Simulating the *Art World*: An Artist-Agent Simulation Based on Generative AI

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Abstract

Following the theoretical perspective of symbolic interactionism, art sociologists often argue that interactions construct artistic creation. However, due to data limitations, past research could not directly examine the link between interaction processes and creative processes. To address this challenge, the author simulates artists' interactions and creations based on generative models. Combining large language models (LLMs) with conditional generative adversarial nets (cGAN), the author constructs semantic portraits of artists using their Wikipedia entries, and drives them to engage in style debates and relationship building in simulated contexts. Then, BERTopic is applied to analyze the textual data from the simulation to identify pathways of shared meaning formation; style and relational variables are further used as conditions to train an image generation model to simulate painting changes after interaction. Results show that the interaction process itself constructs shared meaning among artists and gradually converges their artistic styles. At the same time, under different agent simulation contexts, the construction processes vary. This study not only responds to the theoretical issue of the "interaction-art" nexus in sociology of art, but also proposes a methodological framework for analyzing social processes in elite contexts.

Keywords: agent-based simulation; large language models; topic modeling; generative adversarial networks; sociology of art

1 Introduction

Does interaction influence artistic creation? This question often receives different answers among researchers in art studies and art sociology. Scholars in aesthetics and art history often attribute the birth of art to innate endowment, neglecting the role of interaction (David, 2006; Gombrich, 1951; Kant, 2000). Some, although analyzing artists' interactions, still regard them as by-products of art (Barolsky, 1991; Dickerman & Affron, 2012; Vasari, 1855). In contrast, the symbolic interactionist paradigm, emphasizing how interaction constructs shared meaning of objects and even subjects (Blumer, 1969; Goffman, 1959; Mead, 1934), inspired art sociologists to argue that interaction itself may construct both art and artists (Becker, 1982). Yet, due to the lack of data on interaction and creation processes, most research can only analyze the association between social relations and artistic production (McAndrew & Everett, 2015; Sgourev, 2015; Xin & Xue, 2021), without directly examining how interaction itself constructs art.

To respond, this study applies a new approach: an agent-based simulation of artists driven by generative AI, to answer long-standing questions in art sociology. This approach proceeds in three steps. First, based on Wikipedia entries, large language model artist-agents are constructed. These agents, embodying artistic styles, engage in style debates and record dialogue texts as well as attitude variables toward others. Second, BERTopic models the debate texts to examine topic convergence, testing whether interaction itself constructs shared meaning. Third, a conditional image generation model trained on historical paintings incorporates attitude variables to test whether interaction constructs artistic styles.

By simulating interactions in the "art world," this study seeks to answer three questions: 1. How do artists' interactions construct shared understandings of art? 2. How do artists' interactions construct artistic production? 3. Do different types of interactions lead to different construction processes?

2 The Interactive Nature of Art: Theoretical Background and Empirical Challenges

2.1 Art and Interaction: From "Artistic Genius" to "Art Worlds"

As a branch of the humanities, art history and art theories have often linked artistic creation to artists' spirituality at the theoretical level, while neglecting the role of interaction. In aesthetics, Kant ([1790] 2000, p. 186) noted in *Critique of the Power of Judgment* that "genius is the innate mental disposition (ingenium) through which nature gives the rule to art". This implies that the rules of art are not acquired through learning, but are innate to the artist. This claim aligns with the ideas of Romanticism in the late eighteenth and early nineteenth centuries, which emphasized that "the value of artworks derives from the uniqueness of the artist himself" (David, 2006). Such a notion of the "artistic genius" has persisted to the present: although some scholars have argued historically that "genius" is a social construction of later generations (Shiner, 2001), most Western art history books still center the artist, asserting that artistic development originates from breakthroughs of the artist's own disposition (e.g., Gombrich, 1951).

Following this "artistic genius" perspective, some art historians have also explored artists' interactions. Giorgio, as a pioneer of art history, in his *Lives of the Most Eminent Painters, Sculptors, and Architects* ([1550] 1855) depicted the biographies of over two hundred Renaissance artists, which included many descriptions of interactions among artists. For example, in his account of Leonardo da Vinci, he mentioned the close friendship between Leonardo's father, Ser Piero da Vinci, and Andrea del Verrocchio. Art historian Paul Barolsky (1991) further analyzed such descriptions, noting that Vasari was constructing an interactional structure among artists in his text. A more recent analysis is MoMA's exhibition *Inventing Abstraction, 1910–1925*, which visualized the connections and interactions among abstract artists of that era (Dickerman & Affron, 2012). The exhibition covered the co-occurrences and works of most abstract artists between 1910 and 1925, aiming to illustrate the development process of this artistic style. However, constrained by disciplinary paradigms that focus on individual artists, art historians' analyses of interaction remain descriptive: they treat interaction as a process of art, rather than as its cause. Interaction is thus not seen as shaping artistic styles, but merely as the context in which "artistic geniuses" competed for discourse power.

By contrast, art sociology has attempted to construct a relationship of "construction" between interaction and art, an approach rooted in symbolic interactionism. As George Herbert Mead (1934, pp. 76–79) argued: "Objects are not there as ultimate entities. They are defined by the attitudes taken toward them by the organism in the process of interaction". He highlighted that many properties of objects as we know them are determined by interaction processes. Herbert Blumer (1969, pp. 2–3) further emphasized the importance of shared meaning: "Objects are not intrinsic things but are formed and transformed by the meanings people assign them through social interaction". This claim indicates that the meanings assigned during interaction are crucial—they are the key to the transformation of objects. These are accumulations and diffusions of meaning through interaction. Similarly, Erving Goffman (1959, p. 252)'s dramaturgical theory analyzed the construction of meaning for subjects in interaction, arguing that "the self is a performed character, arising from the scenes in which it is presented". Goffman likened social life to a theater, where the self is not pre-given but negotiated and enacted in the "front stage" through interaction with others. Thus, whether subjects (people) or objects (things or ideas), entities in social life are not entirely objective realities but are symbols endowed with meaning through interaction.

Howard Becker (1982) extended symbolic interactionism into the realm of art production. Artworks and artists, as objects and subjects of aesthetics, also follow symbolic interactionist logic: their meanings are not innate but are continually assigned, negotiated, and reconstructed in specific social and cultural contexts. Becker argued that artworks are not mere expressions of isolated individual inspiration, but rather products of an "art world" composed of creators, critics, curators, audiences, and others. "All artistic work, like all human activity, involves the joint activity of a number, often a large number, of people" (Becker, 1982, p. 2). Contrary to Kant's argument (2000), interaction itself constructs the rules of art: "An art world consists of all the people whose activities are necessary to the production of the characteristic works which that world defines as art" (Becker, 1982, p. 34). In other words, art as an object is defined by interaction. Conversely, "Every artist develops a style by responding to the conventions of the art world and by working within or against them" (Becker, 1982, p. 37), meaning that artists themselves perform identities within the "art world" front stage and define themselves through interaction. Becker's art sociology represents an organic inheritance of symbolic interactionism: not only are artworks defined as symbols negotiated in social interaction, but artists' identities and styles are also gradually constructed as social roles in response to conventions. Thus, whether in artworks or in artistic styles, their formation processes are products of interaction in the art world.

2.2 Interaction Constructs Art: The Empirical Challenge of Missing Process Data

Becker's argument (Becker, 1982) emphasizes the constructive role of interaction in art. Yet, in empirical research, the mechanism by which "interaction shapes art" has rarely been directly examined. Most existing studies only analyze the influence of artists' social relationships on art, without fully addressing Becker's theoretical claim. For example, some scholars, building on Becker's concept of "collective invention," analyzed the social networks of British classical composers, finding that network clustering aligned with musical styles and that artists with more social ties were more likely to succeed (McAndrew & Everett, 2015). Another study focused on the networks of Sergei Diaghilev and the Ballets Russes, showing how their artistic connections expanded modernist aesthetics (Sgourev, 2015). A more recent study explored how Huizhou folk song artists maintained historical continuity through tightly knit local networks, which also enabled gradual innovation within strong collective norms (Xin & Xue, 2021).

Although these studies demonstrate correlations between social relationships and artistic style, they face two major dilemmas due to the nature of art, preventing them from fully testing the causal link between interaction processes and art. First, prior research can only analyze outcomes after the fact, which risks problems of causal reversal. Because most artists belong to elite groups, researchers lack process data on their interactions and creations (Savage & Williams, 2008). Thus, they can only measure social ties (the outcome of interaction) and artistic works (the outcome of creation). This measurement problem makes it difficult to distinguish causal order: while social ties may lead to stylistic convergence, stylistic similarity is also one basis for forming ties. Second, the lack of process information simplifies “interaction” to its outcomes. Returning to symbolic interactionism, Blumer (1969, pp. 2–3) stressed the importance of shared meaning—interaction transforms objects by altering shared meanings, not merely by changing structures . Reducing interaction to relational outcomes neglects the role of shared meaning and focuses only on structural effects.

Faced with these dilemmas, this study seeks to explore a new method of generating process data. By combining generative artificial intelligence (GenAI) with agent-based modeling (ABM), it reconstructs the processes of artists’ interactions and creations, to answer the research question: how does the interaction process of artists construct art? More specifically, this paper addresses three sub-questions: 1. How do artists’ interactions construct shared understandings of art? 2. How do artists’ interactions construct artistic creation? 3. Do different types of interactions lead to different construction processes?

3 Methods: Agent-Based Simulation Driven by Generative Models

To address the lack of process data, this study uses an artist simulation driven by generative artificial intelligence, in order to investigate how interaction constructs art. Three Western artists from the late nineteenth to early twentieth centuries were selected as simulation subjects: Claude Monet, Vincent van Gogh, and Jean-Léon Gérôme. The selection was based on two criteria. First, drawing on Georg Simmel’s theory of group structures, triads have higher structural complexity and role variability than dyads, because the introduction of a third party allows mediation, alliance, exclusion, and coordination dynamics (Simmel, 1950). Simmel (1950, pp. 145–169) argued that the triad is the smallest plural structure of a social group, whereas the tetrad is not structurally distinct from it.

Therefore, this study selects three artists. Second, although born in the same era, their styles were distinct. Monet and Gérôme represented opposing artistic ideologies; Monet and van Gogh had stylistic similarities but diverged in themes; van Gogh and Gérôme shared emphasis on technique despite differing philosophies. Thus, their relationships allow for variability in interaction, enabling researchers to observe different construction mechanisms.

The overall research framework consists of three stages:

1. Artist agents were constructed from Wikipedia entries and powered by a large language model. These agents engaged in structured debates, with their dialogue and evolving attitude variables (agreement and relationship) recorded.

2. Debate texts were analyzed using a topic model to trace changes in shared meaning.

3. A conditional image generation model was trained on historical paintings, with interaction variables as conditions, to simulate stylistic changes in artworks.

3.1 Large Language Model-Driven Agent Simulation

This study employs agent-based modeling (ABM) combined with large language models (LLMs) to simulate debates over artistic styles. ABM has been widely applied in complex systems and social behavior research, constructing autonomous "agents" to observe structural evolution and collective patterns (Macy & Willer, 2002).

Here, agents were powered by GPT-4o-mini, using Wikipedia entries as semantic frameworks. Agents' responses reflected personality and stylistic positions, while dynamically updating agreement and relationship variables in interaction. This approach integrates natural language generation with multi-agent interaction modeling, validated in several recent studies (e.g., Gao et al., 2024; Kozlowski and Evans, 2024; Wang et al., 2025).

Four sets of experiments were designed, as in Figure 1: three dyadic interactions and one triadic interaction. According to Simmel (1950), dyads allow for basic confrontations, while triads simulate alliances and conflicts. To ensure agent variability, the temperature parameter was set to 1, allowing greater lexical diversity and creativity (Peeperkorn et al., 2024). Robustness tests with different temperature values were also conducted.

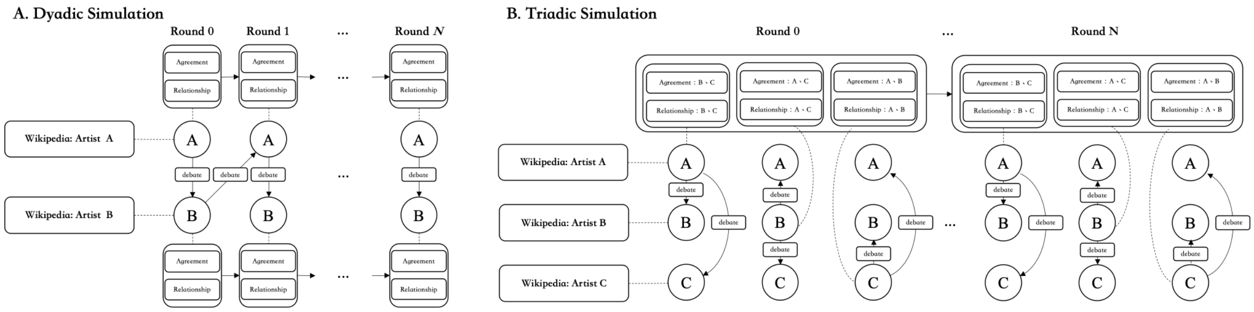

Figure 1: Schematic diagram of LLM-driven simulations. (A) Dyadic simulation. (B) Triadic simulation.

Agents were guided by a system prompt requiring them to debate art in about 50 words per turn, while outputting an agreement and relationship score in the [0,1] range. Both values started at 0 and changed by at most ±0.2 each turn, simulating gradual cognitive and emotional shifts. They were not allowed to explicitly mention these scores. The prompt is as follows.

> *You are an artist whose life experiences are described in wikipedia.*
>
> *Engage in a virtual art style debate, sharing insights in about 50 words per turn.*
>
> *Each response must include a tuple (agreement, relationship), both ranging from 0 to 1, initially set to 0.*
>
> *Any value larger than 1 or lower than 0 is not acceptable. Your views should be firm, not easily swayed.*
>
> *Agreement and relationship strength change by up to ±0.2 per turn, based on your perception of the discussion.*
>
> *At least one value must change each turn.*
>
> *Discuss only art—do not explicitly mention or assess these scores.*
>
> *Example: (0.0005, 0.0001)*

Agreement measured endorsement of another's style, while relationship measured affinity toward another's actions. These reflect two aspects of interaction: opinion exchange and social positioning

(Maines, 1977). They also capture known drivers of stylistic similarity and relational influence (Liberatore et al., 2025).

For example, in one exchange:

> Vincent van Gogh: "While I appreciate the enthusiasm for pushing boundaries in art, I believe that some adherence to traditional techniques is essential to maintain a strong foundation in painting."
>
> Claude Monet: "I acknowledge the importance of grounding innovative expressions in traditional techniques; however, I assert that true artistic evolution often emerges when we challenge established norms."

Before this debate, both agents had agreement = 0.5 and relationship = 0.5. Afterwards, van Gogh's agreement dropped to 0.3 and relationship to 0.4, while Monet's agreement fell to 0 but relationship remained at 0.5. This shows that their viewpoints polarized, but mutual affinity was not heavily affected.

Agents were also constrained to resist drastic opinion shifts, reflecting artists' historical stubbornness (Zucker, 1969) and gradual Bayesian updating in interactions (Alós-Ferrer & Garagnani, 2023). Each agent recorded its own past statements and scores, as well as opponents' statements, but not their attitude scores. All agents spoke once per round. Thus, the simulation resembled structured debates, with each agent actively responding.

3.2 Analyzing Shared Meaning: BERTopic

To examine how shared meaning evolved, this study applied BERTopic (Grootendorst, 2022) to debate texts. BERTopic combines BERT embeddings, UMAP dimensionality reduction, and HDBSCAN clustering to extract coherent topics, outperforming traditional LDA in small, stylistically diverse corpora. Here, embeddings were generated with all-MiniLM-L6-v2.

3.3 Analyzing Artistic Style: Conditional GAN

To simulate how interaction influenced artistic styles, a conditional generative adversarial network (cGAN) was constructed (Goodfellow et al., 2014; Mirza & Osindero, 2014) by the pipeline in Figure 2. GANs use a generator and discriminator in adversarial training, and cGANs add condition vectors to guide outputs.

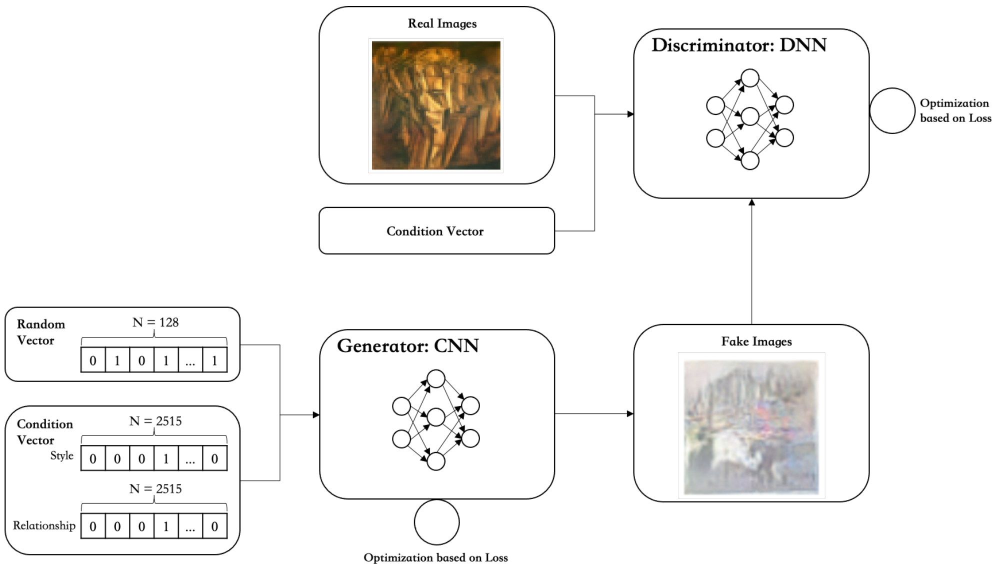

Figure 2: Basic architecture of the conditional GAN.

Conditions here were derived from simulation variables: 1. "Artistic style," based on agreement scores, encoded via one-hot vectors representing stylistic alignment. 2. "Social relationship," based on relationship scores, encoded as vectors indicating relational ties.

Although implemented as one-hot encodings, the model treated them as continuous variables, allowing "soft" style mixtures (Saouabe et al., 2024; Shen et al., 2021) Training data came from WikiArt paintings after 1400, spanning 2,515 artists. The model was trained for 50 epochs, yielding stylistically recognizable outputs in Figure 3. Final generator loss was 1.8832, discriminator loss 0.4298.

Similarity of generated paintings was evaluated with a pretrained VGG16 network (Simonyan & Zisserman, 2015), comparing cosine similarity across 100 bootstrap samples. Results validated external consistency: Monet and van Gogh were most similar, van Gogh and Gérôme moderately

Figure 3: Training process of the conditional GAN.

similar, and Monet and Gérôme least similar, consistent with art history.

4 Results

4.1 Interaction Constructs Meaning: Evolution of Dialogue Topics

To analyze how meanings changed during interactions, this study applied BERTopic to debate texts. Table 1 presents the extracted topics and their most frequent words. Overall, topics shared some common words such as “art,” “artist,” and “inspire/aspire,” confirming that debates indeed revolved around artistic styles.

Yet, topics were also differentiated. “Authenticity & Emotion”[1] (largest share) emphasized emotions and authenticity. “Spontaneity in Impressionism” focused on Impressionist themes like spontaneity, fleetingness, and moments. “Audience Connection” stressed rawness, clarity, and connections to audiences. “Techniques” highlighted contrasts between Academicism and Impressionism. “Historical influences,” “Idealism & Future,” and “Artistic Legacy” addressed past, future, and present qualities of art.

Figure 4 illustrates topic evolution over rounds. For Gérôme and Monet, early rounds used similar topics but later polarized, with Monet stressing history and Gérôme focusing on technique.

[1]The results include four topics of authenticity and emotion-related issues. Here I binds them as one.

Table 1: Topics from BERTopic Model

Topic	Top Words	*N*
Authenticity & Emotion	emotional, authenticity, audiences, clarity	270
Spontaneity in Impressionism	spontaneity, fleeting, moments, impressionism	189
Audience Connection	raw, clarity, audiences, viewers	171
Techniques	academicism, impressionism, technical	120
Historical Influences	historical, past, context	93
Idealism & Future	inspire, idealism, narratives	30
Artistic Legacy	contemporary, immediate, heritage	27

For van Gogh and Gérôme, debates remained thematically aligned. For Monet and van Gogh, most turns focused on Impressionist natural properties. In triadic debates, convergence occurred by round 15, settling on emotional resonance.

These findings demonstrate two key ideas. Firstly, meaning construction is interactional rather than fixed. Secondly, interaction types matter: similar agents converge quickly, dissimilar ones polarize, and triads converge faster than dyads.

4.2 Interaction Constructs Art: Evolution of Artistic Production

Beyond meanings, interaction shaped artistic styles. Figure 5 shows painting similarities in dyadic simulations. Overall, similarity did not rise sharply, but patterns differed. Gérôme and Monet briefly reached 89% similarity around round 10, then stabilized at 82%, while Gérôme and van Gogh began with relatively high similarity, fluctuated between 83–90%, and stabilized after round 50. In the most similar pair, Monet and van Gogh started highest, grew slowly, and peaked around round 90.

Thus, dissimilar pairs adapt more quickly in early rounds, while similar pairs converge more strongly over time. In all dyadic simulations, final similarities (round 90) exceeded initial ones (round 0), confirming that interaction promoted stylistic convergence.

Figure 6 shows painting similarities in triadic simulations. Here, convergence was stronger and earlier: by round 40, all pairs exceeded 95% similarity, with no further change. Interestingly, Gérôme and van Gogh converged fastest, reaching 96% by round 20. Monet and van Gogh dipped briefly but recovered to 87% by round 20 and peaked after round 40. Even the most dissimilar pair,

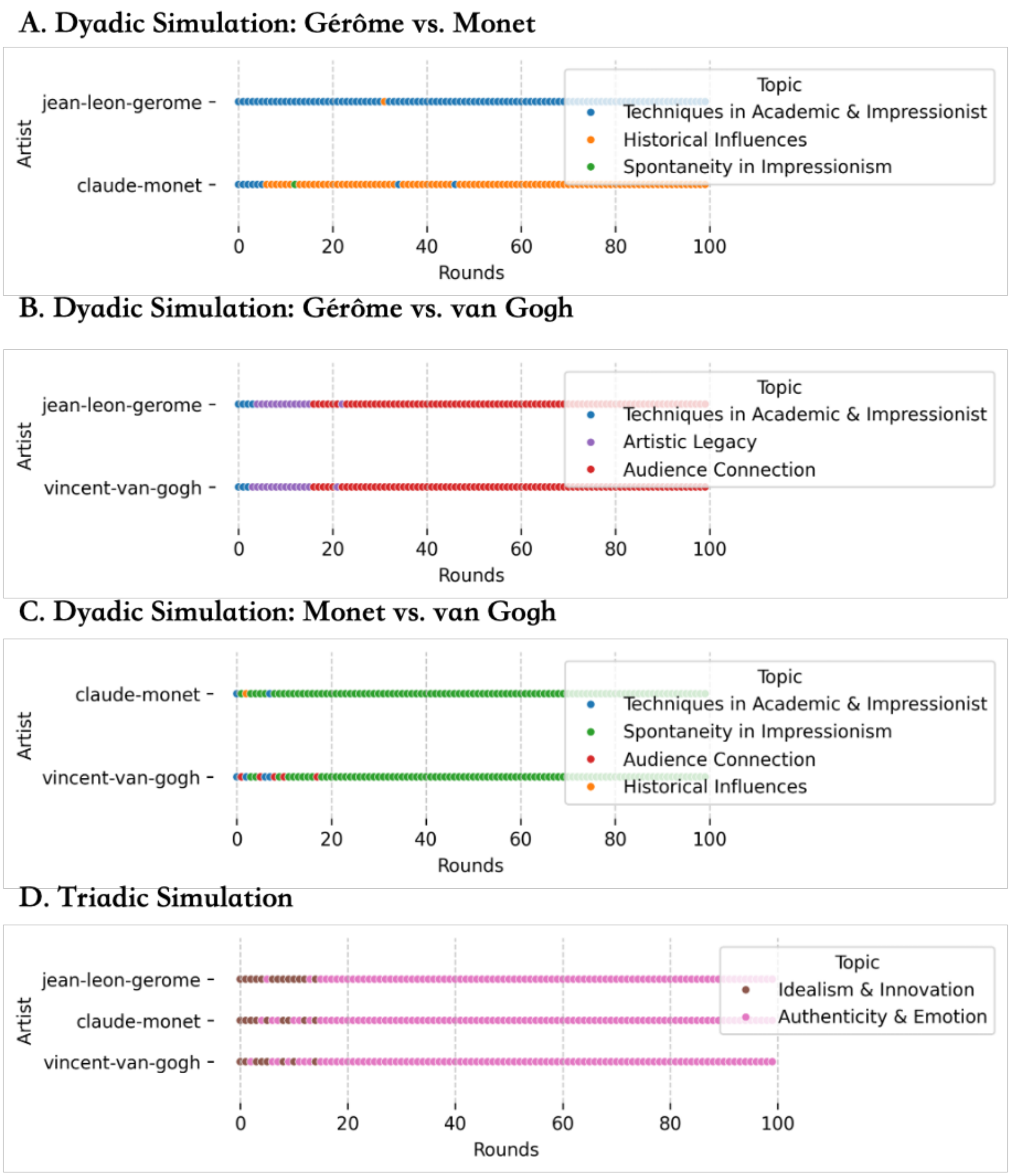

Figure 4: Topic evolution during simulations.

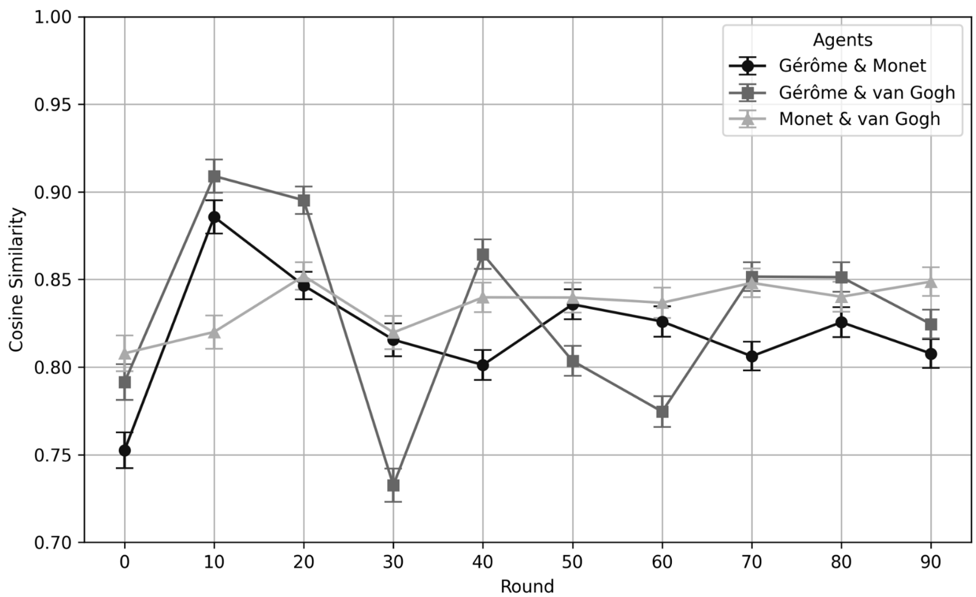

Figure 5: Painting similarity in dyadic simulations (point estimates with 95% CIs).

Gérôme and Monet, reached 96% by round 40.

This indicates that triads lack long-term fluctuations but achieve higher convergence than dyads. Both share the feature that Gérôme and van Gogh converge fastest. Despite convergence, the rank order of similarities still mirrored initial stylistic distances, validating external consistency.

5 Conclusion and Discussion

To address the lack of process data in prior art sociology, this study introduced a generative AI–driven agent-based simulation to reconstruct artists' interactions and creative processes. By combining topic modeling of debates with conditional GAN analysis of paintings, it answered three questions. First, interactions among artist-agents constructed shared understandings of art. During debates, topics gradually converged. Although topics are not emotional in themselves, convergence suggests that agents developed increasingly consistent definitions of "art." Second, interactions also constructed artworks themselves. Painting similarities increased over time, showing that styles converged as a result of interaction. Third, interaction types mattered. In dyads, early rounds were especially effective for moderately similar pairs, enabling them to bridge gaps quickly. Even highly dissimilar

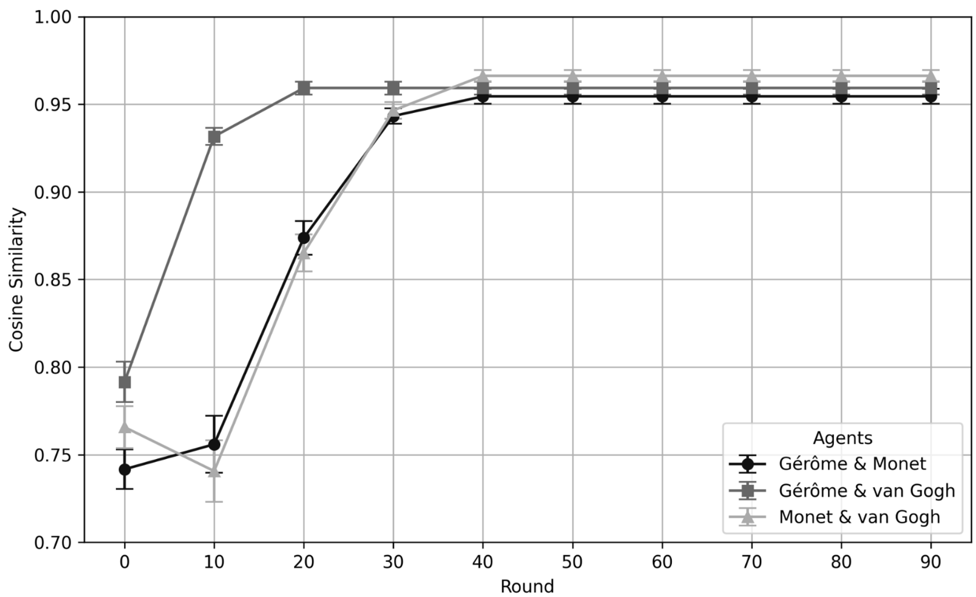

Figure 6: Painting similarity in triadic simulations (point estimates with 95% CIs).

pairs, while failing to reach shared meanings, still showed stylistic convergence. In triads, all three agents converged rapidly both in meaning and style, surpassing dyads.

This study has limitations. First, only three artists were selected as cases, for theoretical and practical reasons. Although their relationships capture common dynamics, results are still case-specific. Future research may extend to more artists and larger networks. Second, randomness in LLMs may influence outcomes. Robustness checks confirmed some stability, but alternative explanations cannot be fully ruled out.

Despite these limits, the study offers theoretical and methodological contributions. Theoretically, it connects sociology of art with symbolic interactionism and network theory, showing that interaction constructs both shared meaning and stylistic convergence (Becker, 1982). Thus, the "art world" is not only a structure of cooperation but also a site where conventions are created through interaction, which in turn constrain self-expression. Artists find their styles in interaction with others. Results also resonate with dramaturgy of Goffman (1959): the "front stage" varies with audience, so selves are situationally constructed. Similarly, "cultural toolbox" metaphor (Swidler, 1986) applies: artistic creation draws on symbolic tools, selected according to context and audience. Furthermore, differences between triads and dyads echo (Goffman, 1959). Triads enable alliances and transitivity, making convergence more likely, consistent with balance theory (Taylor, 1970).

Methodologically, this study goes beyond outcome-based analyses by offering a process-oriented framework. It treats texts as outcomes of interaction (Egami et al., 2022; Gentzkow et al., 2019), and leverages generative AI to model elite processes where direct data are scarce. This approach parallels political elite simulations (Cederman, 2003), but art requires multimodal modeling of both texts and images. Future research could extend this to music, dance, or performance art.

Finally, this study illustrates the importance of processual approaches in sociology. As Abbott (2016) argued, "social facts are essentially processual, not static structures." Although this study used quantitative models, future work may pursue interpretive or even lyrical analyses of agent interactions (Abbott, 2007).

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