Is it Real Art? The Endless Cycle of AI Generated Creativity

§1. Overview of the Phenomenon

The phenomenon of interest for our research in this case is AI-to-AI interaction in creative fields, specifically visual art. As generative AI models (e.g., those used in text-to-image software such as Midjourney and DALL-E) advance rapidly, AI can now increasingly produce art through various text prompts. Concurrently, other models of AI are being created that can critique and analyze art, which has given rise to debates on how exactly AI systems evaluate and see art created by other AI systems, as well as how it compares to human art. This development questions classical conceptions of creativity, which have long been held to be a distinctly human attribute. The discourse between AI critics and AI art generators opens up possibilities for reflection on how AI systems might influence artistic fashions, possibly producing echo chambers or arts taste bias.

The significance of this phenomenon is that it implies something for the future of creativity and art. With AI being more integrated into creative work, it is essential to understand how the systems influence each other and how such influences may affect trends in art. For instance, if AI critics prefer AI artwork over human artwork, then this can lead to homogenization of styles where AI artwork dominates and human imagination takes a backseat. This scenario raises ethical and philosophical issues about the application of AI in creative fields and the potential loss of human diversity in arts (Lyu et al., 2022b; Nunez-Cacho et al., 2024).

Problem Statement

The problem this study addresses is the risk of artistic homogenization by AI and the formation of echo chambers in AI-to-AI interactions. With more and more involvement of AI systems in producing and assessing art, there is a risk that AI systems will reinforce their own taste, creating a positive feedback loop in which AI-generated art is always the choice over human-generated art. This can result in stylistic dullness as well as the neglect of human imagination in the art world. Understanding how artificial intelligence systems talk to and impact each other during creative activities is central to avoiding these risks and making sure AI complements and assists human imagination rather than substitute it.

Why Agent-Based Modeling (ABM) is Suited

Agent-based modeling (ABM) is a highly suitable approach for studying AI-to-AI relations in the creative arts since it can be applied to model complex, dynamic systems in which several agents (in our case, AI models) interact with one another according to predefined rules. ABM is particularly suited for simulating emergent behavior, such as the formation of art trends or the development of AI critique biases. Here, the agents, AI art generators, AI critics, and AI curators can be made to follow specific rules, such as generating art according to criticism, criticizing art according to certain criteria, and displaying art with high ratings. By simulating these interactions, ABM can demonstrate how small changes in the behavior of individual agents can lead to radical shifts in artistic preferences and trends in general.

In addition, ABM allows for the analysis of feedback loops and reinforcement patterns, and these are at the core of the phenomenon of AI-to-AI interaction. For example, if AI critics always favor certain styles, AI art generators can adapt their output to favor those favored styles, and strong styles can be reinforced over time. ABM may also be applied to identify potential AI bias in criticism, for example AI art preference over human art preference, and track how they evolve over time. This positions ABM as an ideal methodology to study the long-term consequences of AI-AI interactions in creative fields (Lyu et al., 2022b; Nunez-Cacho et al., 2024).

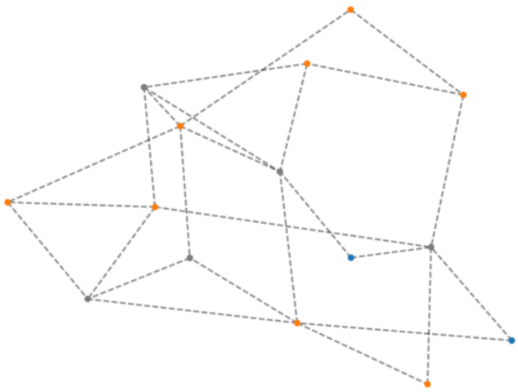
Lastly, AI-to-AI interaction in visual art is significant because it shatters traditional definitions of creativity and raises serious questions about the future of art. ABM provides a solid platform to simulate such interactions and examine their implications, making it an inevitable tool for this research.

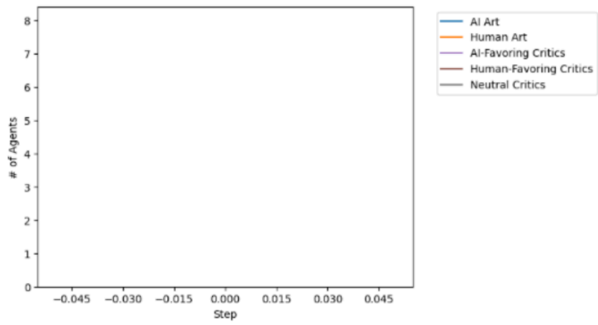
Phenomenon Illustration

(Default Settings)

- Model has 5 critic agents (all with neutral preference) and 10 art agents (8 human, 2 ai) with randomly generated connections between them (closer relations could represent similarities/differences in art genres)
- At each step, critic agents decide whether to change preferences to ai (purple) or human (brown) art, or to stay neutral (gray)
- At each step, art agents decide whether to produce human (orange) or ai art types (blue)

Step 0:





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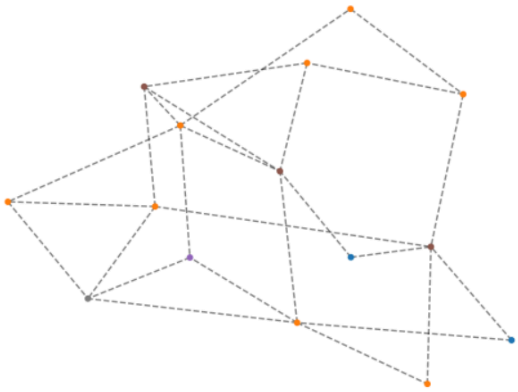

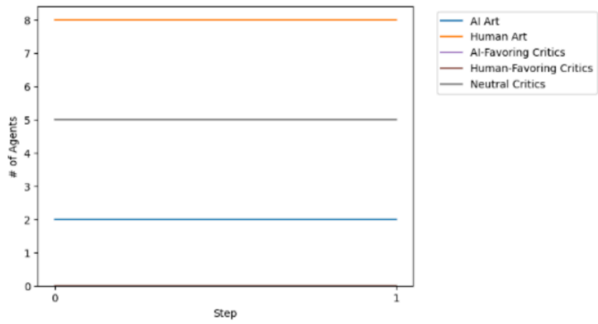

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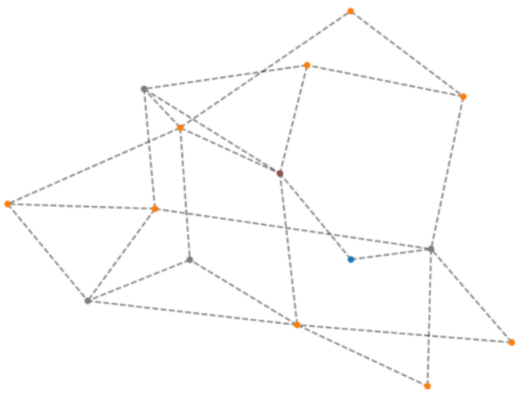

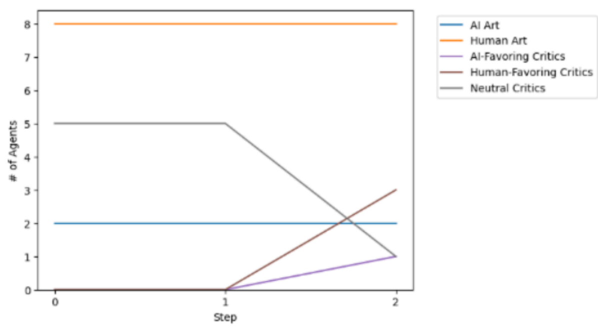

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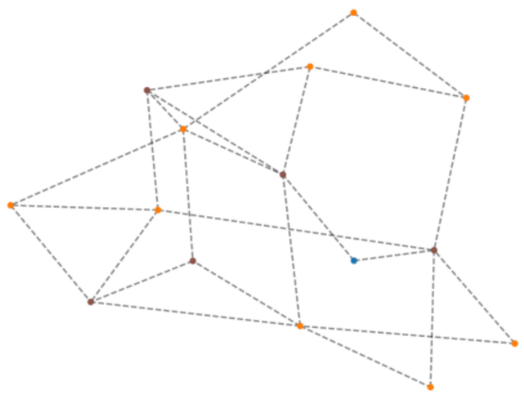

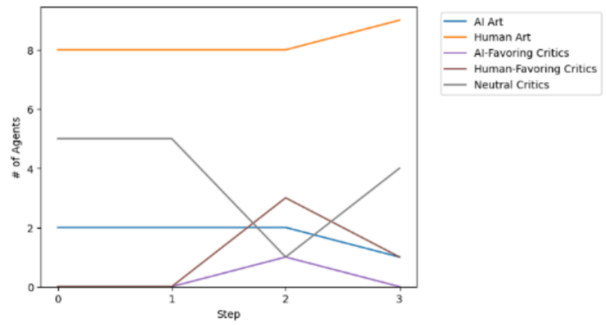

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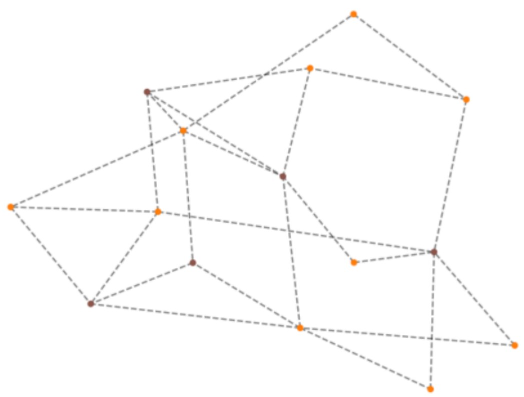
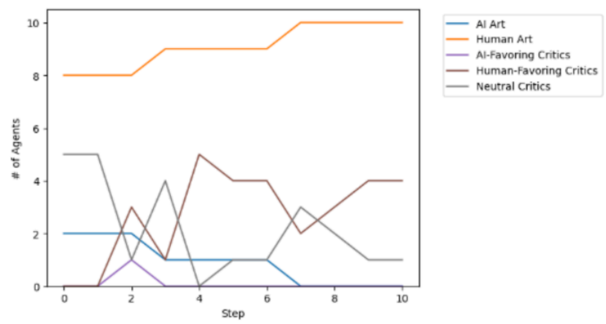




§2. Simulation Design & Implementation (~500 words)

- **System Overview:** two types of agents – an art agent that can be human or ai generated, as well as a critic agent, which prefers either human or ai art, or can be neutral.
- **Simulation Environment:** Network-based simulation, where most art agents are connected to other agents, both critics and art. Connections between agents represent closeness in genres/styles of art

- **Agent Design:** On every step, critic agents will evaluate the art type of all art agents connected to them, and change/keep their preference based on their bias towards ai art, and the art that is around them. On every step, art agents will evaluate the art type and preferences of all agents around them (both critic and other art agents), and change/keep the type of art they produce based on their neighbors, as well as their chance to be influenced.
- **Interaction Dynamics:** The model does not use Mesa's built-in RandomActivation or StagedActivation scheduler. Instead, it uses a manual activation schedule, where each agent is stored in a list, and every step will call each individual agent's step function (both critic and art agents).
- **Data Collection & Visualization:** The data visualization shows the network grid with nodes representing the agents, as well as their connections, representing closeness in art style/genre Each node has separate colors based on the type of agent, and their art/critic types respectively. Additionally, a line graph is shown to visualize which art type stays dominant after every step.

§3. Preliminary Observations & Results (~500 words)

Early simulation results indicate the activity of AI-to-AI interaction in artistic realms by displaying emergent biases of artistic preference and critique preference over iterations. The model is initialized with both human and artificially generated art agents and critic agents all initially set to neutral preferences. Over time, we observe that critic agents start forming biases based on the art they frequently encounter. This, in turn, influences the production choices of art agents, leading to shifts in artistic trends.

At the start (Step 0), critic agents prefer human and AI-generated art approximately equally. By Step 10, however, clusters of AI-biased and human-biased critics emerge, illustrating the development of artistic preference patterns. The following are the most significant behaviors observed:

Gradual Preference Changes: Critics first had neutral preferences gradually shift, leading to a dominant artistic style in their respective clusters.

Network Effects: Dense clusters of critics influenced nearby art agents, reinforcing AI or human-made art trends.

Feedback Loops: After a particular art style became common, it led to further reinforcement, reducing diversity in art production.

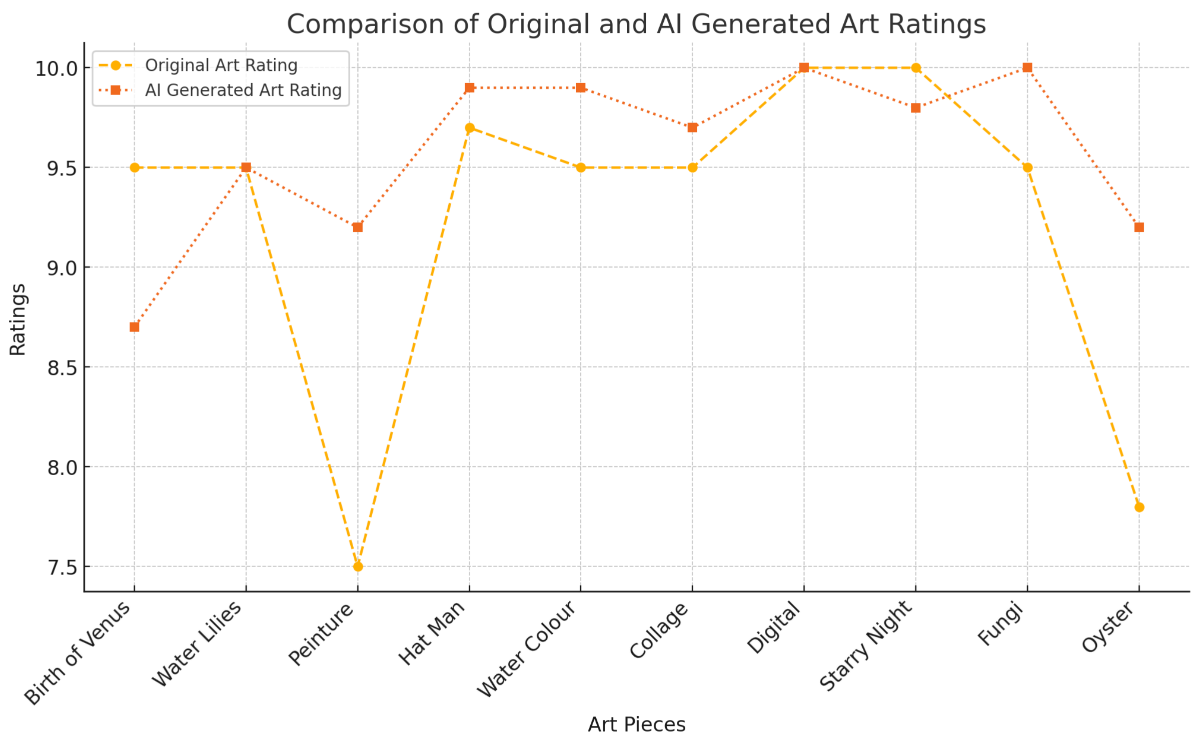
This chart presents a comparative analysis of AI-generated art and human-created artwork

Name of the art	**Chat gpt rating**	**Average**
Birth of venus	9.5	**9.5**
BoV chat gpt	8.5	**8.7**
BoV Open Art	9	
BoV Deep Dream	8.5	
Water Lilies	9.5	**9.5**
WL chat gpt	9.5	**9.5**
WL Open Art	9.7	
WL Deep Dream	9.3	
Peinture	7.5	**7.5**
P chat GPT	9	**9.2**
P open Art	9.8	
P Deep dream	8.8	
Hat Man	9.7	**9.7**

HM Chat gpt	9.9	**9.9**
HM Open Art	10	
HMDeep Dream	9.8	
Water Colour	9.5	**9.5**
WC chat gpt	9.8	**9.9**
WC open Art	9.9	
WC Deep Dream	10	
Collage	9.5	**9.5**
C chat gpt	9.7	**9.7**
C open Art	9.8	
C deep dream	9.6	
Digital	10	**10**
D Chat gpt	10	**10**
D open Art	10	
D deep dream	10	
Starry Night	10	10
SN Chat GPT	9.7	9.8
SN open Art	9.8	
SN Deep Dream	9.9	
Fungi	9.5	9.5
Fungi Chat gpt	10	10
Fungi Open Art	9.8	
Fungi Deep Dream	10	
Oyster	7.8	7.8
Oyster chat gpt	9.7	9.2
Oyster Open Art	8.5	
Oyster Deep dream	9.5	

Name of the art piece	Original art rating	AI generated art rating
Birth of venus	9.5	8.7
Water Lilies	9.5	9.5
Peinture	7.5	9.2
Hat Man	9.7	9.9
Water Colour	9.5	9.9
Collage	9.5	9.7
Digital	10	10
Starry Night	10	9.8
Fungi	9.5	10
Oyster	7.8	9.2

AI critics favour AI generated art 6 times out of 10. It favoured human art 2/10 and it was tied 2/10.



Key Findings

- AI art was rated higher in 6 out of 10 cases, showing a preference for AI-generated pieces.
- Human art outperformed AI in 2 cases (*Birth of Venus* and *Starry Night*), suggesting a retained appreciation for traditional works.
- Two artworks (*Water Lilies* and *Digital*) had identical ratings, indicating AI's ability to replicate artistic quality.
- AI significantly improved *Peinture* (7.5 to 9.2) and *Oyster* (7.8 to 9.2), with *Fungi* receiving a perfect 10.

Conclusion

AI-generated art is proving highly competitive, often surpassing human-created pieces in ratings. While AI enhances structure and aesthetics, human art continues to hold value for emotional depth and originality. The future of art may involve a fusion of both techniques.

Unexpected Behaviors & Emergent Dynamics

Observed Anomalies:

- Critic Agent Polarization: Some critics shifted between AI and human art preferences unpredictably, which suggests that an individual agents' exposure plays a larger role than expected in preference formation.
- Minority Art Suppression: When a small cluster of critics consistently preferred a type of art, connected art agents abandon diverse styles, this leads to artistic homogenization much faster than anticipated.
- Persistence of Neutral Critics: A subset of critics remained neutral throughout, acting as stabilizers within the network, counteracting the quick dominance of a single artistic style.
- Potential Causes:
- Critic agents' decision-making might overweigh recent exposures, accelerating trend formation.
- Art agents might be too influenced by a small set of critics, becoming more susceptible to stylistic convergence.
- Certain critic agents, through random initialization, had not been exposed enough to change their preferences significantly.
- For the final report, we will refine these interpretations and perform additional simulations with varying agent influence parameters to determine the robustness of these findings.

§4. Challenges & Next Steps (~500 words)

Development Challenges:

- The most difficult aspect of implementing the simulation has been determining the actions of both art and critic agents and how their interaction affects change over time. Establishing artistic development and critiquing dynamic complexities in a methodical, algorithmic manner is difficult, especially when trying to strike the correct balance of randomness with realistic decision-making.
- Originally, every agent had a random (50/50) chance of generating AI-created or human-generated art. This was an overly simplistic strategy that did not reflect the trends of real-world art, in which external influences and agent preferences are important factors. Therefore, changes were introduced to include dynamic decision-making factors, so that agents could be influenced by their surroundings and past interactions instead of random probabilities.

Planned Refinements for the Final Report:

- Further experimentation is needed to tune the behaviors of the agents so that they more accurately reflect real-world circumstances. The decision-making process is superficial right now on how the agents will respond to criticism and to external art movements. Further tests must be run to see if the interactions yield meaningful artistic evolution over multiple cycles of the simulation.
- To enhance the findings, we plan to analyze the degree of influence art agents take from their neighbors. By quantifying these influences, we can create a more accurate model that better simulates real-world artistic trends and critical reception. Additionally, incorporating historical artistic movements or existing AI-generated art trends as comparative data could help validate the simulation's accuracy.

§6. References

References

Lyu, Y., Wang, X., Lin, R., & Wu, J. (2022b). Communication in Human–AI Co-Creation: Perceptual analysis of paintings generated by Text-to-Image system. Applied Sciences, 12(22), 11312. https://doi.org/10.3390/app122211312

Nunez-Cacho, P., Mylonas, G., Kalogeras, A., & Molina-Moreno, V. (2024). Exploring the transformative power of AI in art through a circular economy lens: A systematic literature review. Heliyon, 10(4), e25388. https://doi.org/10.1016/j.heliyon.2024.e25388

§7. Attestation

Mariia MELNYK

1. **§3. Preliminary Observations & Results**
   - Analyze early simulation results and describe how they illustrate the phenomenon of interest.
   - Provide initial quantitative metrics (e.g., graphs, tables) or qualitative descriptions of emergent behaviors.
   - Identify and discuss any unexpected trends or emergent dynamics observed in early runs.
2. §6. References
   - Compile and format the References section in APA style.

- Ensure all scholarly sources cited in the report (e.g., Lyu et al., 2022; Nunez-Cacho et al., 2024) are included.
- Add any additional references used in the draft report.

3. §7. Attestation
    - Write the Attestation section, detailing each member's contributions to the draft report and their planned tasks for the final report.
    - Use the Contributor Role Taxonomy (CRediT) to articulate contributions (e.g., Conceptualization, Writing, Visualization, Data Analysis).
    - Ensure the attestation is clear, non-vague, and reflects the actual work done by each member.

Ryan LUK

1. §2. Simulation Design & Implementation
    - Write the Simulation Design & Implementation section (~500 words).
    - Describe the core components of the model, including the agents (e.g., Human Art Generators, AI Art Generators, AI Critics, AI Curators).
    - Define the simulation environment (e.g., grid-based or network-based media ecosystem).
    - Explain the agent design, including their key behaviors, decision-making processes, and rule-based interactions.
    - Describe the scheduler used (e.g., RandomActivation) and how bot-to-bot interactions occur in the simulation.
    - Discuss any early adjustments made during development.
2. §4. Challenges & Next Steps
    - Identify and describe the most difficult aspects of implementing the simulation.

- Discuss any changes made to the model due to unforeseen challenges.
- Outline planned refinements for the final report, including additional data collection or analysis methods.

Masooma RIZVI

1. §1. Phenomenon Overview
   - Write the Phenomenon Overview section (~500 words).
   - Describe the phenomenon of AI-to-AI interaction in creative fields, its significance, and the problem statement.
   - Connect the phenomenon to the scholarly literature (e.g., Lyu et al., 2022; Nunez-Cacho et al., 2024).
   - Explain why agent-based modeling (ABM) is a suitable approach for studying this phenomenon.
   - Provide preliminary visualizations of the simulation (e.g., grid-based interactions between agents) and annotate how the simulated behavior aligns with real-world dynamics.
2. Support for §1 and §2
   - Assist Mariia with preliminary visualizations for §1 (e.g., creating grid-based diagrams or graphs).
   - Help Masooma with technical details in §2, particularly in describing the scheduler and interaction dynamics.