respectively) were associated with significant differences in perceived creativity within or between any of the processes.

Within Part 0, participants were simply asked whether they had a background in visual arts and then whether they had a background in computer science. In responding to these questions, participants could answer "Yes," "No", or "Somewhat." As described further in the Results and Discussion chapters, this information was later used to sort participants into groups of "No Experience" and "Any Experience" per discipline. These groups were then compared and examined for potentially different trends.

Within Part 1, participants were given a vignette describing a text-to-image generator named NINA. This vignette gave participants a brief overview of NINA's data-driven training process, describing how it learns associations between images and captions, developing a networked semantic understanding of particular words and corresponding visual features. While this description referenced NINA by name, it did not use distinctively anthropomorphic language, leaving users to project those qualities onto NINA only by their own discretion. Given this context behind NINA's ability to generate images that match given textual prompts, participants were asked a series of questions based on the work of Waytz et al. to gauge the extent to which they anthropomorphized NINA (Waytz et al., 2014). These questions asked viewers how smart NINA was, how aware NINA was of the world around it, how well NINA understood the relevance of its work to particular prompts, and how much NINA could plan the artworks it produced. The latter two questions were changed slightly from the previous study to account for NINA's role as an AI that creates art rather than an AI that drives. However, like the previous study, each question drew upon a specific human keyword and measured the participant's willingness to map this trait onto NINA. Participants responded to each of these questions on a 7-point Likert scale.

Both the inclusion of this section in the survey and its structure were inspired by the existing research as described in the Related Works chapter. The works of Epstein and Waytz et al. indicate that when AI is anthropomorphized, people are willing to allocate increased responsibility to it, both in the context of autonomously moving vehicles and AI-powered artists (Watyz et al., 2014; Epstein et al., 2020). Since anthropomorphization affects perceptions on the acceptability of granting responsibility to AI, it almost certainly bears on creativity, which is grounded in the establishment of a balance between artist agency and external control. This applies directly to Part 2, where participants were asked to describe their perceptions of creativity in artistic processes that delegated different levels of responsibility to computational agents. Part 1 was thus included in the survey to test whether tendencies towards anthropomorphization did change perceptions of creativity in AI-based artistic processes. Part 1 was also useful in measuring whether high anthropomorphization of AI also affected perceptions of creativity with other computational tools. Existing studies have not tested whether those who anthropomorphize AI trust other computational entities to the same extent, affording these tools the same capacity for autonomy and creativity. With the results from Part 1, participants were sorted based on their anthropomorphization scores, and these hypotheses (among others described in the Results and Discussion chapters) were examined.

Part 2 was the largest section of the survey and the most original to this study, thus requiring considerable effort to conceive of, design, and eventually write up. As justified in the Related Works chapter, this survey prioritized a process-based approach. At a basic level, this meant that instead of having participants assess creativity in images of finished artistic products, the survey prompted them to assess creativity in descriptions of artistic processes. To answer Research Question 1, it was essential to gauge creativity as it was perceived across artistic processes that delegated different levels of agency to computational entities. Research Question 2 demanded that the set of artistic processes described to participants should include at least a few non-computational processes whose results could be compared with the body of computational processes. Lastly, to answer Research Question 3, artistic processes had to be delineated into particular stages for participants to explicitly reference in justifications of their perceptions of creativity in each process. The structure of Part 2 needed to accommodate the needs of each of these research questions.

Formulating a set of artistic processes that delegate agency to computational entities in different ways meant working backwards, first defining the structure of stages which would be available for this delegation. These stages were eventually termed as "modes of creativity," given that they comprised the distinct areas within the process that participants could identify creativity in. These modes were determined based on a mixture of academic writings and research. An early model (Wallas, 1945) of the creative process separates it into:

1. Preparation — exploring an idea and obtaining knowledge about it
2. Incubation — subconsciously iterating on the idea

3. Illumination — conceiving of a creative solution to express the idea
4. Verification — testing or otherwise assessing the strength of this solution

This set of stages has persisted as a popular touchstone for the discussion of creative processes within social psychology. While the Preparation, Incubation, and Illumination modes emphasize the importance of ideation in creative processes, the model pays little note to how ideas are eventually realized. The Verification stage, which suggests that creative processes inherently include some form of evaluation, only comes into play after the process has been completed.

More contemporary research (Botella et al., 2013) consulted practicing artists to define six new stages of creative artistic processes:

1. Idea/Vision — coming up with an initial vision for a work
2. Documentation/Reflection — gathering information about the materials, technologies, and constraints for the project
3. First Sketches — first attempts at giving the project shape with models, forms, and other plans
4. Testing Forms — testing the viability of these forms through experimentation, communication, and confrontation with the art project
5. Provisional Objects/Drafts — completing an initial version of idea
6. Series — completing a final version of the idea after inputs and feedback from the initial draft

Both the Series stage of the Botella et al. model and the Verification stage of the Wallas model highlight the importance of developing analytical opinions about the final product. Thus, both models confirm the importance of ideation and evaluation as crucial parts of the creative process. However, the work of Botella et al. places additional importance on the actual creation of the product itself with the Documentation/Reflection, First Sketches, Testing Forms, and Provisional Objects/Drafts stages—while the language used to describe these stages is quite specific to traditional artistic processes, these stages informed the other modes of creativity included in this survey. The Documentation/Reflection stage mapped nicely onto a broader design stage, where inherent constraints within the framework of the initial idea are defined and grappled with. Similarly, the First Sketches stage could be described as a general composition stage, where specific forms are organized in a blueprint that expresses the initial idea. Finally, the Testing Forms and Provisional Objects/Drafts were combined into an implementation stage, where plans are executed into a finished product. The final descriptions for each of the five modes of creativity as defined in this study—ideation, design, composition, implementation of formal elements, and evaluation—are stated in Table 1.

Once the modes of creativity were defined, salient artistic processes were identified and articulated for participants to be surveyed on. Within each artistic process, an artist would have varying degrees of

Mode of Creativity	**Definition**
Ideation (IDE)	The practice of developing a vision, conception, or purpose for an artwork to be created.
Design (DES)	The framework which constrains how compositional decisions can be made within an artwork.
Composition (COM)	The way that the visual elements of the artwork are organized to create the unified whole.
Implementation of Formal Elements (IMP)	The actual implementation that creates and produces the visual elements of the artwork — the practical execution of the plan decided upon in the previous stages.
Evaluation (EVA)	The practice of assessing the aesthetic qualities of the produced work, explaining their significance, and understanding the reasoning for why particular artistic choices were made.

Table 1: Labels and Definitions for Modes of Creativity

	IDE	DES	COM	IMP	EVA
DI	Artist	External	Artist	Artist	Artist
WC	Artist	External (non-computational)	Artist	Artist	Artist
PP	Artist	Artist	External	External	Artist
GE	Artist	External	Artist	External	Artist
ED	Artist	External	External	Artist	Artist
CP	Artist	External (non-computational)	External (non-computational)	Artist	Artist
FS	Artist	External	External	External	Artist
IS	External	External	External	Artist	Artist
AI	Artist	External	External	External	External

Table 2: Source of agency in modes of creativity per process. Non-computational external agents are marked as such in parentheses. Processes are sorted from top to bottom based on the number of modes controlled by external agents. In cases where the same number of modes is controlled by external agents, processes with later controlled modes appear higher. In cases where the same combination of modes is controlled by external agents, computational processes appear higher than non-computational processes.

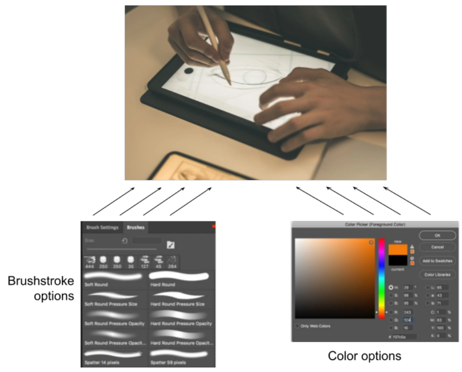
agency across modes. For example, within one process, the artist may retain control over ideation, design, and evaluation but surrender agency to an external entity for the implementation of formal elements and composition. For the chosen set of processes to be useful, it was important that different combinations of modes were delegated to external agents. Furthermore, chosen artistic processes were required to be well-established or relatively common while also being simple to understand conceptually (to the extent this was possible). As such, none of the processes addressed the base cases where either all modes were under artist control or no modes were under artist control.

Nine artistic processes were eventually included in the survey, out of which seven were computational processes and two were non-computational processes. The non-computational processes were each paired with a corresponding computational process; both members of the pair delegated the same set of modes. Table 2 summarizes which modes are controlled by artists versus external agents for each process. Each process was described in a short vignette and informative graphic presented to participants. Each vignette was explicitly separated into subheadings corresponding to the modes of creativity, which sorted the process into the work that was done per mode. While the vignettes distributed to participants can be found in the full version of the survey in the vignette, Table 3 provides short descriptions of each process. The graphics were included to visually illustrate the procedure being discussed. Graphics (or components of graphics) that were not originally created for this study were credited and cited at the end of the survey. Figures 1a-i display the informative graphics that were distributed to participants. The text and graphic for each vignette was paired with two accompanying questions. The first asked participants to rate the creativity of the process on a 7-point Likert scale. The second question followed up on this score, prompting the participant to explain their score in two to four sentences with reference to the modes of production that most influenced their answers. The full survey provided to participants can be found in the Appendix.

Ultimately, framing artistic processes in terms of the modes of creativity was the key structuring mechanism for Part 2 of the survey. This guided participants to specifically consider process-based factors, especially artist agency versus external agency within particular modes, while explaining their creativity scores. This allowed the significant insight into the research questions, particularly Research Question 3, generating data about the impact that specific modes had on perceptions of creativity.

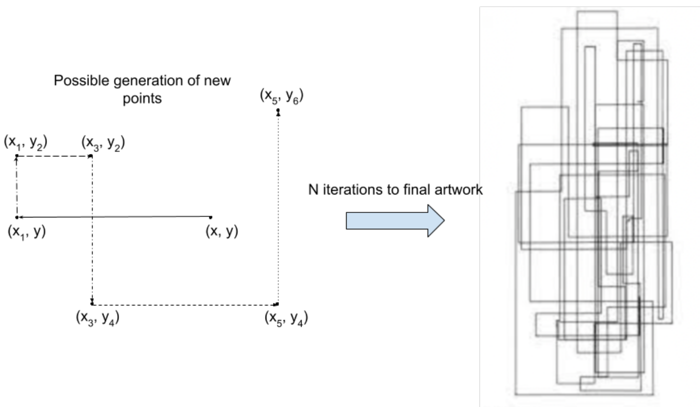
Process	Description
[Computational] Digital Illustration (DI)	An artist works within the constraints of a digital illustration application to organize and draw a visual scene, after which they explain their aesthetic choices.
[Non-computational] Watercolor (WC)	An artist works within the constraints of the medium of watercolor to organize and draw a visual scene, after which they explain their aesthetic choices.
[Computational] Pen Plotter (PP)	An artist defines a coordinate system and instructs a computer to choose points within this system based on rules they create. A computer then draws lines to connect these generated points. The artist can change or modify rules if they see fit.
[Computational] Graphics Engine (GE)	An artist defines objects and their geometric/compositional characteristics based on specifications required by a graphics engine. The engine then draws the artist's specified scene. The artist then evaluates and describes the significance of their artistic decisions.
[Computational] Edge Detector (ED)	An artist uses a camera to capture the view from their window and then uses an edge detection software to select salient lines from this image. They then trace the lines outputted by this software to create a line drawing. The artist identifies the strengths and weaknesses of this work.
[Non-computational] Classical Proportion (CP)	An artist uses classical rules of proportion to capture and select their salient facial features. They then draw these features based on those highlighted by these conventional rules. The artist identifies the strengths and weaknesses of this work.
[Computational] Fractal Set (FS)	An artist thinks of a repetitive pattern and selects a mathematical formula to describe it. This mathematical formula determines the design and composition of the formula. A computer graphs the formula, after which the artist assess the success of this visualization of their idea.
[Computational] Image Segmentation (IS)	A computer randomly chooses an image from a web and separates it into color-based segments using machine learning. An artist fills in these preselected colors and considers the strengths and weaknesses of the final work.
[Computational] Artificial Intelligence (AI)	An artist thinks of an idea and verbalizes it in a textual prompt. An AI system then leverages its training data and built-up network of visual-semantic relationships to match the prompt to a matching image. It makes certain random adjustments to this image and outputs the result. The artist cannot explain the aesthetic choices made by the AI system.

Table 3: A list of the survey's processes with short descriptions of the tasks that each one entails. The status of each process is specified as computational or non-computational in brackets prior to its name and identifier.

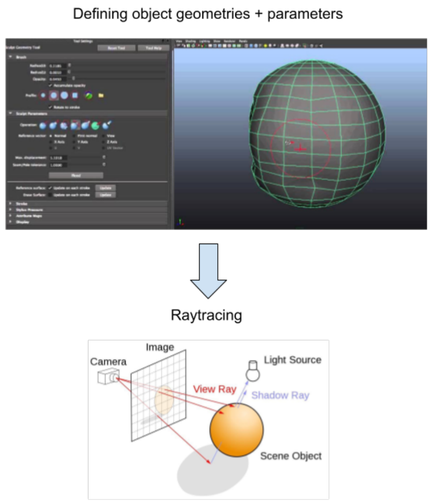


(a) Digital Illustration (DI) Graphic

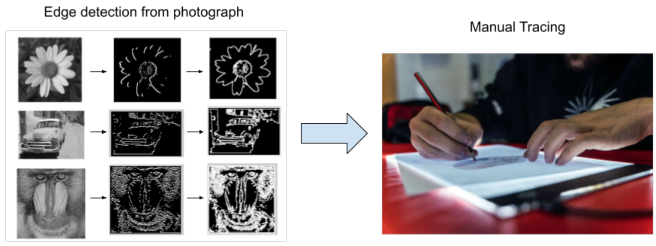
(b) Watercolor (WC) Graphic



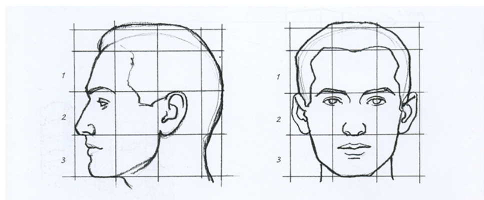
(c) Pen Plotter (PP) Graphic



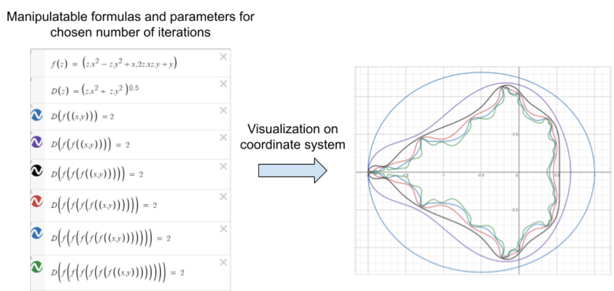
(d) Graphics Engine (GE) Graphic



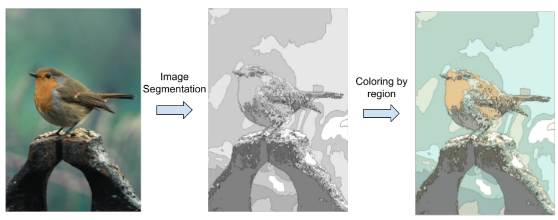
(e) Edge Detector (ED) Graphic



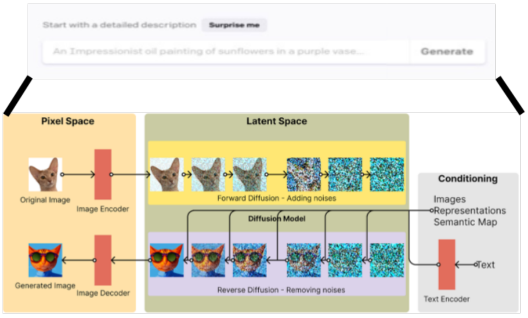
(f) Classical Proportion (CP) Graphic



(g) Fractal Set (FS) Graphic



(h) Image Segmentation (IS) Graphic



(i) Artificial Intelligence (AI) Graphic

Figure 1: Informative graphics distributed to participants alongside each process vignette.Figures 1a and 1b have been truncated from the distributed survey, but the full versions are visible in the appendix.

4 Methods

Once this survey design was realized in a preliminary draft, it went through several rounds of revision before being released to participants online.

4.1 Study Revision

To finetune the wording of the survey, three rounds of pilot surveys were conducted.

In the first round, four volunteers took a preliminary version of the survey. In each case, the survey was conducted over an in-person meeting. After an online copy of the survey was shared with the participant, they completed the survey, thinking aloud as they came to an answer for each question. This feedback was transcribed live and then used to inform changes to the survey. Although the researcher was present and had access to each volunteer's working document, the researcher did not clarify doubts, answer questions, or provide explanations to any participant until the survey was complete.

The first round of pilot surveys identified several fixable issues with the survey. Initial anthropomorphism questions included direct reference to DALL-E, OpenAI's popular (c. 2023) AI-based image generator, which immediately prompted respondents to draw on their own disparate personal experiences with the tool. The next iteration of the survey substituted direct references to "DALL-E" with references to a fictional text-to-image generator "NINA." NINA uses the same methodology as DALL-E, but no participants would have personally used NINA, allowing them to think critically about NINA's process. Other issues identified in the first pilot round included clarifications about the raytracing algorithm described within the Graphics Engine (GE) process and the Sobel filters described within the Edge Detector (ED) process. More precise wording and extensive explanation were included in the next survey iteration to aid participants without a computer science background.

The second and third rounds of pilot surveys (composed of three volunteers each) used the same structure of in-person meetings as the first round. The second round prompted smaller clarifications with wording in a couple of the vignettes and one of the anthropomorphism questions. Participants also seemed to consistently compare vignettes against each other, which required researchers to standardize certain wording across vignettes. This prevented participants from perceiving differences in creativity based on discrepancies in specific phrasing. Results from the third round demonstrated that the issues identified in the previous two rounds had largely been mitigated. There remained some confusion over how to evaluate the creativity of an artistic process, but this was the very question that the survey sought to implicitly ask — it was appropriate for participants to dwell on this idea.

The version of the survey that resulted from these three pilot rounds was finalized, formatted, and uploaded online.

4.2 Participants

Survey participants were recruited via Prolific, an online research platform. As per Prolific's requirements, certain logistical information about the survey was specified upfront to participants before opt-in. Participants were told that they would not need audio, camera, or microphone capabilities to complete the study. The expected duration of the survey was specified to be 30 minutes; survey results have suggested that this was accurate with the actual median time turning out to be 29 minutes and 57 seconds. Lastly, participants were given a short description of the structure and content of the survey.

To take part in the study, participants had to pass a screen that verified they were over 18 years old, residents of the United States and fluent in English. Those who met these requirements and opted into the study were then redirected from the Prolific platform to the survey. Following the completion of the survey, they were redirected back to the Prolific website, where they marked their participation as complete. Researchers were given a chance to approve or reject these answers based on a set of criteria provided by Prolific — responses could only be rejected if the participant skipped mandatory questions or objectively demonstrated low effort. For responses that were approved, respondents were paid based on the amount of time they took to complete the study at a rate of $12/hour.

Out of the 120 total responses received, 113 responses were approved and 7 were rejected within the initial round of data cleaning based on Prolific criteria. However, out of the 113 responses that were approved on Prolific, another 46 were rejected in a second round of data cleaning based on a stricter set of criteria. This second set of criteria will be described more in detail in the discussion on data analysis in Section 4.3. This two-round approach to the filtration of responses was necessary because Prolific only allows responses to be rejected in extremely specific cases (to ensure their participant pool is reliably paid). Thus, the second round of cleaning was required to ensure that the quality of study data was adequate. Ultimately, the final dataset included responses from 67 participants. No demographic or personally identifying information was collected in this study, though Prolific has internal checks to monitor the quality and diversity of its participant pool.

4.3 Data Analysis

After data collection and the first round of data cleaning, a second round of data cleaning was conducted. This round eliminated responses which met one or more of the below conditions for a majority of answers:

i. The response does not reference any of the modes of creativity.

ii. The response does not reference creativity (including cases where the response references personal aesthetic preference as a substitute for creativity).

iii. The response does not reflect comprehension of the specific content of the vignette (including cases where the response addresses the contents of the graphic to the exclusion of the written contents of the vignette).

Cleaning the data based on these conditions left 67 valid responses for data analysis.

Anthropomorphization scores were calculated by taking an equally weighted average of the responses to each of the four questions in Part I, resulting in a number between 1 and 7. While each of the four questions independently assessed participant perceptions of AI's smartness, awareness, understanding of the world, and ability to plan, this information had to be aggregated to encompass tendencies toward anthropomorphization as a whole (Waytz et al., 2014).

The raw creativity scores collected in Part II did not require complex data treatment — scores were only mapped onto a 0 to 6 scale to ease later analysis. However, thematic analysis was required to reasonably interpret the freeform explanations of these scores. A preliminary codebook, largely tied to the modes of creativity, was used in order to identify themes in certain responses. The codebook included two codes corresponding to each mode of creativity — the abbreviation of the mode followed by either an -AFF suffix or a -NEG suffix. -AFF codes are applied when a response mentions the artist agency present in the relevant mode as an enhancer of creativity. Similarly, -NEG codes are applied when a response mentions the lack of artist agency present in the relevant mode as an impediment on creativity. An additional two codes, KNOSKI and CHOLIM were added to identify explanations that discussed knowledge/skill required in a particular process or the agency in the initial choice to use a particular process as related to creativity. Table 4 provides a full account of each code and its exact definition.

While all codes were analyzed for prevalence, the -AFF and -NEG codes were additionally used in conjunction with raw creativity scores to calculate weights for each mode of creativity. Each vignette corresponded with a set of "correct" codes based on which modes were controlled by artists versus which modes were controlled by external agents. For example, referencing the sources of agency described in Table 3 for the Digital Illustration (DI) vignette, its "correct" set of codes would be [IDEAFF, DESNEG, COMAFF, IMPAFF, EVAAFF].

Code	Definition
IDEAFF	The respondent mentions the artist agency present in the Ideation (IDE) as a reason to make the creativity score higher.
DESAFF	The respondent mentions the artist agency present in the Design (DES) mode as a reason to make the creativity score higher.
COMAFF	The respondent mentions the artist agency present in the Composition (COM) mode as a reason to make the creativity score higher.
IMPAFF	The respondent mentions the artist agency present in the Implementation of Formal Elements (IMP) mode as a reason to make the creativity score higher.
EVAAFF	The respondent mentions the artist agency present in the Evaluation (EVA) mode as a reason to make the creativity score higher.
IDENEG	The respondent mentions the lack of artist agency present in the Ideation (IDE) mode as a reason to make the creativity score lower.
DESNEG	The respondent mentions the lack of artist agency present in the Design (DES) mode as a reason to make the creativity score lower.
COMNEG	The respondent mentions the lack of artist agency present in the Composition (COM) mode as a reason to make the creativity score lower.
IMPNEG	The respondent mentions the lack of artist agency present in the Implementation of Formal Elements (IMP) mode as a reason to make the creativity score lower.
EVANEG	The respondent mentions the lack of artist agency present in the Evaluation (EVA) mode as a reason to make the creativity score lower.
KNOSKI	The respondent mentions knowledge or skill as a prerequisite to or component of creativity.
CHOLIM	The respondent mentions the ability to choose to give up agency or choose to act under certain limitations as additive (or at least not reductive) to creativity.

Table 4: Preliminary Codebook: Codes and Definitions

From here, researchers calculated mode weights, measures that could facilitate comparisons between various modes' perceived importance. To calculate these weights, creativity scores were split into affirmative scores and negative scores. Affirmative scores were the original creativity scores, while negative scores were the affirmative scores subtracted from the maximum possible creativity score. Negative scores essentially represented the creativity points that a participant chose not to include in their score. For example, if a participant scored creativity as a 4 for a particular process, the affirmative score would be 4 and the negative score would be $6–4 = 2$. From here, each response's codes (out of those that were in the "correct" set for a particular question) were compared against their affirmative and negative scores, after which a weight could be derived.

For example, take a specific vignette that had the "correct" set [IDEAFF, DESNEG, COMNEG, IMPNEG, EVAAFF] and a participant who gave it a creativity score of 1 with the codes [COMNEG, IMPNEG, EVAAFF]. This would give this response an affirmative score of 1 and a negative score of 5. As the only -AFF code identified, EVAAFF would be entirely responsible for explaining the affirmative score, giving EVA a weight of $1/6 = 0.167$. Since ideation wasn't considered, IDE would be given a weight of 0. Similarly, since COM and IMP were the only two -NEG codes identified, the negativity score would be split amongst these modes to calculate their weights. Thus, both COM and IMP would have weights of $(5/6)/2 = 0.417$. Since the lack of agency within the design stage was not addressed as a detriment to creativity, DES would be given a weight of 0.

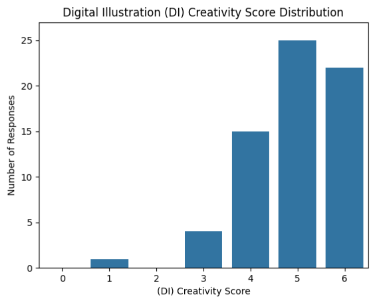
Along with anthropomorphism scores, creativity scores, and the codes themselves, these weights were the primary data analyzed within the study.

5 Results

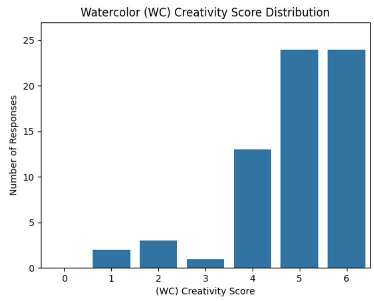
Once the data was cleaned, the codebook was applied to each relevant response and weights were calculated, each valid response included information about participant backgrounds in computer science and the visual arts, an anthropomorphism score, one raw creativity score per vignette, and one set of weightings per vignette.

5.1 Differences in Perceived Creativity Across Artistic Processes

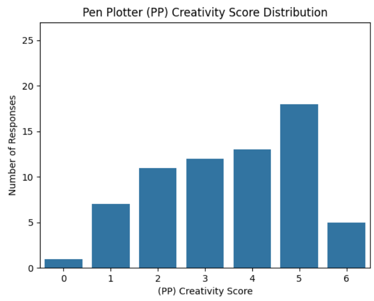
To begin with, raw creativity scores were compared between artistic processes. This approach aimed to identify any salient differences in perceived creativity between artistic processes. Table 5 shows summary statistics regarding the distribution of scores for each artistic process. These distributions are visualized in Figures 2a-i.



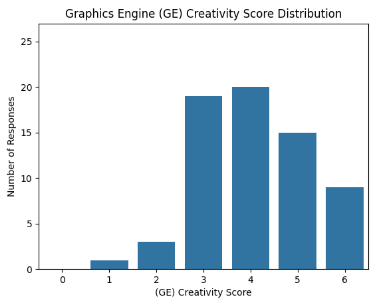
(a) Score distribution for the DI process



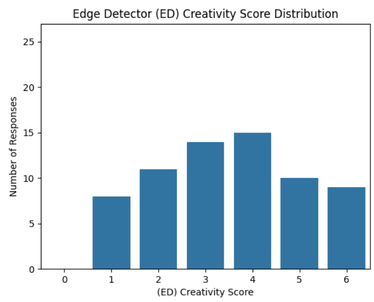
(b) Score distribution for the WC process



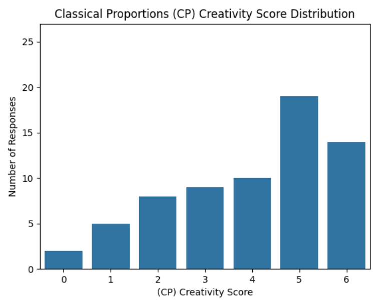
(c) Score distribution for the PP process



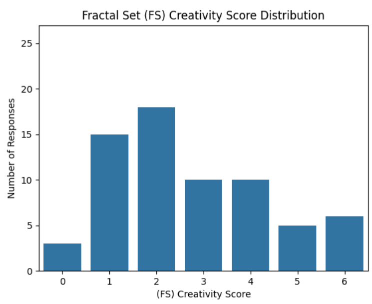
(d) Score distribution for the GE process



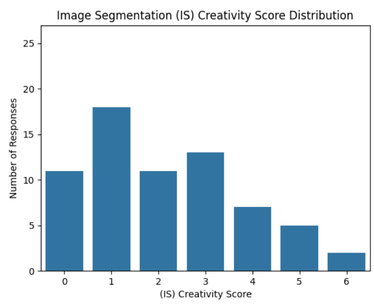
(e) Score distribution for the ED process



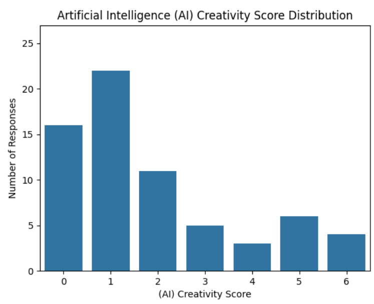
(f) Score distribution for the CP process



(g) Score distribution for the FS process



(h) Score distribution for the IS process



(i) Score distribution for the AI process

Figure 2: Score distributions for the raw creativity scores of each process

	Mean	Standard Deviation
Digital Illustration (DI)	4.925	1.020
Watercolor (WC)	4.881	1.225
Pen Plotter (PP)	3.537	1.550
Graphics Engine (GE)	4.075	1.172
Edge Detector (ED)	3.522	1.560
Classical Proportion (CP)	3.985	1.710
Fractal Set (FS)	2.716	1.668
Image Segmentation (IS)	2.149	1.645
Artificial Intelligence (AI)	1.866	1.825

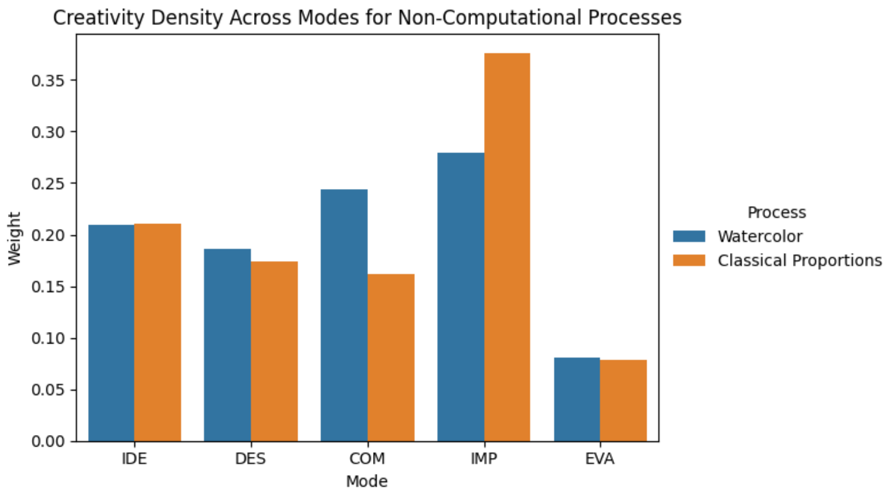
Table 5: Averages and Standard Deviations for Creativity Scores Across Artistic Processes

	DI	**WC**	**PP**	**GE**	**ED**	**CP**	**FS**	**IS**	**AI**
DI	N/A	$W = 1116.5$ $p = 0.886$	$W = 259.5$ **$p < 0.001$**	$W = 432.0$ **$p < 0.001$**	$W = 246.5$ **$p < 0.001$**	$W = 575.0$ **$p < 0.001$**	$W = 152.0$ **$p < 0.001$**	$W = 24.0$ **$p < 0.001$**	$W = 58.0$ **$p < 0.001$**
WC	$W = 1116.5$ $p = 0.886$	N/A	$W = 254.5$ **$p < 0.001$**	$W = 491.5$ **$p < 0.001$**	$W = 296.0$ **$p < 0.001$**	$W = 580.0$ **$p < 0.001$**	$W = 172.5$ **$p < 0.001$**	$W = 41.0$ **$p < 0.001$**	$W = 103.5$ **$p < 0.001$**
PP	$W = 259.5$ **$p < 0.001$**	$W = 254.5$ **$p < 0.001$**	N/A	$W = 794.5$ **$p = 0.030$**	$W = 1078.5$ $p = 0.703$	$W = 852.0$ $p = 0.071$	$W = 615.0$ **$p < 0.001$**	$W = 372.0$ **$p < 0.001$**	$W = 343.0$ **$p < 0.001$**
GE	$W = 432.0$ **$p < 0.001$**	$W = 491.5$ **$p < 0.001$**	$W = 794.5$ **$p = 0.030$**	N/A	$W = 780.0$ **$p = 0.023$**	$W = 1099.0$ $p = 0.800$	$W = 291.5$ **$p < 0.001$**	$W = 169.5$ **$p < 0.001$**	$W = 135.0$ **$p < 0.001$**
ED	$W = 246.5$ **$p < 0.001$**	$W = 296.0$ **$p < 0.001$**	$W = 1078.5$ $p = 0.703$	$W = 780.0$ **$p = 0.023$**	N/A	$W = 881.0$ $p = 0.105$	$W = 658.5$ **$p = 0.003$**	$W = 305.0$ **$p < 0.001$**	$W = 311.5$ **$p < 0.001$**
CP	$W = 575.0$ **$p < 0.001$**	$W = 580.0$ **$p < 0.001$**	$W = 852.0$ $p = 0.071$	$W = 1099.0$ $p = 0.800$	$W = 881.0$ $p = 0.105$	N/A	$W = 510.0$ **$p < 0.001$**	$W = 323.5$ **$p < 0.001$**	$W = 317.0$ **$p < 0.001$**
FS	$W = 152.0$ **$p < 0.001$**	$W = 172.5$ **$p < 0.001$**	$W = 615.0$ **$p < 0.001$**	$W = 291.5$ **$p < 0.001$**	$W = 658.5$ **$p = 0.003$**	$W = 510.0$ **$p < 0.001$**	N/A	$W = 713.5$ **$p = 0.007$**	$W = 567.5$ **$p < 0.001$**
IS	$W = 24.0$ **$p < 0.001$**	$W = 41.0$ **$p < 0.001$**	$W = 372.0$ **$p < 0.001$**	$W = 169.5$ **$p < 0.001$**	$W = 305.0$ **$p < 0.001$**	$W = 323.5$ **$p < 0.001$**	$W = 713.5$ **$p = 0.007$**	N/A	$W = 930.0$ $p = 0.187$
AI	$W = 58.0$ **$p < 0.001$**	$W = 103.5$ **$p < 0.001$**	$W = 343.0$ **$p < 0.001$**	$W = 135.0$ **$p < 0.001$**	$W = 311.5$ **$p < 0.001$**	$W = 317.0$ **$p < 0.001$**	$W = 567.5$ **$p < 0.001$**	$W = 930.0$ $p = 0.187$	N/A

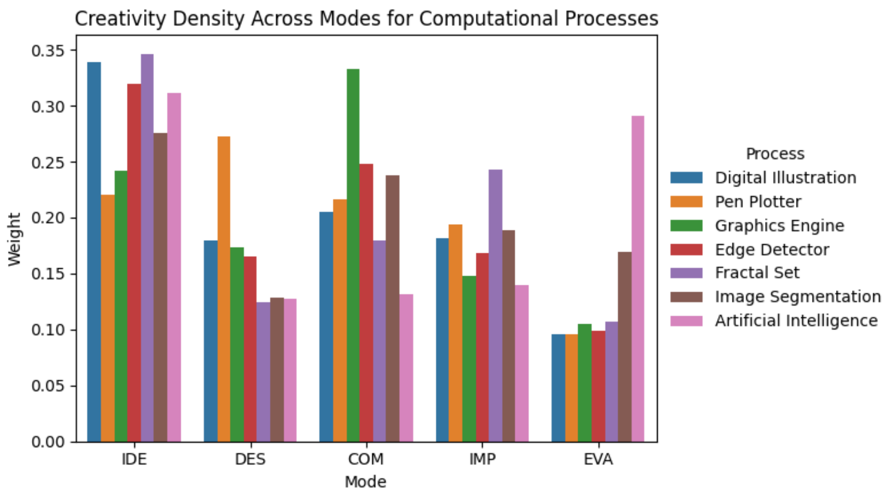
Table 6: Comparison of raw creativity scores between each artistic process using the Wilcoxon signed-rank test. Significant p-values are bolded and highlighted in yellow.

As seen in both the distribution charts and Table 5, artistic processes with more modes delegated to computational agents generally had higher standard deviations. This change suggested lesser agreement over perceived creativity within processes where control had been increasingly shifted away from the artist. The histograms present this lack of consensus visually, particularly in the wide spread of scores seen for the PP and ED processes in Figures 1d and 1e. Mean creativity scores followed the opposite trend, generally decreasing across processes as relatively more modes were delegated to computational agents. Although these slight differences are visible in Table 5, direct comparisons of creativity scores between processes were required to rigorously determine which specific differences were significant. As per the Shapiro-Wilk test, more than one of the artistic processes demonstrated score data which was not normally distributed. Thus, each comparison between creativity scores of artistic processes was conducted using a Wilcoxon signed-rank test. The detailed results of these comparisons can be visualized in Table 6.

Most of these comparisons were statistically significant, demonstrating that creativity scores were meaningfully different across artistic processes, however slight these differences were. The only insignificant comparisons were between DI versus WC, GE versus CP, PP versus ED, PP versus CP, ED versus CP, and AI versus IS. The FS artistic process was significant from every other process. Additionally, both the DI-WC pair and the AI-IS pair were significantly different from every process except each other.



(a) Creativity density across modes within non-computational processes



(b) Creativity density across modes within computational processes

Figure 3: Creativity densities across modes

5.2 Justifications for Perceived Creativity

Following the comparison of raw creativity scores between artistic processes, it was important to examine the specific reasons that respondents drew on to explain their score for each artistic process.

5.2.1 Summary Statistics for Mode Weights Across Artistic Processes

Given that the survey was structured around modes of creativity, an analysis of these modes and their weights was a valuable approach to understanding these scores. Because each artistic process delegated a different combination of modes to external agents and some processes delegated modes to non-computational agents rather than computational agents, researchers expected mode weights to differ between processes. Even so, a comparison of weights was relevant for an investigation into how specific stages of the artistic process differed in their impact on perceived creativity when delegated to a computational agent. A preliminary aggregation of these weights is displayed in Figure 3a for non-computational processes and Figure 3b for computational processes. The differences between these trends is further discussed both later in this chapter and in the Findings chapter. Exact mode weights can be seen in Table 7, which displays average weights for each mode in each artistic process.

A Shapiro-Wilk test indicated that the weights were not normally distributed for any of the modes on any of the processes. Implementation was weighted highest in both non-computational processes; A

	IDE	DES	COM	IMP	EVA
DI	0.339	0.179	0.205	0.182	0.096
WC	0.210	0.0187	0.244	0.279	0.081
PP	0.221	0.273	0.216	0.194	0.096
GE	0.242	0.173	0.333	0.148	0.105
ED	0.319	0.165	0.248	0.169	0.099
CP	0.210	0.174	0.162	0.376	0.107
FS	0.346	0.125	0.280	0.243	0.096
IS	0.275	0.129	0.238	0.189	0.169
AI	0.311	0.127	0.131	0.140	0.290

Table 7: Average mode weights per process. In a particular row or artistic process, cells are filled in red if the relevant mode was delegated to an external agent and green if the mode was fully under artist control.

	KNOSKI	CHOLIM
DI	0.104	0.075
WC	0.269	0.299
PP	0.060	0.060
GE	0.104	0.045
ED	0.045	0.149
CP	0.254	0.120
FS	0.119	0.015
IS	0.030	0.030
AI	0.030	0.0

Table 8: Prevalences (out of 1) of the KNOSKI and CHOLIM codes in each process. Prevalances are calculated across the 67 total valid responses.

Wilcoxon signed-rank test verified that the weights for the IMP mode were significantly different from the weights for each of the other modes within both non-computational processes. By contrast, ideation was weighted most highly in five out of the seven computational processes.

5.2.2 Summary Statistics for Miscellaneous Justifications

While the KNOSKI and CHOLIM codes did not factor into mode weights directly, they provided insight into how respondents discussed creativity in the context of these modes. Table 8 displays the prevalence of the KNOSKI and CHOLIM codes across artistic processes.

The KNOSKI code appeared most frequently in the WC and CP processes with prevalences of 0.269 and 0.254 respectively. As noted in Table 3, these were the only two processes which delegated modes to non-computational external agents. Within the FS process — which had the next highest prevalence for the KNOSKI code — the code occurs less than half as much, with a prevalence of only 0.119. The CHOLIM code occurred most frequently in the WC process, where its prevalence was 0.299. The processes with the next highest prevalences were the ED and CP processes at 0.149 and 0.120 respectively.

For processes that had a prevalence greater than 0.15 (¡ 10 responses) for one of the KNOSKI or CHOLIM codes, the Matthew's Correlation Coefficient (MCC) was used to assess whether there was a significant correlation between the prevalent code and any of the mode-specific codes. However, no significant correlation was discovered between either KNOSKI or CHOLIM and any of the mode codes.

5.2.3 Differences Between Computational Versus Non-Computational Processes

As outlined in Table 3, seven of the artistic processes presented to respondents involved a delegation of some modes of creativity to computational agents. However, the WC and CP processes were included as complements to the DI and ED processes to gauge whether there was a change in perceived creativity when the same set of modes were delegated to a non-computational (but still external) agent.

	DI vs WC		ED vs CP	
	W	**p-value**	**W**	**p-value**
IDE	698.0	**0.006**	769.0	**0.021**
DES	1106.0	0.835	1101.0	0.814
COM	992.0	0.358	747.5	**0.014**
IMP	797.0	0.032	544.5	< **0.001**
EVA	996.5	0.366	985.0	0.331

Table 9: Results for a Wilcoxon signed-rank test between the weights for each mode of creativity for the DI versus WC comparison and the ED versus CP comparison. Significant p-values are bolded.

A comparison of raw creativity scores alone provided interesting leads, but did not open into any rigorous conclusions. As per Table 5, the WC mean creativity score was comparable to the mean score for DI. By contrast, the CP mean creativity score exceeded the mean scores for the ED process and even the PP process. This broke the larger trend of decreasing mean creativity scores with greater external agency. However, this difference was not large enough to be notable — there was no significant difference in perceived creativity between either the DI and WC processes (W = 1116.5, p = 0.886) or the ED and CP processes (W = 881.0, p = 0.105). The ways in which participants justified these raw scores revealed more about how perceptions of creativity differed between computational and non-computational processes.

First, delegated mode weights were compared to determine whether people perceived delegation to computational agents as more of an impediment to creativity than delegation to non-computational agents. In the DI versus WC comparison, only the DES mode was delegated. There was no significant difference in the weights of this mode between these processes (W = 1106.0, p = 0.835). In the ED versus CP comparison, both the DES and COM modes were delegated. There was no significant difference in the weights for DES mode ($W = 46.0, p = 0.255$), but COM mode was weighted significantly higher when delegated to a computational entity than a non-computational entity ($W = 28.0, p = 0.010$). This result suggests that, at least for some modes, delegation to a computational agent detracts from perceived creativity more strongly than delegation to a non-computational agent. Still, the specific circumstances associated with this phenomenon — including whether it is unique to the COM mode — remain unclear and warrant further study.

There were interesting patterns worth exploring in the weightings of computational processes versus non-computational processes even beyond just the modes that were delegated. Non-computational artistic processes followed a different distribution of weights than their computational counterparts. The IDE mode was weighted significantly lower for non-computational processes, both with the DI versus WC comparison (W = 698.0, p = 0.006) and with the ED versus CP comparison (W = 769.0, p = 0.021). The IMP mode was also weighted differently; higher weights were observed for IMP mode in non-computational processes versus computational processes. Wilcoxon signed-rank tests showed the significance of this difference for both the DI versus WC comparison ($W = 797.0, p = 0.032$) and the ED versus CP comparison ($W = 544.5, p =< 0.001$). A detailed and full account of the two comparisons can be found in Table 9.

The KNOSKI and CHOMSKI codes also reflected interesting perceptions about creativity in non-computational processes. As seen in Table 8, the prevalence of the KNOSKI code was more than doubled in non-computational processes as compared to computational processes. Occurrences of the CHOLIM code were similarly disparate, with the WC process having a CHOLIM prevalence that was nearly double that of the CP process. Barring the ED process, whose CHOLIM prevalence was comparable to the CP process, all computational processes had less than one-fourth as many CHOLIM occurrences as the WC process.

5.2.4 Impact of Directness of Implementation

To determine whether directness of implementation had a bearing on perceived creativity, the study investigated whether there were significant changes in IMP weight between processes where implementation was under the control of the artist versus delegated to a computational agent. However, responses also showed an interesting relationship between IMP and COM weights. When the COM and IMP modes were grouped together — either both under artist control or both delegated — their mean weights tended

	DI vs GE		ED vs FS		FS vs IS	
	W	**p-value**	**W**	**p-value**	**W**	**p-value**
IDE	868.0	0.090	1052.0	0.587	892.5	0.123
DES	1092.5	0.770	1000.5	0.386	1133.5	0.972
COM	731.0	**0.011**	897.5	0.131	810.0	**0.039**
IMP	1021.5	0.462	782.0	**0.026**	924.0	0.179
EVA	1093.5	0.773	1134.5	0.977	836.5	0.057

Table 10: Results for a Wilcoxon signed-rank test between the weights for each mode of creativity for the DI versus GE comparison, the ED versus FS comparison, and the FS versus IS comparison. Significant p-values are bolded.

to be quite close together. In fact, occurrences of the COMNEG and IMPNEG codes were moderately correlated for processes where both the COM mode and the IMP mode were delegated to computational agents: PP ($MCC = 0.546$), FS ($MCC = 0.383$), and AI ($MCC = 0.639$). However, in several artistic processes where one of these modes was delegated but the other was not, the COM mode ended up being weighted significantly more than the IMP mode. This was the case within the GE process ($W = 542.0$, $p < 0.001$), where IMP was delegated but COM was not, and in the ED process ($W = 778.0$, $p = 0.024$) and IS ($W = 755.5$, $p = 0.024$) where COM was delegated but IMP was not. This trend was relevant to several process comparisons that concerned directness of implementation in an artistic process: DI vs GE, ED vs FS, and FS vs IS.

The Digital Illustration (DI) and Graphics Engine (GE) processes both defined artwork geometry via a computational tool. However, in the DI process, this geometry was implemented directly by hand, whereas in the GE process, it was drawn by an algorithm. Creativity scores for the GE process are significantly lower than the DI process ($W = 432.0$, $p =< 0.001$). In a comparison of the mode weights for each process, only COM was weighted significantly differently ($W = 731.0$, $p = 0.011$).

The Edge Detector (ED) and Fractal Set (FS) processes were also compared — both processes use computer-generated designs and compositions, but the physical actions to execute these plans are completed directly by an artist in the ED process and by a computational agent in the FS process. The FS process, where implementation was delegated to a computational agent, had significantly lower creativity scores ($W = 658.5$, $p = 0.003$) than the ED process. In a comparison of weights, the IMP mode had a significantly higher weight in the FS process ($W = 782.0$, $p = 0.026$).

Lastly, the Fractal Set (FS) and Image Segmentation (IS) processes were compared. Both processes again use computer-generated designs and compositions, but while the FS process has the artist ideate and a computational agent implement, the IS process has a computational agent ideate and the artist implement. This comparison directly compares the impacts of originality of idea versus directness of implementation on creativity. The IS process has significantly lower creativity scores than the FS process ($W = 713.5$, $p = 0.007$). However, in a comparison of mode weights, no significant differences were found between either the IDE weights ($W = 892.5$, $p = 0.123$) or the IMP ($W = 924.0$, $p = 0.179$) weights. The only significant difference in mode weights was with the COM mode ($W = 810.0$, $p = 0.039$).

A detailed account of these comparisons is displayed in Table 10.

5.2.5 Impact of Human Design Constraints

Next, the analysis examined the impact of human design constraints on creativity. This analysis investigated the extent to which human-driven design constraints impacted perceived creativity in artistic processes that were otherwise mostly computationally driven. In the PP process, artists had full agency to establish design constraints; the computational agents responsible for the composition and implementation stages worked within these limitations. This was the only artistic process that did not delegate design to an external agent. As seen in Table 7, the PP process has the highest mean weight for the DES mode amongst all artistic processes. Researchers compared DES weights the PP process and other computational processes to discern whether participants thought that design contributed more to creativity when controlled by the artist rather than a computational agent. As shown in Table 11, the results of Wilcoxon signed-rank tests demonstrated that the DES mode weights for the PP process were significantly higher than nearly every other process, only excluding the DI process.

	PP	
	W	**p-value**
DI	854.0	0.075
GE	744.5	**0.014**
ED	783.5	**0.026**
FS	575.0	**0.036**
IS	643.5	$<$ **0.001**
AI	570.0	$<$ **0.001**

Table 11: Results of Wilcoxon signed-ranks test between the DES weights of PP versus every other computational process. Significant p-values are bolded.

	AI	
	W	**p-value**
DI	464.5	$<$ **0.001**
PP	422.0	$<$ **0.001**
GE	584.0	$<$ **0.001**
ED	538.5	$<$ **0.001**
FS	535.0	$<$ **0.001**
IS	776.0	**0.023**

Table 12: Results of Wilcoxon signed-ranks test between the EVA weights of AI versus every other computational process. Significant p-values are bolded.

5.2.6 Impact of Understanding Computational Agents

As seen in Table 7, weights for the EVA mode were consistently low until the AI process, which had the highest mean EVA weight at 0.290. As Figure 3b visually illustrates, EVA weight within AI process is very much an outlier, over double the next highest EVA weight. It is important to note that the AI process is the only process where the artist was not entirely agent over evaluation, surrendering control over this mode to a computational agent. This reflected the lack of understanding and oversight that the artist had over actions taken by the computational agent in previous stages of the process. To determine whether this significantly impacted perceived creativity within the AI process, EVA weights were compared between the AI process and other computational processes in a series of Wilcoxon signed-rank tests. These tests demonstrated that there was a significant difference between EVA weights for the AI process and each other computational process. Specific and detailed results are displayed in Table 12.

5.3 Differences Across Anthropomorphism Measure

Overall, the anthropomorphization scores ranged between 1 and 7 with a mean of 4.418 and a standard deviation of 1.316. Figure 2 visualizes the distribution of anthropomorphization scores.

Participants were split into two groups based on their anthropomorphization score; a high anthropomorphization group included the 13 participants with scores greater than 5.724 (the mean anthropomorphism score plus one standard deviation) while a regular anthropomorphization group contained the rest of the survey participants. Since a Shapiro-Wilk test indicated that anthropomorphism scores were normally distributed (W = 0.538, p = 0.839), the high anthropomorphization group was established as the population with the top 15% of scores. The raw creativity scores for the high anthropomorphization group were then compared with the regular anthropomorphization group using a Mann-Whitney U Test. This helped determine if there was a significant difference in perceived creativity in any of the processes based on tendencies towards anthropomorphization. These results can be seen in Table 13.

As shown, the only artistic process within which perceived creativity differed between the high anthropomorphization group and the regular anthropomorphization group was the AI process. Within the AI process, an analysis of mode weights revealed that the high anthropomorphization group weighted IDE significantly higher ($U = 226.5$, $p = 0.043$) and the regular anthropomorphization group weighted

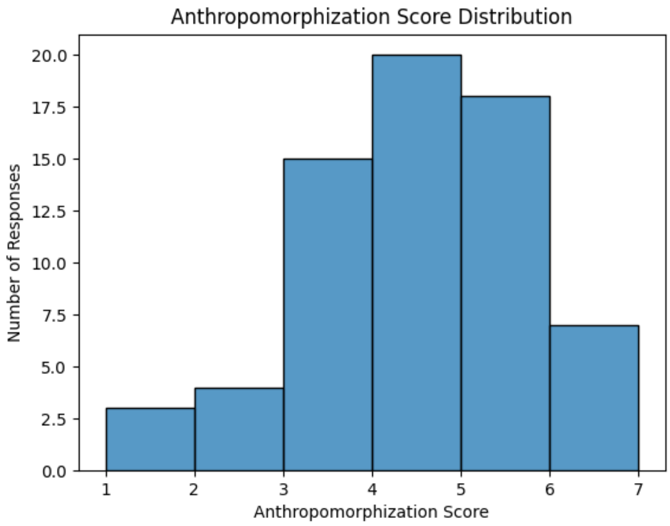


Figure 4: Distribution of anthropomorphism scores across participants

	W	**p-value**
DI	276.0	0.213
WC	280.0	0.239
PP	311.0	0.523
GE	320.0	0.617
ED	302.0	0.416
CP	300.0	0.414
FS	349.5	0.987
IS	331.0	0.753
AI	226.5	**0.043**

Table 13: Results of a Mann-Whitney U Test on the raw creativity scores given to the AI process versus each other artistic process. Significant p-values are bolded.

EVA significantly higher ($U = 184.0$, $p = 0.008$). There were no significant differences in mode weights for any of the other processes.

5.4 Differences Across Participant Backgrounds

Lastly, participants were split into groups according to their self-reported backgrounds in visual arts and computer science. In the survey, participants were asked whether they had a full background, some background, or no background in each of these disciplines. The breakdown of participant responses can be seen in Table 14.

Because so few participants identified as having a full background in either discipline, the "Full Background" and "Partial Background" groups were combined into an "Any Background" group. Mann-Whitney U tests were then used to determine whether there were significant differences in raw scores or weights between the "Any Background" group and the "No Background" group for each discipline.

Within the computer science discipline, the Mann-Whitney U test ($U = 332.5$, $p = 0.038$) found significant differences between EVA weights for the FS process. The mean weight for participants with any computer science background was 0.05, while the mean weight for those with no computer science background was 0.131. Within the visual arts discipline, significant differences were found between the COM and EVA weights in the GE process and raw creativity scores for the CP process. Participants with any visual arts background typically weighted the COM mode higher ($U = 367.5$, $p = 0.015$) and the EVA mode lower ($U = 698.5$, $p = 0.041$) as compared to the group with no visual arts background. The mean weight for the COM mode was 0.408 for those with any visual arts background versus 0.263

Level of Background	Discipline	
	Computer Science	Visual Arts
Full Background	6	9
Partial Background	47	23
Any Background	53	32
No Background	14	35

Table 14: Numbers of participants that identified as having a full background, partial background, any background, or no background in visual arts and computer science. Participants who identified as either having a full background or a partial background were included in the counts for "Any Background."

for those without any visual arts background. The mean weight for the EVA mode was 0.064 for those with any visual arts background versus 0.142 for those without any visual arts background. Participants who had any visual arts background also gave higher overall creativity scores to the CP process, with a mean score of 4.469 as compared to 3.543 for the group with no visual arts background.

6 Findings

6.1 AI as Part of a Larger Trend of Computational Art

6.1.1 F1: Perceived Creativity in AI Art Is Not an Outlier

Overall perceptions of creativity generally seemed to sustain an awareness of the modes of creativity and the extent to which artists retained or surrendered control over these modes within any given artistic process. As shown in Table 5, artistic processes which had more modes controlled by computational agents consistently received generally lower creativity scores. The AI-based process, in which the artist only controlled ideation, had the lowest mean creativity score out of all the processes respondents were surveyed on. These results were statistically significant from every other process except the IS process. This trend is consistent with previous research about public perceptions of AI art, which suggests that humans are significantly negatively biased towards AI art and less inclined to attribute artistic intentions to computational agents (Mohammad and Kiritchenko, 2018). However, this study's findings demonstrate that there isn't a steep drop-off in perceived creativity as soon as AI enters the picture. Rather, perceived creativity in AI-based artistic processes fits into a larger gradual trend of decreasing perceived creativity as external agents are given power over more modes of an artistic process. While perceived creativity in non-computational processes was justified differently (further discussed in Section 5.2.1), their raw scores also fit into this trend. Perceived creativity within non-computational artistic processes was never significantly different than computational processes which delegated the same modes.

This affirms the relevance of process and agency in understanding perceptions of creativity, particularly with AI-based processes. When the use of AI is contextualized within its artistic process, perceived creativity within the process may still be relatively low, but it is not an outlier amongst artistic processes. The creativity scores allocated to the AI process were only slightly (an average of 0.850 points out of a range of 6) less than the next least creative process. This suggests that the use of AI in an artistic process is not necessarily perceived as singularly uncreative. Understanding more about this framework that people use to judge other artistic processes that utilize different computational tools could provide valuable insights on how to increase perceived creativity in AI art.

6.1.2 F2: Anthropomorphization Levels Uniquely Impact Perceived Creativity in AI Processes

It is also important to note that this framework for perceptions of creativity in computational processes differs amongst different groups and populations, especially where AI is concerned. Previous research suggests that populations that are willing to anthropomorphize AI are also willing to trust it and ascribe it more responsibility (Placani, 2024). The anthropomorphization of AI is sometimes described in the context between conflicting views of AI as a tool and AI as an agent (Epstein et al., 2020). When people anthropomorphize AI, they see it as less of a fully controllable tool and more of an independent agent. It is therefore notable that the high anthropomorphism group found AI-based creative processes to be significantly more creative than the regular anthropomorphism group. The high anthropomorphization group sees AI as an agent that the artist does not control and acknowledges that this agent — rather than the artist— is responsible for large parts of the creative process. However, they still see the process as more creative than those that see AI as more under the influence of the artist. This suggests that instead of seeing AI as a factor that impacts artist creativity, people that anthropomorphize AI are even willing to see it as a source of creativity in itself. Ten out of the thirteen participants in the high anthropomorphization group described the AI's actions as creative in themselves, recognizing "originality by employing abstract representational coding" (P54) and "creativity by leveraging ... data to make complex associations between messages and images" (P53). However, this perspective did not extend to other computational tools. This may serve as the underlying reason why so much rhetoric around generative AI demarcates it so firmly from other types of computational artistic tools. Regardless, this phenomenon sets up a fundamental divide between populations that anthropomorphize AI highly and those that do not, many of whom see creativity as something inherently human (Bellaiche et al., 2023). To be generally perceived as creative, AI-based art needs to find ways to cater to both of these perspectives.

6.2 Non-Computational Processes Versus Computational Processes

6.2.1 F3: Experience in Visual Arts Increases Perceived Creativity in Some Non-Computational Processes

As briefly mentioned above, overall creativity scores were comparable between non-computational and computational processes. The only caveat to this was the significantly higher creativity scores given to the Classical Proportion (CP) process by people who had some level of background in the visual arts. This may be because of their direct experience engaging with established visual conventions like rules of proportions. While those without a visual arts background criticized the process as "cookie-cutter" (P13) or just "following directions" (P6), those with a background in visual arts were more likely (16 out of 32 versus 5 out of 35) to emphasize the variety of ways in which the artist could work within these constraints creativity. These participants attributed creativity to the artists' responsibility for making choices about "color," (P3, P10, P14, P25, P30, P37, P60, P64) "shading," (P3, P14, P55, P60) and "mood" (P60) even within a larger conventional framework. This makes sense in the context of previous research that has verified the connection between perceived difficulty of a task and perceived creativity in its completion (Espedido and Searle, 2018). Those who were more well-versed in the difficulty of the task through their own prior experience perceived it as more creative.

6.2.2 F4: Ideation is Considered Less Creative in Non-Computational Processes

Even more interestingly, the entire population of participants were shown to weigh modes of creativity noticeably differently in non-computational processes as compared to computational processes, reflecting that the use of computational tools highlights different aspects of the artistic process as creative. Participants gave ideation much more importance in their impressions of creativity within computational processes, often at the expense of the implementation stage. An examination of participant responses suggested that ideation contributed less to perceived creativity in the contexts of watercolor paints and classical canons of portraiture because those tools were understood to conform to "traditional rules" (P2, P27) that have been "used for many centuries" (P8) and "been done before" (P50). Ideation stages that chose to use these non-computational entities were thus penalized. Ideas that drew upon technological tools, most of which have not been available to artists for as long as comparable non-computational entities, were more likely to be seen as novel and therefore creative by some participants.

6.2.3 F5: Implementation is Considered More Creative in Non-Computational Processes

By contrast, participants were hesitant to emphasize the creative power of implementation within the computational processes, citing the dilution of the "element of hands-on" (P62) engagement due to computational entities' mediation of earlier stages of these processes. In non-computational processes, however, implementation was consistently weighted as the most important mode, suggesting that when implementation is hands-on, it supplements perceived creativity significantly. This explains the differences between IMP weights when computational processes were compared to their non-computational counterparts; implementation was weighted significantly higher in both non-computational processes. This trend is particularly evident in the comparison between the Edge Detector (ED) process and the

Classical Proportion (CP) process, where implementation is weighted over twice as much in the non-computational process.

6.2.4 F6: Knowledge/Expertise Is Associated with Creativity More in Non-Computational Processes

Beyond these modes of creativity, explanations of creativity scores for non-computational processes frequently mentioned the skillfulness required to paint or draw. This is evidenced by the high prevalence of the KNOSKI code within both non-computational processes. The KNOSKI code was less than half as prevalent in computational processes as it was in either of the non-computational processes, where over a quarter of total participants (18 out of 67) mentioned an inherent necessity for skill or knowledge. Even beyond participants with a background in visual arts, non-computational processes were described to require "a great deal of skill" (P18) and "good baseline art techniques" (P35). By contrast, mentions of skill or technical background in computation processes peaked within the Digital Illustration (DI), Graphics Engine (GE), and Fractal Set (FS) processes, where only up to eight total participants addressed the difficulty or complexity of using computational tools. This suggests that proficiency in using computational tools is not as directly tied to creativity as their more traditional counterparts.

6.2.5 F7: Opting into Structural Limitations is Associated with Artistic Agency More in Non-Computational Processes

Furthermore, although non-computational constraints were recognized as structural limitations, many responses also recognized that artists were in control in choosing to work within these constraints in the first place. The responses marked with the CHOLIM suggested that surrendering agency in the face of constraints selected by the artist was not an affront to creativity — and non-computational processes clearly had the highest prevalences for this code. Almost one third of participants (20 out of 67) praised artists working within the Watercolor (WC) and Classical Proportion (CP) processes for their ability to "creatively adapt to the schematic limitations" (P15) and "understand the most appropriate medium for their work" (P45). By contrast, computational constraints were consistently described as "dictated" (P67), "imposed" (P40), "strictly hamper[ing]" (P33), and generally adversarial towards artists. This attitude fails to consider that artists working within computational constraints are responsible for obtaining into these specific sets of limitations as well. The far lesser prevalence of CHOLIM codes when addressing creativity within computational processes reflects the lack of recognition of this fact.

6.3 Delegation of Modes of Creativity in Computational Processes

6.3.1 F8: Ideation is Consistently Valued as Creative Across Artistic Processes

An examination of participants' justifications for their raw scores provided valuable information on which modes of creativity had the largest impacts on perceived creativity. It is important to note that ideation was consistently weighted highly within all computational artistic processes; this was the highest weighted mode in the majority of computational processes. This suggests that, while ideation is preserved in the human artist's domain, computational processes will be perceived as creative to a meaningful degree. However, while some modes were weighted relatively consistently across processes, others saw significant changes in trends, reflecting that participants valued various modes differently based on the specific ways they were being controlled or delegated in particular processes.

6.3.2 F9: Evaluation is a Base Condition for Creativity in AI-based Artistic Processes

Analysis demonstrated that the evaluation mode was weighted significantly higher in the AI-based process than any other artistic process participants were surveyed on. Survey responses consistently identified the artist's inability to explain what artistic choices and elements led to the artwork's final manifestation as entirely prohibitive of creativity. Nearly half of all participants (29 out of 67) said that if an artist could not understand the process of how their final artwork was created, creativity would be severely impaired. In explaining this effect, participants suggested that a lack of understanding of their process means that an artist "relies heavily on the random" (P34) or uses "more luck than creativity" (P27) to come up with their final outcome. Despite the fact that AI was agent over the design, composition, and implementation stages in addition to the evaluation stage, the other stages were mentioned as deterrents for perceived creativity only around half as much (DES: 16 out of 67, COM: 16 out of 67, IMP: 17 out of

67). Creativity was clearly perceived to be contingent on not only understanding an artistic process, but being able to attribute characteristics of a final work to specific actions and choices, even if they were undertaken by a computational agent. This combination of mode weights and qualitative explanation highlights the prevailing attitude that evaluation is a central arbiter of creativity.

Oddly, creativity justifications for other processes did not highlight evaluation as very important. Evaluation was the lowest weighted mode of creativity in every process except the AI-based process. However, it is possible that people view many of the components of evaluation — understanding the process of how an artwork was made and being able to delineate the specific choices that influenced the translation of the work from idea to product — as a given in creating art. This could explain why the weights for the evaluation mode remained relatively low until participants were confronted with an artistic process where these aspects of evaluation were not guaranteed.

The need for greater evaluative power and understanding over AI results is not a problem unique to art. Many AI experts recognize the impossibility of relying on black-box AI systems in real-world scenarios — medical applications of AI in particular have reflected that most people prefer to defer to a human who produces fair but explainable results than an AI that produces excellent but uninterpretable results (Quinn et al., 2020). Part of the field of explainable AI focuses on creating deep generative AI models that maintain a high quality of results while being interpretable to the humans using them (Xu et al., 2019). Several existing explainable AI models are able to process with visual data to perform scene recognition, image corrections, and image captioning (Goebel et al., 2018; Han et al., 2020), but there is little to show for generative models that can produce images while explaining the reasoning behind its aesthetic decisions. This is the limitation that seemed to most hold back the recognition of creativity in AI-based artistic process.

6.3.3 F10: Granular Composition Can Support Creativity as Much as Direct Implementation

Directness of implementation was certainly one factor that determined perceived creativity in computational processes. However, as discussed in F5, implementation did not contribute to creativity as much as in non-computational processes, where this stage was considered more organic and more hands-on. Participants certainly placed some value on the implementation stage in computational processes, directly citing "human touch" (P2) and individual "artistic eye" (P11) as additive to creativity. However, because this stage was inherently viewed as less immediate, participants placed comparable or greater amounts of importance on the other stages.

As analysis demonstrated, composition and implementation were weighted similarly when they were grouped together, but composition was considered more important when one of the modes was delegated and the other was not. This suggests that people often conflate the planning and the execution of compositional decisions when both are responsibilities of the same entity. However, when people were forced to confront the distinction between the two, they consistently weighed composition as more important. It is possible that when participants failed to see an inherent immediacy in implementation, they saw the composition mode as a more powerful way to achieve granular control over the final artistic product. An examination of participant responses provides support for this idea. In the context of numerous artistic processes, participants described the ability to dictate compositional choices as the "substance of artistic license" (P65), allowing an artist to shape their creative expressions. This may better explain the results of the Digital Illustration (DI) versus Graphics Engine (GE) comparison and the Fractal Set (FS) and Image Segmentation (IS) comparison. While the delegation of the implementation mode was being changed, it was the composition mode that participants recognized as a means to granular control. Thus, the mode weights that differed significantly between these two comparisons were those that applied to the composition stage.

Ultimately, the relationship between perceived creativity and directness of implementation is a complicated one. The immediacy of the implementation stage is central to perceptions of creativity in non-computational processes, which are heavily contributed to by the pure human character of these processes' methods of execution. However, in computational processes, where earlier modes are mediated by computational tools, the implementation stage loses some of its claim to human directness and impacts creativity less. Within this context of computational processes, participants ended up weighing other modes like composition more highly as alternate ways to granularly control the final artwork. Thus, while implementation is an important component of creativity, this study suggests that people may also be willing to recognize directness and creativity in other, more macro modes of creativity in computational artistic processes. The relatively high weights for the ideation mode across all computational processes further supports this idea.

6.3.4 F11: Artist-Controlled Design Meaningfully Enhances Creativity

While only the Pen Plotter (PP) process did not delegate the design mode to an external agent, the weight attributed to the design mode during this process was significantly higher than any of the other artistic processes that participants scored. Many (39 out of 67) participants associated high levels of creativity with the artist's ability to create "boundaries and rules of what the system can do" (P37), essentially defining the structure that the computational entity acts within. While acknowledging that the computational agent completed much of the other work in the artistic process, participants felt that human control over design could keep the artist "responsible for how the image is constructed" (P47) to some extent. This willingness to assign responsibility over the final work to the artist suggests that human design conditions are perceived to influence other modes of an artistic process even if a human is not directly agent over them.

Since this evidence only stems from mode weight data and qualitative explanations regarding one artistic process, the strength of these interpretations is limited. Further research is required to confirm the magnitude of impact that human-imposed design constraints can have on perceived creativity in computationally executed artistic processes — perhaps by surveying more participants on a larger set of artistic processes that employ human-controlled design. However, existing literature does confirm that human involvement in AI system design is crucial in fostering broad acceptance of AI results across sectors (Inkpen et al., 2019). AI systems that center upon "human-in-the-loop" mechanisms — which involve the human in the pipeline itself rather than exclusively during the creation and tuning of the model — allow humans to collaborate with computational agents while retaining agency, achieving superior overall results (Dellermann et al., 2021). In conjunction with existing research, the results of this study suggest that using these kinds of hybrid intelligence systems to engage humans in design is worth exploring as a way to increase perceived creativity in computational and AI-based artistic production processes.

7 Recommendations

These findings have important implications for future development of AI models for the production of art. This study demonstrates that not only that perceptions of creativity in AI perceptions of creativity are impacted by human agency in evaluation, design, and composition — modes beyond just implementation. Moreover, AI is not perceived as singularly uncreative (F1). It follows that AI systems ought to be conceived with adjustments in each of these modes that allow for greater human involvement. This study's recommendations focus on what types of adjustments could be considered — firstly pertaining to evaluation (drawing on F9) and then pertaining to design (drawing on F11). The final category of recommendations examines the way in which subconscious perceptions about AI and computational tools impacted creativity scores. Both tendencies towards anthropomorphization (F2) and stereotypes about the unskillfulness or laziness in using computational tools (F6) are related to characterizations of AI in the media; this study suggests that special attention should be devoted to public descriptions of AI-based artistic tools, ensuring that their nuance is captured accurately.

The established dichotomy between AI art and human art reduces artistic process to just the implementation stage, asserting that humans have total control over implementation in non-computational processes and have no control over it in computational processes. Not only does this study assert that there is a range of computational processes which do allow human artists control over implementation, but that it demonstrates how this mindset obscures the subtle differences between different modes and their varying impact on perceptions of creativity. While implementation is valued disproportionately most in non-computational processes, people's frameworks to assess creativity in computational processes are adapted to also rely significantly on other modes — F10 tells us that people recognize scope for creativity in unique ideas about how to leverage software and compositional decisions that allow for granular control over execution. Moreover, delineating artistic processes into modes makes clear that evaluation is the driving factor that detracts from perceptions of creativity in AI-based artistic processes.

This study suggests that efforts to build AI systems for artistic applications must consider this shortcoming seriously. If AI art is to be perceived as creative, the artists who utilize AI systems must be able to understand, explain, and justify the artistic choices made in reaching a certain final product. Although some (8 out of 67) participants expressed that AI systems' use of "pre-existing data" (P10) and "the work of millions of human artists" (P51) diminished its own creativity, a much higher number (26 out of 67) of participants primarily took issue with the fact that artists were alienated from these references. Participants took issue with the idea that artists weren't able to "describe what led up to the creation" (P4), "explain what elements resulted in the final piece" (P14), or "reflect on what they created" (P37).

Thus, for the use of AI to be perceived as creative in artistic fields, the references it uses must be made explicit to the artist. As briefly mentioned earlier, explainable AI is not a new field, but scene recognition and image classification tasks have dominated visual computing efforts to make AI systems more interpretable. Some research has investigated outputs of existing generators to improve their explainability, but even in these cases, explainability is overwhelmingly technical for some user groups (Ribera and Lapedriza, 2019). For example, one project examines image samples that result from the linear interpolation of prompts containing two contrasting keywords, eventually defining particular weights that the model has implicitly assigned to these words based on its training dataset (Zhang, 2023). This is certainly relevant — the weight of various linguistic embeddings in a dataset begins to explain why certain image references are chosen over others in the process to generate an output from a particular prompt. However, this type of analysis is not accessible to most artists, who lack experience in computer science and artificial intelligence. To integrate AI into common artistic practice, efforts to make AI more interpretable must translate into models that maintain these characteristics for the general public.

Beyond evaluation, AI-based systems could also incorporate greater artist involvement in other modes of creativity. People are increasingly willing to see high-level modes of creativity such as design as ways to meaningfully exert control over the artistic process. While involving humans in composition or implementation level modes may be a harder and more systemic change to bring to an AI system, design level adjustments to this end may be feasible. The hybrid intelligence systems being explored in the work of Dellermann could be one way of achieving this (Dellermann et al., 2021), but implementing simpler channels for artist input in existing AI models — self-selection of a subset of training data, adding weights to training data to reflect personal preference, etc. — could also be productive. The results of this study demonstrate that using human-driven constraints to govern computational actions is viewed as additive to creativity and worth exploring.

The technophobic and technophilic ideas exposed in this study are also interesting to think about as subconscious influences on people's perceptions of creativity. The extent to which anthropomorphization affected creativity scores suggest that high anthropomorphism populations may be willing to accept AI art as creative even as of today. Their lower weighting of the evaluation mode, in particular, reflects the lack of importance they place on a human artist understanding what the AI does — they view the AI as self-contained, capable of being agent and creative on its own. However, it is clear that this attitude only applies to a small portion of the overall study population. The prevalences of the KNOSKI and CHOLIM codes show real biases against the use of computational tools as easy, unskillful, and oppressive against the artist. However, when people had experience working with any of the computational tools described in the vignette, these attitudes often subsided. A participant (P67) who had worked with Blender, a graphics software tool, described the "imagination" and "mastery" required to work successfully within the medium at length. Similar sentiments were visible within justifications for creativity when participants had worked with digital illustration tools like Adobe PhotoShop and even a text-to-image generator.

The ideas that technological tools require no skill, make artistic processes trivially easy, or work against the artist are therein untrue — firsthand experience within computational mediums dispels these notions. However, they still persist in public consciousness. This means that language being used to discuss AI systems can be equally pivotal towards perceptions of creativity as changes made to how artists work with them. Even as AI experts avoid anthropomorphizing and attributing human characteristics to AI, they must take care to be precise about the nature of collaboration between artist and tool. Today's AI systems cannot accurately be likened to humans, but characterizing them as banally mechanical is also misleading — they should be both designed and described to be capable of dynamism and dialogue with the artist.

8 Limitations

As a work of formative research, this study has several limitations that are important to note. Firstly, the scale of the study was relatively small, both in terms of the participant pool and the questions contained in the survey itself.

All participants were sourced through the platform Prolific, where participants are paid to take online surveys. While the platform guarantees a diverse participant pool within the study's specified filters, participant data is kept anonymous, so exact demographic information is unavailable. Additionally, the participants sourced via this platform may be more tech-savvy or at least more comfortable using digital tools than the general population.

Furthermore, this study was limited by the number of artistic processes that were presented to artists as part of the survey. As part of this survey, participants were surveyed on nine (seven computational and two non-computational) artistic processes and seven unique combinations of delegated modes. Future works could expand on the content of the survey to new combinations of delegated modes. Particular attention should be given to describing more artistic processes that involve human-driven design and computationally driven evaluation. Each of these scenarios corresponded to only one relevant artistic process in this iteration of the survey. Additionally, future versions of survey should include numerous artistic processes per combination of delegated modes to more robustly establish the relationship between creativity scores and delegated modes.

The distillation of each artistic process into modes of creativity was productive in prompting participants to distinctly interrogate their personal opinions about each of these modes. However, most artistic processes are not easily separable into these five distinct stages — artists could easily complete multiple modes simultaneously or go back and forth between them. Furthermore, while this survey treated the delegation of modes as a binary — full computational control versus full artist control — the use of computational tools is more accurately reflected as a spectrum. Artists often cede control to computational entities to a certain extent but not fully. Every artistic process is subject to some amount of external influence and control — no artist operates in a vacuum — and some amount of individual human agency — for the moment, AI is not sentiently generating artworks. However, operating under this assumption while simplifying the delegation of modes to a binary limited the survey's ability to include baseline condition case (where the artist controlled all modes or lacked control of all modes). Future research could develop a more complex and comprehensive survey design that accounts for these ambiguities and inexactitudes while keeping them legible to participants.

Lastly, the codebook that was used to perform thematic analysis and later calculate mode weights was a preliminary version worked on by a single researcher. It was not verified with a kappa or official measure of inter-coder reliability. While the trustworthiness of the -AFF and -NEG codes is likely strengthened by their ties to explicitly mentioned modes of creativity, future work should calculate a robust measure of inter-coder reliability to verify how consistent the codes are across multiple researchers.

9 Future Work

Beyond adjustments to make this study more robust in answering the same research questions (as described in Section 6) and efforts to adapt existing AI-based image-to-text generators for greater creativity in artistic applications (as described in Section 5.3), future work could involve looking at measures beyond anthropomorphism. While this study only surveyed participants about their background in computer science and visual arts as general disciplines, it may be interesting to specifically obtain information about participants' experience levels with the particular tools used to see if this has a significant impact on creativity. Another interesting variable to examine could be age, which could reveal any differences in how younger generations perceive digital tools and their conduciveness to creativity.

While this study moves away from purely product-oriented assessments of creativity — asserting that people recognize significant creativity in the specific processes and contexts within which artworks are created — it could also be interesting to take a comparative approach to product-based and process-based conceptions of creativity. Studies could be designed to assess participants' perceptions of creativity of particular artworks, initially with information about the product alone and then again after seeing information about the process that was used to make each product. It would be interesting to see if participants were more likely to change their creativity scores for certain types of processes, especially computational and AI-based processes.

Lastly, future works could expand upon this study to look at ideas beyond creativity. While this study examined how creativity in various artistic processes, computational versus non-computational, other work could compare the same artistic processes focusing on perceptions of aesthetic beauty, emotional impact, or meaning. The aforementioned comparative approach between product-based judgements and process-based judgements could also apply here.

10 Conclusions

This study investigated perceptions of creativity in artistic processes where different combinations of modes were delegated to computational and non-computational external entities. Information about participants' tendencies to anthropomorphize artificial intelligence and participants' backgrounds in computer science and the visual arts was also collected to determine whether these factors had a significant impact on perceived creativity. Ultimately, perceived creativity steadily decreased across both computational and non-computational processes as more modes were delegated (and thus not fully under the control of the human artist). Findings also demonstrated that the degree to which various stages of artistic processes were weighted in participant justifications for creativity scores differed between computational and non-computational processes. These weights also differed based on combinations of delegated modes within particular processes. While ideation was consistently weighted highly across computational and non-computational processes, other modes saw significant differences. Implementation influenced perceptions of creativity especially highly in non-computational processes, but in computational processes, higher-level modes such as design and composition were weighted higher. Additionally, the evaluation mode spiked in importance in the one scenario when it was delegated, suggesting that this mode is also crucial in perceptions of creativity. While experience in visual arts increased perception of creativity in some common non-computational processes, experience in computer science did not have such obvious impacts. Anthropomorphization of artificial intelligence, on the other hand, was clearly linked to higher perceptions of creativity in AI-based artistic processes, though no significant impact was found in the context of other computational processes.

Overall, the insights of this study show that a wide range of computational processes are perceived as somewhat conducive to creativity, though in different ways than non-computational processes. AI developers can leverage these principles to create more avenues for human artist involvement in design and evaluation in current text-to-image AI generators, improving perceptions of creativity in AI-based artistic processes.

11 Acknowledgements

First and foremost, I want to thank my advisor, James Tompkin, who this thesis would not be possible without. From Day 1, James bought into and even encouraged the interdisciplinary niche that I wanted to approach this thesis from. That support allowed me to dive headfirst into the concepts that interested me the most, making the process to write my thesis a fundamentally fun one.

I'd also like to thank my reader, Lindsay Caplan, who was incredibly generous with her time, thoughts and feedback as I worked on this thesis. Lindsay's insights on the intersection between technology and art were truly my entry point into so much of subject matter I have spent the last eight months exploring.

Additionally, thank you to Shriram Krishnamurthi, who taught the first computer science class I took at Brown (on Zoom in the middle of the night) and brought me onboard my first research project. Both of those firsts changed the trajectory of my time at Brown, and I wouldn't be here without his encouragement.

Lastly, thank you to my friends (many of whom took pilot versions of my survey) and my family for their constant encouragement.

Appendices

A Full Distributed Survey

Part 0

1. Do you have a background in visual art?
    - Yes
    - Somewhat
    - No
2. Do you have a background in computer science?
    - Yes
    - Somewhat
    - No

Part I

NINA (Neural Imaging Network Application) is an AI system that generates art based on textual prompts. NINA was trained on millions of images and accompanying captions, from which it is able to learn associations between the two. The vast quantity of training samples is key for the system in building a general understanding of how different captions describe related images. For example, assume the model is trained on the following caption with a corresponding image:

Caption: "A rambunctious teenager excitedly rips open the wrapping paper of her Christmas gift to reveal a brand-new skateboard"

The more image-caption pairs that the model encounters, the more that it can associate visual elements with different words (e.g. "rambunctious," "brand-new," or "Christmas") in context. The size of NINA's training dataset means that it has likely seen hundreds of thousands of combinations of common words like these. Through training, it develops an intricate network of associations that later inform its incorporation of different visual elements in response to particular prompts, including those not within the training data. A comprehensive training dataset is therein crucial in teaching NINA to associate visual features with relevant connected words amidst complicated semantic relationships.

1. How smart is NINA?

	1	2	3	4	5	6	7	
Not Smart	○	○	○	○	○	○	○	Extremely Smart

2. When creating artwork, to what extent is NINA aware of the world around it?

	1	2	3	4	5	6	7	
Not Aware	○	○	○	○	○	○	○	Extremely Aware

3. To what extent does NINA understand the relevance of its artwork to a particular prompt?

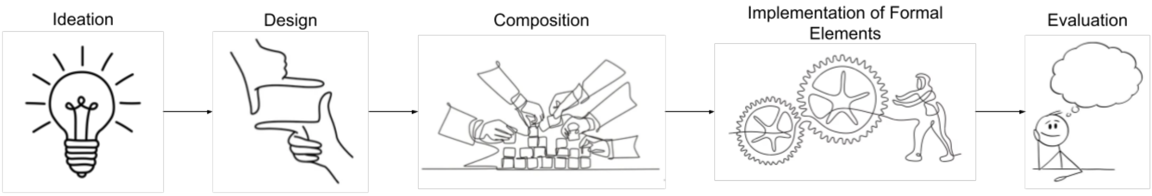
	1	2	3	4	5	6	7	
Does Not Understand	○	○	○	○	○	○	○	Understands Completely

4. To what extent does NINA plan the artworks it creates?

	1	2	3	4	5	6	7	
Does Not Plan	○	○	○	○	○	○	○	Plans Completely

Part II

Broad Definitions -
Ideation: The practice of developing a vision, conception, or purpose for an artwork to be created
Design: The framework which constrains how compositional decisions can be made
Composition: The way that the visual elements of the artwork are organized to create the unified whole
Implementation of formal elements: The actual implementation that creates and produces the visual elements of the artwork — the practical execution of the plan decided upon in the previous stages.
Evaluation: The practice of assessing the aesthetic qualities of the produced artwork and explaining their significance.



I understand what each mode of creativity is.

- Yes

1. ***Ideation***

   An artist imagines and is inspired to depict a realistic three-dimensional visual scene that feels aesthetically meaningful to them. To impart this meaning, the artist chooses to use a tablet, stylus, and digital illustration computer application to create an artwork.

   Design

   While the application doesn't make decisions for the artist, it provides structural limitations that bear upon the choices that the artist can make. The application not only necessitates that the artist use pixels as their foundational spatial building blocks but also accommodates a fixed set of colors and brushstroke types. The artist works within these constraints of the digital illustration application when making aesthetic choices.

   Composition

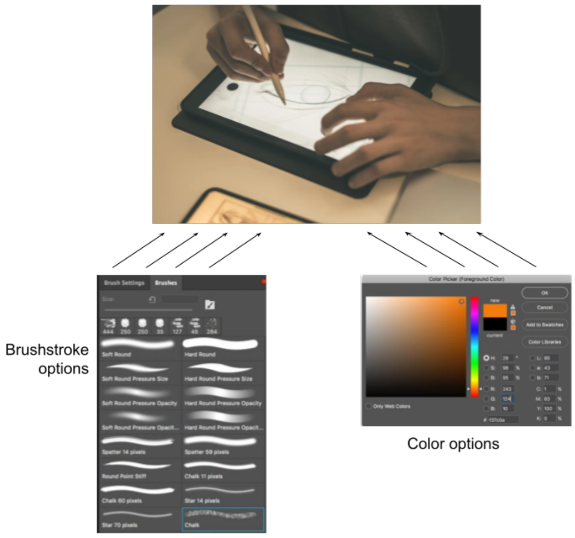
   Within these constraints, the artist is free to organize the artwork as they see fit in whatever way facilitates the formal qualities they initially envisioned. They compose the scene such that it appears as realistic as possible.

   Implementation of Formal Elements

   Though mediated through stylus and displayed on the tablet, the artist is responsible for executing on their vision to produce the artwork. They can use techniques enabled by the application (e.g. undo/redo, toggling between layers) in doing so at their discretion.

   Evaluation

   The artist can assess the artwork's aesthetic content throughout the process and upon completion, fully rationalizing their specific aesthetic decisions or critiquing areas of improvement. The artist can adjust the size/resolution of their canvas to change the number of pixels they are dividing their artwork into, but ultimately, the pixel and color frameworks will still apply to the artwork.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

2. ***Ideation***

An artist imagines a visual scene that holds meaning they want to convey. They use watercolor paints to create an artwork that embodies the characteristics that sparked their own inspiration with the scene.

Design

The implements that the artist has chosen as part of their initial idea provide structural limitations on the artwork. Watercolor paints have a unique texture which necessitates the application of colors in separate layers from light to dark. The paint is also quite transparent, making it infeasible to facilitate large areas that are fully opaque.

Composition

To work within these limitations, the artist chooses a set of colors and carefully plans the application of colors into organized regions so that they can achieve their desired formal qualities.

Implementation of Formal Elements

The artist implements their vision with watercolor paints. Though they work through certain constraints of this medium, they also utilize its various advantageous properties, including the easy blending of colors (allowing for a near infinite array of potential shades) and quick drying to execute their original idea.

Evaluation

The artist is fully able to evaluate the artwork's strengths and weaknesses — both those caused by the characteristics of watercolor paints and by their own artistic decisions. The artist can not only explain these decisions but also change them in effort to achieve different results if they decide to revise the artwork. However, even in this case, the structural characteristics, limitations, and capabilities of watercolor paints will remain and will thus shape these decisions.

---

a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

3. ***Ideation***

While working with a pen plotter to create a graph, an artist notices a glitch in the plotter that created a set of zig-zagging lines. Inspired by this pattern, they imagine what it would look like and the meaning it would carry if recreated. The artist decides to create an artwork that would achieve this effect with the plotter.

Design

The artist defines a coordinate system for the plotter that specifies particular locations on their canvas. While a computer will choose specific points based on this system, the artist imposes a constraint that each chosen point must be on either the same horizontal or vertical axis as the point that came before it. The artist also determines the number of points and lines to be drawn on the canvas by the computer.

Composition

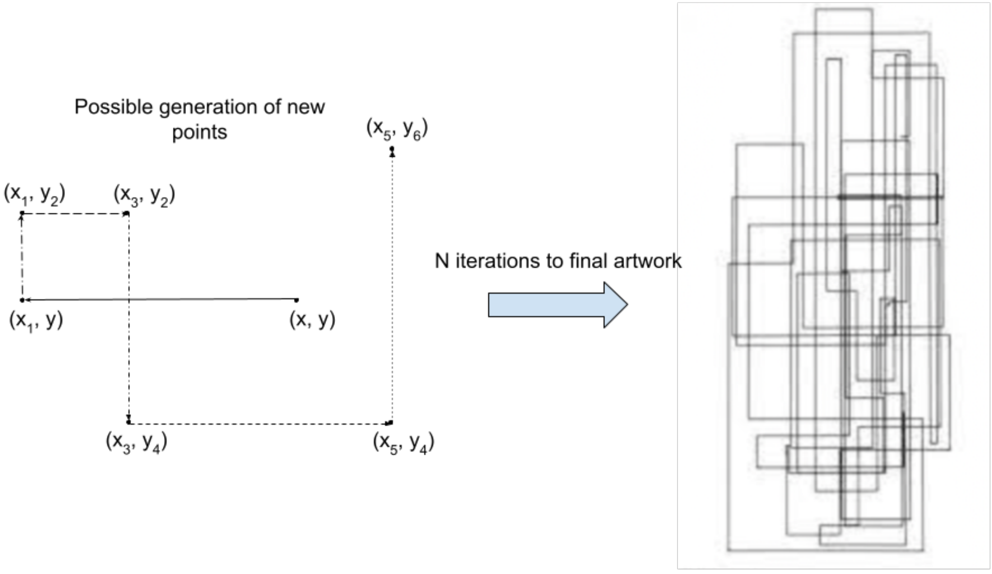
A computer randomly selects point locations on the canvas based on this constraint.

Implementation of Formal Elements

A computer draws lines connecting each point with the point that came before it, creating a specific aesthetic of rectilinear shapes of the abstract density that the artist's parameters specified.

Evaluation

The artist can clearly see and explain how the constraints they chose to formalize have manifested themselves in the resulting artwork, and they can even add or remove constraints until they are satisfied with the work.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

4. ***Ideation***

An artist is inspired to create an aesthetically significant yet realistic three-dimensional scene. They choose to use a 3D graphics engine to make an artwork that depicts their initial imagination of it.

Design

The graphics engine prompts the artist for integer coordinates that specify the locations of each object and light source in the scene as well as the viewpoint the final artwork should convey. The engine also requires the artist to define specific sizes and borders for each object in addition to the object's reflectivity (on a scale of 1-100). The engine also prompts the user to define intensity, direction, and a discrete dispersion style for each light source they want to include. These are the only characteristics of the scene that the artist can toggle, as they are the only ones that the engine has an algorithm to process.

Composition

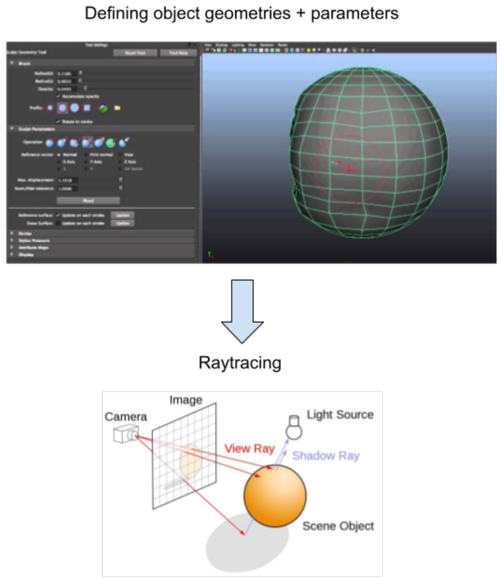
The artist decides each of these parameters — what objects and light sources they want to include in their scene as well as the specific properties these components have. They fully control how the scene is organized in terms of these properties, passing this information to the graphics engine.

Implementation of Formal Elements

The graphics engine runs a raytracing algorithm that follows the paths of individual light rays within the scene as they interact with the scene's objects. This algorithm eventually determines the amount of color and brightness that each pixel in the output image should contain.

Evaluation

The artist is fully able to explain the significance of the choices that they made about objects and lighting in the scene, citing the observed direct impact that small changes in these parameters could have on their resulting artwork. However, the framework that governs the graphic engine unavoidably governs the final artwork too.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

5. ***Ideation***

After encountering an aesthetically pleasing view, an artist imagines what an exact line drawing of such a view would look like. Inspired by this idea and its thematic significance, they try to accomplish this kind of artwork themselves with a camera and image processing tools.

Design

A digital camera is used to capture the view in a photograph, which comprises the baseline rendering of the view to be imitated.

Composition

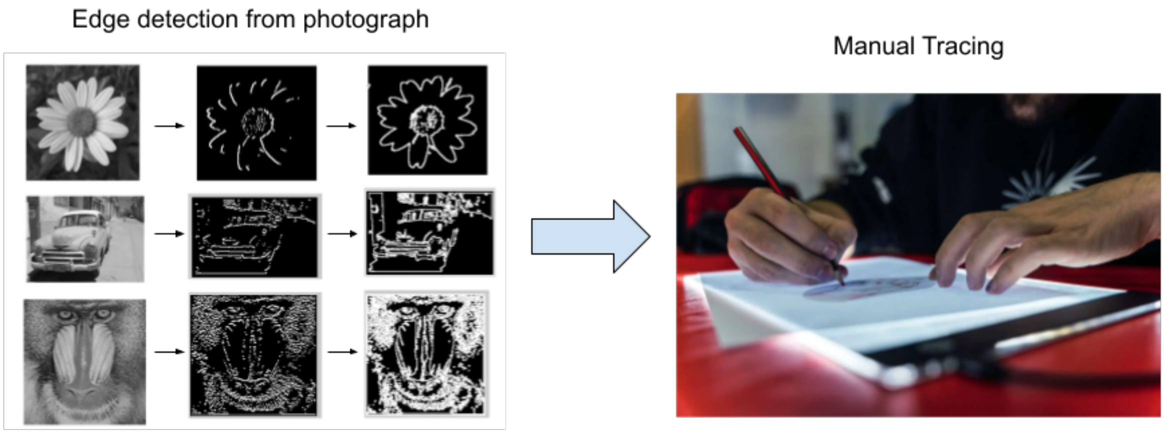
A sobel filter — a software-based edge detector used in image processing — is applied to the photograph, highlighting the most dramatic gradients (edges) present in the image. These selected edges are the lines that are deemed relevant for the artist to emphasize in their line drawing.

Implementation of Formal Elements

The artist uses the edge-detected version of the photograph as a trace for their line drawing. Essentially, they copy the edge-detection image onto a line drawing of their own execution by tracing the image as closely and exactly as possible.

Evaluation

The artist can quite easily identify the strengths and weaknesses of their line drawing, both at the end of the process and at the intermediate stages. This includes not only the tracing that they were responsible for executing, but also the design and composition of the computer-generated trace and specific edges that it may have constructed badly.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

6. ***Ideation***

Inspired by the structure of their face, an artist seeks to draw a self-portrait. They decide to use a classical style and set of rules to realize their imagined portrait in an artwork.

Design

The artist consults existing rules of proportions as established by classical antiquity to structure their drawing.

Composition

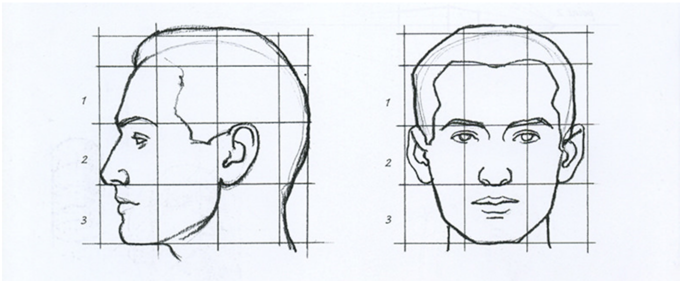
The rules of proportion determine how the drawing is to be composed. By rule of thirds, they divide the face into three equal parts from the hairline to the eyebrows, the eyebrows to the bottom of the nose and the bottom of the nose to the chin. Other rules strictly define the position of the mouth, distance between the eyes, angle of the ears, etc. within this landscape.

Implementation of Formal Elements

The artist uses a collection of colored pencils to illustrate each feature in the final drawing in accordance with their established plan.

Evaluation

The artist can gauge the artwork's aesthetic favor throughout the process, and they can pinpoint the specific ways in which the final product balances between reflecting their own appearance versus universal characteristics of the human face.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

7. ***Ideation***

An artist is inspired to create a repetitive pattern and imagines such a design which is based off of a complex fractal — a pattern with complicated geometries that repeat themselves across spatial scales. Existing mathematical formulas which can render fractal patterns already exist, and the artist chooses to use one to create an artwork. The specific pattern they select is at the core of this idea.

Design

The eventual fractal pattern is largely framed by a specific fractal set/shape, which is defined by a computer formula.

Composition

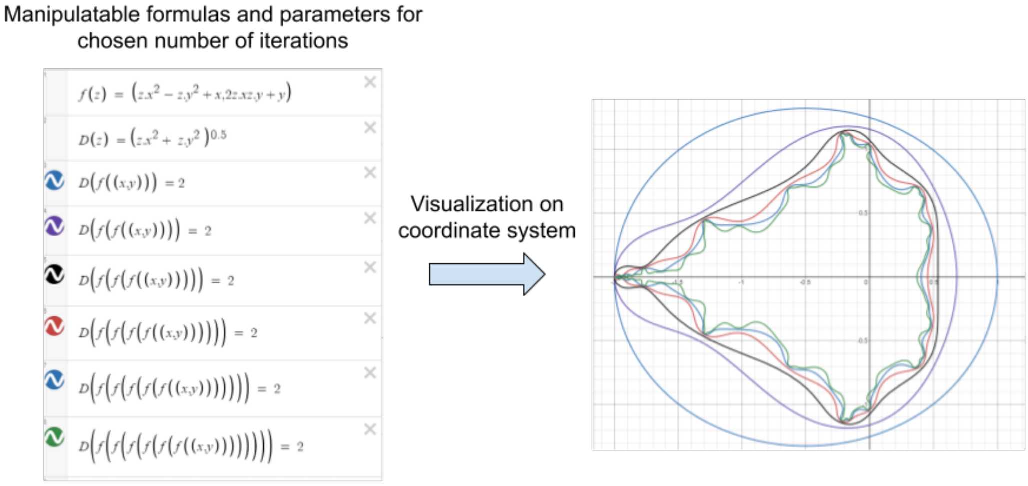
The composition of the artwork is then determined by the computer's application of the mathematical formula that is associated with the chosen fractal set. The artist can choose some initial parameters, but the formula and its computation determines how those initial parameters are transformed. The artist has no control over values that the formula works with at deeper iterative layers of the work.

Implementation of Formal Elements

To create the image, the mathematical formula is iteratively applied by a computer to the base parameters. When the series of modified parameters is visualized , the nature of the repeated mathematical operations on the fractals generates the intricacies and repetitions of the resulting work. Color-mapping on this work is also achieved algorithmically, with colors chosen for different parts of the fractal depending on its stage in the fractal's aesthetic cycle.

Evaluation

The explicit mathematical formulas allow the artist to explain the direct and specific impact that the initial parameters have on the resulting artwork and assess how these parameters may be changeable to address areas of the work they'd like to improve upon.



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

8. ***Ideation***

A computer randomly scrapes a landscape image from the internet.

Design

Using a machine learning algorithm, the computer divides the pixels of the image into 50 subsets based on color. Over a number of iterations, the algorithm assigns each pixel to a subset, calculates the mean color value across the subset, and then reallocates pixels to subsets based on which subset mean they are best matched to.

Composition

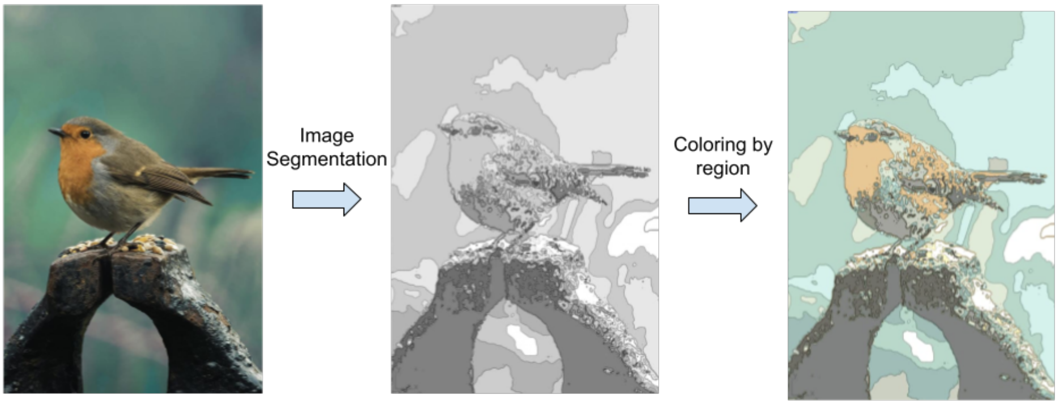
The image segmentation that the machine learning algorithm has completed is used to define 50 color regions within the chosen image.

Implementation of Formal Elements

An artist uses paints to fill in each specified color region with its relevant color as decided by the computer algorithm.

Evaluation

The artist can easily assess the overall aesthetic appeal of the image. They can determine whether segmentation was too granular (too many color regions) or too coarse (too few color regions). The *artist can therefore discern and explain the strengths and flaws in segmentation in addition to its color palette, understanding how these can be changed for improvement in future iterations.*



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a. To what extent was the process to make this artwork creative? Think about the creativity that is manifested each time an artist completes this process, not the creativity that was required to initially think of or invent this process.

	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

b. In two to four sentences, explain your creativity score with reference to the modes of creativity (ideation, design, composition, implementation of formal elements, evaluation) that most influenced your answer. Explain which modes are important to overall creativity and how the subprocesses described in those modes played out in this scenario to influence your score.

Long answer text

9. ***Ideation***

An artist imagines an aesthetic idea that they want to visualize but not the specifics of the visualization itself. They describe this idea in a few sentences, including the meaning they want it to convey, and then enter this prompt into a text-to-image artificial intelligence system.

Design

This system has been trained on millions of image and caption data points. This training data gives the system a powerful capacity to interpret the provided prompt and associate it with a matching image. However, the strength of the system's associative ability is directly limited by the variety and depth of cases within its training data.

Composition

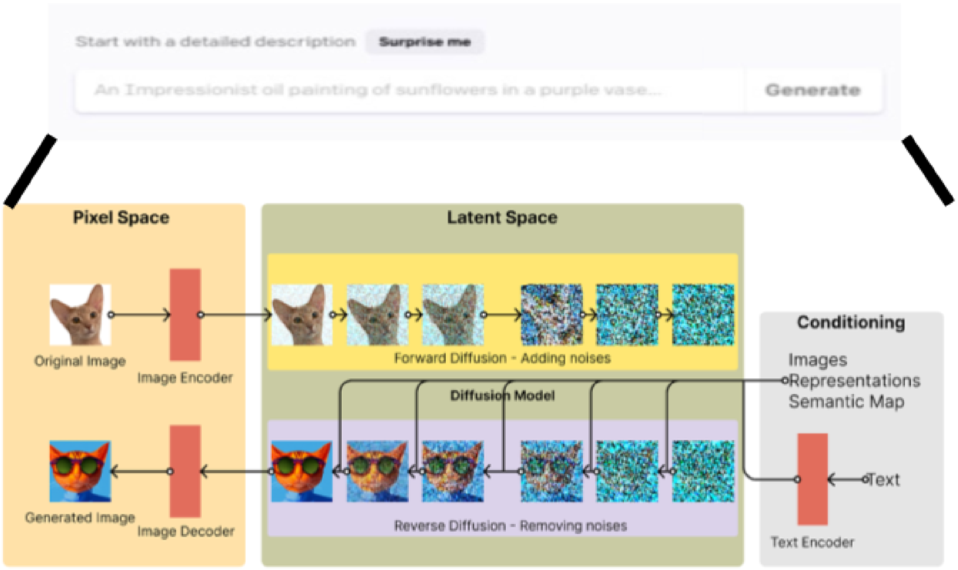
The elements of the artwork that the system engages with are more abstract than color, spatiality, or other human-comprehensible aspects of art. Instead, the system composes the work by first translating the prompt into a complicated representational encoding that it can more easily compare with captions that it has been trained on. Based on these comparison features, the system can map the prompt encoding to a matching image encoding with the right combination and organization of elements.

Implementation of Formal Elements

To create a more novel visual artwork, the system uses a process called diffusion. It takes its matched image encoding, adds noise to it, and then — through a de-noising process that was learned during training — iteratively removes noise until the noisy encoding gets denoised into an artwork that appears new while still emulating certain key characteristics from the original.

Evaluation

The artist cannot directly explain what elements of the prompt led to the resulting artwork, nor can they assess specific aspects of the prompt that could be tweaked to make specific adjustments to the artwork.



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	1	2	3	4	5	6	7	
Not Creative	○	○	○	○	○	○	○	Extremely Creative

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Long answer text