Ad-Ception

When AI Creates and Promotes its Own Ads

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Github Repository Link: https://github.com/jasminSlootweg/AdCeption.git

Document Link (To view figure 1 GIF): https://docs.google.com/document/d/1W1IRWWuKg7-I92mAFv1DA226WCFUEnvXvM1cJFP43xE/edit?usp=sharing

1. Phenomenon Overview

The growing use of artificial intelligence (AI) in digital media ecosystems has changed the way material is created, recommended, and consumed. The increasing collaboration between AI systems—more especially, recommendation algorithms and content creation bots—without direct human supervision is a particularly noteworthy development. With an emphasis on the connection between AI-generated ads and AI recommendation systems within the Instagram advertising ecosystem, our project explores this AI-to-AI interaction. This interaction not only represents a technological achievement, but it also raises serious concerns about the future of media ecosystems, user autonomy, and information variety.

Digital advertising now primarily depends on AI-generated content. Based on data research and market trends, generative AI models can produce text, image, and video ads that are customized for particular audiences (Gao et al., 2023). In order to enhance ad delivery and make sure that viewers are exposed to content that is most likely to increase engagement, AI recommendation systems simultaneously employ behavioral data (Kaput, 2024). With the help of recommendation algorithms, which strategically spread the adverts generated by user activity, these two systems are able to communicate with one other. These systems' feedback loop grows more independent and ambiguous as they learn and develop.

This phenomena is important because it affects consumer behavior and media ecosystems. According to scholars, algorithmic advertising gently directs attention and reinforces engagement habits, influencing user experience in ways that are frequently invisible (López & Sicilia, 2024). The algorithmically curated Explore and Stories features on Instagram, for example, frequently display advertisements to users based on their past interactions and interests. Although this boosts the effectiveness of advertising, it can also result in undesirable dynamics. A smaller variety of content may be presented to consumers over time, which could reinforce preexisting preferences and lead to the creation of "engagement bubbles" or digital echo chambers (Marr, 2021).

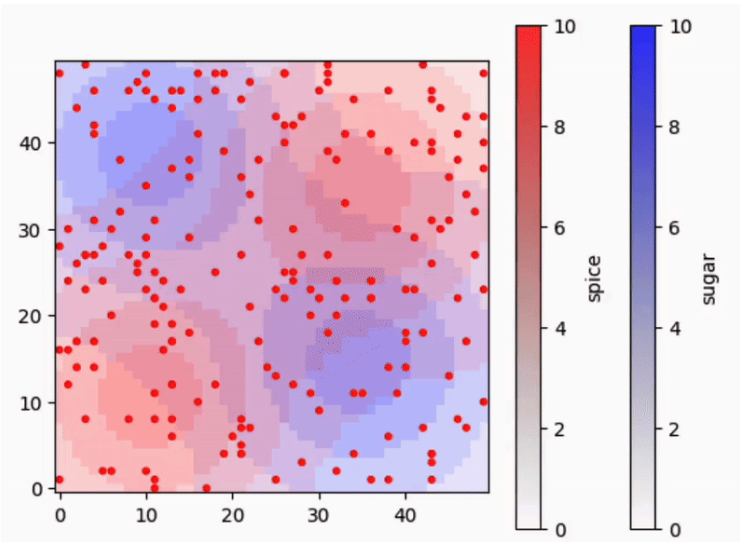
Problem Statement:
This feedback cycle raises ethical, societal, and economic concerns. The self-reinforcing loop of AI-driven content development and recommendation might homogenize information landscapes, restricting exposure to alternative products and various opinions, in addition to privacy problems and algorithmic bias. This may affect market competition, consumer choice, and even public opinion. Examining how these AI-to-AI interactions change over time and what trends show up from their ongoing engagement is therefore essential.

Why Agent-Based Modeling (ABM)?
We use an agent-based modeling (ABM) technique to examine these dynamics. According to Macal and North (2010), ABM is a useful technique for researching emergent phenomena in complex systems, where individual behaviors combine to yield system-level consequences. Three types of agents are included in our model: human users, AI recommendation bots, and AI content generation bots. This enables us to model how individual interactions and

decision-making processes influence more general trends in user engagement and ad distribution.

Illustration of the Phenomenon

This interaction is demonstrated in our simulation by way of a curated GIF. Recommendation bots (red dots) are spread out at random during timestep 0, while AI-generated advertisements (red zones) and human users (blue zones) are positioned in resource zones. By timestep 10, bots are using preference data to match users with advertisements of the same preference type. By timestep 100, engagement clusters start to appear. Weaker recommendation bots vanish by timestep 50, leaving just high-performing recommendation bots. Engagement bubbles, which show how AI-to-AI interactions affect content display and user experience—often without users' knowledge—solidify at timestep 150+.



(Figure 1: Simulation Environment GIF)

2. Simulation Design & Implementation

System Overview

Our simulation was created to depict the intricate interactions between AI content generating bots, AI recommendation systems, and human users in a digital media ecosystem. This model aims to investigate how AI-driven ads are created and distributed by other AI systems, as well as how this cycle affects content distribution and visibility over time. Our underlying architecture for this was the Sugarscape Model with Trading, which we modified to mimic the Instagram advertising ecology.

Three key elements in our model stand in for the actual players in digital advertising. First, the resource "Sugar," which represents the limited attention span of people browsing through their Instagram feeds, is used to represent human users. Secondly, the resource "Spice" represents ads produced by AI content bots. The type of content and target audience determine how these advertisements differ. Third, the "Traders," or AI recommendation bots, navigate the grid-based environment and try to connect ads with the users who are most likely to interact with them. Our simulation shows how clusters of engagement develop through repeated encounters, resulting in the formation of engagement bubbles and the phenomena of content monopolization.

Simulation Environment

The simulation operates within a grid-based environment, inspired by the original Sugarscape model. The grid serves as an abstract representation of Instagram's media ecosystem, where agents (users, ads, and recommendation bots) are distributed across the digital space. Each grid cell can contain either Sugar, Spice, or a Trader, and agents move according to predefined rules.

The behavior of the simulation is defined by a number of important factors. Every user (Sugar) has a preference value that determines whether or not they will interact with a certain advertisement. In a similar vein, each Spice advertisement is grouped according to the kind of substance it depicts. Only when the ad matches the user's preferences can traders effectively "trade" or match it to a user. This exchange is comparable to an effective Instagram ad recommendation. Constraints include limited agent visibility (they can only engage with agents who are nearby) and limited Sugar and Spice availability, which represent the competitive nature of digital advertising.

Agent Design

Three different kinds of agents with distinct, rule-based behaviors are included in our simulation. Human users (Sugar) are static resources with defined preferences; they do not actively move but impact the activities of other agents based on their level of involvement. While they are likewise static, the AI-generated ads (Spice) varied by category to reflect various ad content kinds.

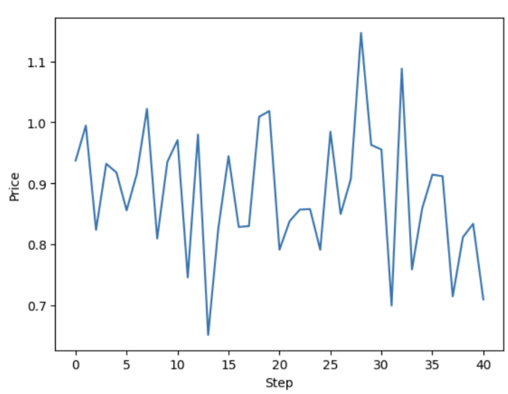
The AI recommendation bots (Traders) are the most active agents. These agents seek for individuals whose interests align with the adverts they are carrying as they move across the grid. They only trade when they discover a preference match, and this is the single rule that governs their activity. We reduced computing complexity by concentrating on localized decision-making and abstracting user engagement decisions into binary outcomes (engaged or ignored) in order to simplify complex real-world behaviors. To guarantee diverse, non-repetitive agent activities, we employed a RandomActivation scheduler. Making sure traders continued to be active even in the absence of instant matches presented a significant problem that required modifying their movement logic. Additionally, to reinforce the role of AI advertisements within the simulation, AI advertisements are given a set number of rounds to be traded before they change their content type to better match the user preferences around them.

Interaction Dynamics

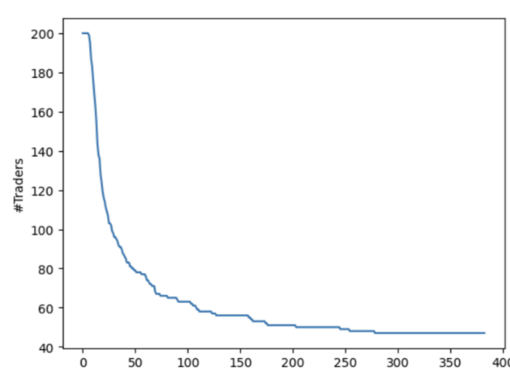
We have included a few aspects in this sugarscape model with traders simulation that will let us simulate the interactions between AI recommendation systems, users, and ads. First, when they appear each resource (users and advertisements) is given a content type of either 1 or 2. This enables consumers to select between one or two content categories, and it also enables ads to target particular content types. Similar to real-world recommendation algorithms that target consumers based on their preferences in order to maximize click-through rates, our AI recommendation system will only exchange resources of the same content kind and preference. The ability for AI ads to dynamically alter their content type after a predetermined number of traders' actions was the second feature we added. This allowed traders to transition between content kinds 1 and 2 or 2 to 1. We put this in place so that a resource will know that the AI recommendation algorithms grabbing consumers' attention are not interested in its type of material if it is not harvested for a predetermined number of cycles. As a result, it will change to become more enticing to the users nearby.

With these features included in our simulation, we can see quite a few bot-to-bot interactions arise. Initially, we see interactions between the various AI recommendation bots. When an AI recommendation bot harvests a resource, such as people or ads, it compels other bots in its area to switch their targets to other resources that can be harvested. When a recommendation system is awarded a contract for a particular advertisement, competing recommendation algorithms are unable to obtain that contract, simulating real-world interactions. The availability of resources changes over time as a result, forcing the resources to adjust and modify the kinds of content they include. The content type preference component that they must take into account while trading is another example of an emergent bot-bot interaction that we observe developing. We observe a clustering of groups where recommendation algorithms will group resources according to their chosen content type when these AI recommendation systems exchange AI ads for users of the same content type. This behavior is similar to real-world AI recommendation systems that modify their ads and actions in response to user interaction.

Data Collection and Visualization



(Figure 2: Price per Step graph of simulation)



(Figure 3: #Traders per step graph of simulation)

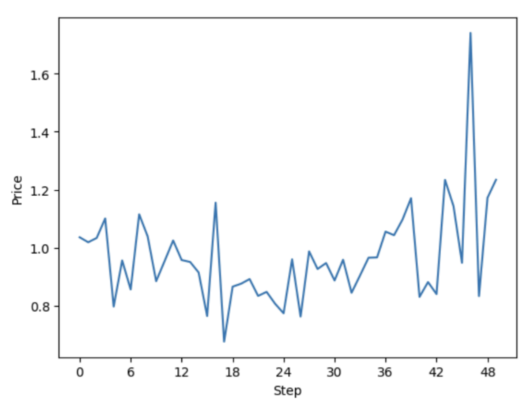
Our simulation currently collects two primary types of data, resource prices per step and the number of active traders in the simulation per step. As the simulation runs, we see that the prices of resources seem to fluctuate (figure 2), which is largely driven by the recommendation bots demand for user attention and advertisement availability, mimicking real world trends in AI recommendation algorithm markets. Tracking the number of traders present throughout the simulation also reveals the simulation's efficiency and the stability of the simulation's interactions as the traders optimize their locations and trade systems(figure 3).

As you can see from figures 2 and 3, our graphs utilize line graphs, which plot the price per step and number of traders per step in the simulation. The visual line graphs help illustrate some of the early results of the simulation, such as the sharp decline of trader population in the beginning of the simulation (figure 3), which can be attributed to the early inefficiency of the trading bots and their saturation in the market, which is later stabilized due to less competition and better trade efficiency from remaining bots.

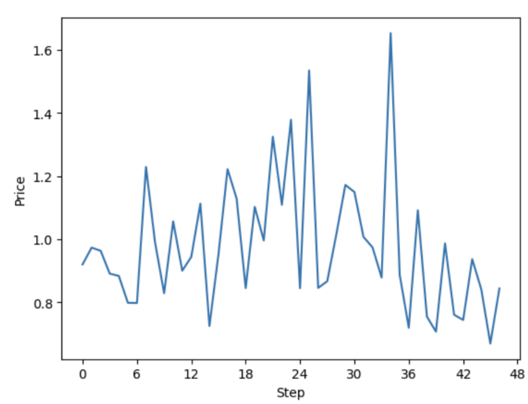
Our key challenges in implementing the data collections and visualization of the simulation included the change of colors as well as names of the model. Whenever a name change was attempted in terms of graph names and agent names, the simulation environment would crash. Numerous attempts were made to change the names, however we were unsuccessful. In the future, implementing these name changes would be beneficial to user experience when running the simulation in order to better understand the simulated dynamics between agents. Another key challenge would be the implementation of color differences to simulate the content preferences of different resources, such as light green vs dark green for content differences in AI advertisements, and light blue vs dark blue for user content preferences.

3. Observations & Results

Our modified simulation of the sugarscape model with traders demonstrates many emergent behaviors that mirror real world interactions in AI driver marketplaces, such as the initial sharp decline of traders in the simulation and the fluctuating prices per step.

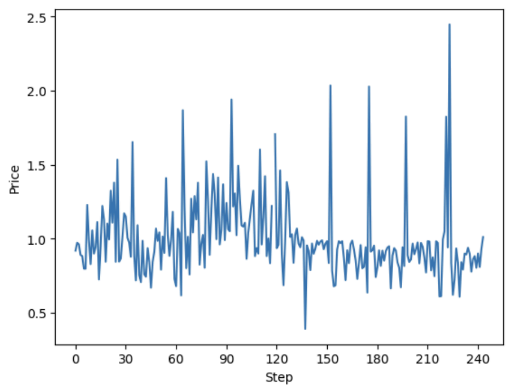


(Figure 4: Simulation 1 first 50 steps of Price per Step graph)



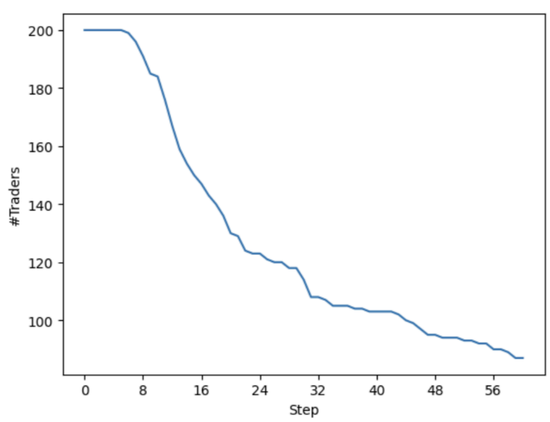
(Figure 5: Simulation 2 first 48 steps of Price per Step graph)

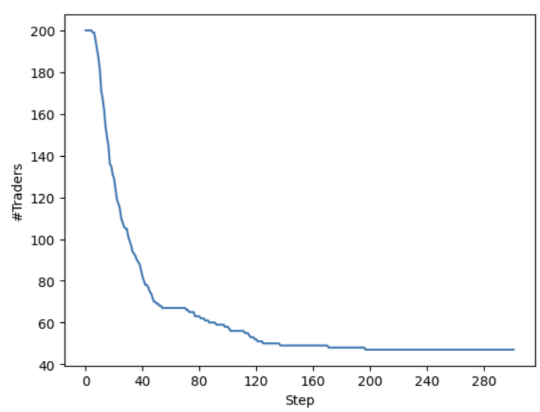
In the graph that collects price per step, we can observe a sharp increase in price within the first 30-50 steps, consistent across multiple instances of the simulation before it begins to stabilize. The initial price of typically around 0.7 to 1.2 increases by about 75-80% reaching a price as high as 1.9 within this early stage of the simulation.This increase in price likely occurs due to AI recommendation algorithms competing for resources, strongly due to the large number of recommendation bots present at the start of the simulation. This behavior mirrors AI driven ad competition, where the demand of AI recommendation algorithms for user attention and advertisement availability raise prices before stabilizing into an equilibrium once the simulation recommendation bots optimize their trading and placements within the simulation.



(Figure 6: Simulation 3 first 250 steps of Price per Step graph)

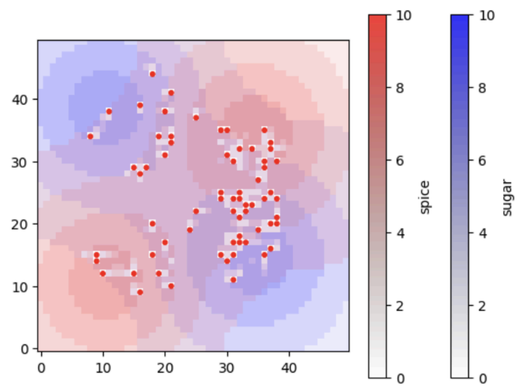
Once we let the simulation run for a longer period of time, we can begin to observe the stabilization of the price per step graph, which begins to follow a consistent pattern of spice, stable, spike, stable, with stable periods only fluctuating around 10% from their average, which indicates the efficiency of the recommendation bots remaining in the simulation, and paralleling market efficiency in real world online ecosystems. Additionally, the spikes that we see between these stable periods reflect seasonal variations in ad markets, such as Christmas time.





(Figure 7: Simulation 1 first 60 steps of #Traders per Step graph) (Figure 8: Simulation 2 first 300 steps of #Traders per Step graph)

In figures 7 and 8 we observe the sharp decline of around 40% in the trader population (recommendation bots) within the first 15-20 steps of the simulation. This initial decline in trader population is a result of the simulations feature to remove recommendation bots that are underperforming, and not completing the required amount of trades. This requirement can be adjusted with the metabolism slider in the simulation, increasing or decreasing the amount of successful recommendations the algorithm must complete, mimicking real world recommendation algorithms being removed due to underperformance. Once we leave the simulation to run, we begin to observe a stable population of traders emerge around steps 160-200, indicating the increased efficiency of the recommendation algorithms due to more efficient recommendation bot placements and interactions.



(Figure 9: Main Simulation Environment)

As the simulation progresses, we can observe recommendation bots (red dots) begin to group based on their content preferences, allowing them to optimize their interactions with other recommendation algorithms to efficiently trade AI advertisements for user attention whose preferences match the content of the AI advertisements. This grouping behavior mimics real world AI recommendation algorithms, where they cluster users with similar content preferences to improve targeting. This grouping behavior tends to emerge around steps 120-150 of the simulation, allowing for recommendation bots within these clusters to trade more effectively with each other.

Overall, the patterns observed in our simulation strongly suggest that AI recommendation algorithms can adjust their behaviors and placements to ensure optimized click rates occur. Recommendation bots that continue to survive after the initial drop off phase demonstrate a strong improvement in performance, supported by the stabilization of trader populations and prices. This reinforces the importance of adaptive learning in systems that are heavily reliant on algorithms. The price fluctuations that occur within the simulation also highlight the validity of emergent behaviors in online spaces with heavy AI competition. Additionally, the grouping formation that occurs within the simulation reinforces the idea that AI algorithms will group users based on what they engage on to maximize click rates.

As we run the simulation, we can begin to take notice of some unexpected and emergent behaviors. One of the unexpected behaviors simulated were the price spikes in figure 6 being more pronounced than expected during the stabilization period, suggesting that recommendation algorithms might be hoarding certain resources. This could simulate the idea that AI recommendation algorithms in real media ecosystems might over-prioritize certain strategies, leading to inefficiency when attempting to target advertisements. This could be a result of later resource abundance, allowing recommendation bots to harvest more resources than needed. As for emergent behaviors, while clustering was expected, the strength of the separation was weaker than expected. Rather than well defined groups being formed, we observed some recommendation bots move in between clusters present in the later stages of the simulations. This may be due to the fact that the resource placement in our simulation forces the traders to move in order to harvest all the resources they need, which inadvertently creates echo chambers that are less strong than simulations like the Boids Flocking Model would demonstrate.

In the future, refinements could include adding a separate graph to track the number of successful trades over time in the simulation in order to more easily track trading efficiency and any emerging behaviors resulting from stabilized recommendation bot populations later in the simulation. Additionally, refinements could be made in the coloring of elements, allowing users to see the different content types within resources like users and AI advertisements. A slider could also be introduced to increase or decrease topic diversity as well, allowing for more customization to occur. Overall, these changes would enhance the simulation's ability to demonstrate real world behaviors on a more complex level.

4. Ethical & Societal Reflections

Ethical Considerations

AI-driven advertisements rely heavily on customer data, their engagement metrics, and preferences. The recommendation algorithm takes this data into consideration and based on this the advertisements are curated for customers. This collection and assessment of customer data raises many ethical and privacy concerns. When using this data for analysis, businesses must always protect the customer data by maintaining significant data protection protocols. (Alhitmi et al., 2024, Section 3.1.2, para. 1) Our agent-based simulation does not directly integrate real-world data such as social media interactions or live user behavior. Instead, we use the simulation to model these real-world situations where agent-based interactions based on user preferences and AI recommendations form clusters, showing how echo chambers in real-world social media are formed. Based on the guide provided by the Universal Conscious Attention Economy (CAE), some ethical concerns related to AI-driven advertisements that needs to be considered are discussed below:

<u>Right-to-Privacy:</u> Since AI-driven advertisements are heavily reliant on sensitive user data, there are different surveillance tactics used by social media ecosystems like Instagram. With the advancements in different communication technologies, surveillance tactics, especially in the digital media have seen widespread advancements as well. “Perhaps the most powerful aspect of digital surveillance is that it can transcend the boundaries of time and space. All kinds of cases can be monitored using digital surveillance.” (Bekman, 2023, p. 377). This continuous tracking can create detailed behavioral profiles, leading to privacy invasions where advertisers predict and influence user actions without their explicit awareness. Moreover, large social media

platforms such as Instagram, in order to maximize their own and the advertisers' engagement and revenue, sell the gathered data to third-party vendors.

Transparency: Even with the advancements with technology and people's understanding about core technological concepts, still most users of platforms such as Instagram do not understand the depth to which their data is collected. They often do not intentionally consent to this extent of data collection and surveillance as these platforms are not transparent enough with the users and do not give the users the ability to have control over how much of their data can be collected and used. Users make assumptions regarding how much of their data are actually being used and big platforms like Instagram take advantage of their users by exploiting this misinformation.

Fairness and Inclusivity: In order to maintain an ethical platform, stakeholders should try and promote equal access, non-discrimination and social justice. However, AI-driven advertisements and the recommendation algorithms often have biases. As AI-generated advertisements rely mostly on collected data from the users, it often lacks diversity and disproportionately targets certain demographic groups, leaving the rest of the population excluded. This can also affect marginalized communities of the society, excluding them from different opportunities, important healthcare options or educational resources.

For example, a case study conducted regarding the discrimination by AI in a commercial electronic health record, which aims to predict the likelihood of a patient missing out on an appointment in the future. The study revealed how marginalized patients, with disabilities or belonging to a lower socioeconomic status were predicted to be more likely to miss appointments, reinforcing the systemic inequity which already exists in the healthcare system. (Murray et al., 2020)

Freedom from Exploitation: Social media platforms such as Instagram, with access to all the information about each individual user, can use this information to draw a picture of the personality of that individual. From that data they can calculate, derive, and predict the behavior of the users. Moreover, they can also influence and manipulate user behaviors. Using targeted advertisements generated by AI, which is then constantly presented to the users by the AI recommendation systems, these platforms exploit their users to generate personal revenue.

Societal Implications

Digital advertisements created by AI following data collected by AI algorithms have been integrated deeply within all major social media platforms. Social media platforms like Instagram have a variety of users distributed in a wide age-range. These users have different societies, cultures, beliefs and values. AI-driven advertising has managed to integrate itself with all the different users, consciously curating itself to better match the engagement metrics of each different user. As a consequence, AI advertising has impacted each level of the sociological structures.

Micro-level: From the simulation we have seen how individuals can be funneled into their own personalised filter bubbles. When AI-driven algorithms such as the recommendation systems of Instagram continuously and consciously refine their recommendations based on the user preferences and what the user is more likely to engage with, the formation of digital echo chambers form around that individual. The individual is not presented with the opposing view and their own self-beliefs, even if it is misinformation or disinformation, it is reinforced by the recommendation systems.

For example, a study was conducted on how social media induced polarisation during covid-19. The study revealed that social media platforms divide individuals based on their shared ideologies, whether they are followers of the Republican party or the Democratic party, and reinforce these divisions based on government policies, economic principles etc. Personalization algorithms create filter bubbles, exposing users only to content that aligns with their existing beliefs. This reinforces ideological biases and leads to systemic polarization. Further, the reliance on familiar but potentially biased sources of information creates online echo chambers. (Modgil et al., 2021)

Meso-level: In our simulation model it is highlighted how there is a constant competition between AI systems for user attention, trying to maximise engagement and revenue in the process. This can lead to various manipulative ad targeting as well. Especially the vulnerable parts of the society and users with psychological vulnerabilities such as people who are struggling to overcome their personal addictions.

Macro-level: At a broader societal scale, AI-driven advertising has the potential of reshaping public discourse and consumer behavior. In our simulation model we have seen the formation of clusters around traders with matching preferences. This perfectly aligns with the real-world phenomenon of public opinions regarding certain subjects being massively polarised by AI-powered Instagram news feed algorithms. Moreover, AI-driven advertisements and recommendation systems can also act as major amplifiers of misinformation and disinformation which ultimately affects the whole society.

For example, a study was conducted about how AI-generated advertising influences consumer buying behavior. The study was conducted with four top level marketer participants. The study revealed that engagement metrics for advertisements is relatively higher for AI created advertisements compared to those that are made by humans. Moreover, advertisements generated by AI have a higher conversion rate with customers. This can be explained with the vast engagement metrics and data they have at their disposal and psychological factors that these AI tools use while the creation of their advertisements. The study showed that 30-50% of the ad creation process is currently contributed by AI with projections of this number going up to 80% in the near future. (Ratta et al., 2024)

5. Lessons Learned & Future Directions

Design and Development Reflections

The development of our agent-based simulation using the MESA sugarscape framework presented our group with a few challenges. In designing an effective and computationally efficient model, one of the primary difficulties we faced was with the agent behaviors. The initial implementation of the simulation had performance bottlenecks, particularly because of the initial trading mechanism of the agents. The agents were trading based on their needs of the type of resource they desired. However, our phenomenon focused on the preferences of the users and how the recommendation systems only promoted the content which aligned with the user preferences. So, in order to better match our phenomenon, we changed the trading pattern of the agents. We implemented a more selective approach to the trading behavior of the agents. The agents had a preference for a type of content and only traded for that. This better represented the real-world phenomenon, where advertisements and recommendation systems produced by AI work together to gain more user attention and engagement.

Additionally, the initial trading mechanism of the simulation assumed a very simplified version of trader preferences and homogenous AI behaviors where if there is no match between preferences, traders simply move on to find a match. This did not reflect the real-world phenomena correctly since AI-driven advertisements dynamically change their content to better align with user preferences. We changed the trading mechanism in such a way so that if there is a mismatch between the preferences, the traders have a certain limit imposed on them after which they will dynamically change their content type to match the preferences. This limit can also be manipulated in our simulation. This change helped our simulation portray the real-world phenomena better and also increased the formation of clusters within our simulation model.

Another challenge we faced was with the movement patterns of the agents. The initial movement of the agents focused on iterating through all neighboring agents and their resources and trading with them as needed. This posed performance issues for the simulation, especially when the predefined parameters are scaled up. While changing the trading mechanism of the agents based on their preferences, we also changed the movement protocols for the agents. The initial movement pattern of the agents was purely based on resource availability but after changes were made, the agents effectively prioritised locations with their preferred resource type. This effectively represented the real-world phenomenon of the formation of clusters. Moreover, this also mitigated the performance issues of the simulation when scaled up as the computational overhead in each step was reduced.

Model Limitations and Areas for Improvement

Despite all the advancements, the model still contains a few limitations. One of the key limitations of our model is that it only operates with two trading resources. This simplifies the interaction dynamics between human users, AI recommendation bots and AI advertisement bots. In the real-world scenario this is much more complex, where multiple resources, such as user attention, ad budgets, engagement metrics, and personal data, are traded simultaneously. The simulation model can portray a much better and accurate picture of the real-world dynamics if more trading resources such as user feedback, types of user engagement (like, share, comment, time spent) and dynamically changing advertisement structure of the same content type, were incorporated within the simulation.

Another constraint is the lack of external influences. In the real-world, preferences and engagement can be influenced by external factors such as economic situations, seasonal trends, government policies. However, in our simulation model the trading between agents is not affected by any such external factor. Incorporating exogenous variables, such as real-world ad engagement datasets or economic indicators, would enhance the fidelity of the simulation.

Additionally, our simulation model assumes the perfect execution of trade between agents whenever there is a match in preferences. This is not true in real-world scenarios. Real world AI interactions often involve various misinterpretations, noise, emergent behaviors, and unintended consequences. Incorporating factors such as inaccurate targeting or algorithmic bias in the simulation in the future can help simulate the unintended consequences of AI-driven advertising.

Future Applications

In recent times, the issue that is becoming more prevalent with AI-driven digital advertisement and recommendation systems is the reinforcement of harmful biases that already exists in society. “AI Bias is when the output of a machine-learning model can lead to the discrimination against specific groups or individuals. These tend to be groups that have been historically discriminated against and marginalised based on gender, social class, sexual orientation or race, but not in all cases.” (Belenguer, 2022, para. 15) Our simulation model also portrayed how AI recommendation agents can amplify the spread of misinformation, echo chambers or polarisation of communities by only promoting certain types of content based on user engagement. To reduce the reinforcement of biases, policymakers can put regulations on digital platforms like Instagram to maintain diversity in content exposure, reducing the risk of algorithmic bias. They can use our simulation model to better understand whether such platforms and their algorithms are adhering to these regulations or not.

Most AI systems operate like a black-box model. “A black-box model in XAI refers to a machine learning model that operates as an opaque system where the internal workings of the model are not easily accessible or interpretable.” (Hassija et al., 2023, “Black-Box Model” section). Even the digital platform developers are unable to comprehend the extent of unintended consequences of the AI recommendation systems. So, in order to better understand and predict the outcomes, developers of these platforms can use our simulation model to simulate different advertising and recommendation strategies by running thousands of simulations under different conditions, before deploying them in the real-world digital platforms.

With the advancement of generative AI, popularity of AI-driven advertisements is increasing. These AI tools use real-world data and engagement metrics to curate its ads. However, if faulty data is collected by them, then the advertisements generated can contribute to the spread of misinformation or disinformation. Our simulation model can be used to observe and rectify such behaviors of the AI-advertisement tools.

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7. Attestation

All group members contributed actively and fairly to the creation of this report. Below is a clear summary of what each person did throughout the project:

Name	Del3
Jasmin Slootweg	**Conceptualization:** Defined research focus and aligned the simulation with AI advertising. **Writing – Original Draft:** Wrote sections on Significance of Agent Modeling (ABM), Interaction Dynamics, and Data Collection and Visualization. **Writing – Original Draft:** Authored Section 3 (Observations & Results) including graph and data collection analysis. Authored Section 2 (Interaction Dynamics & Data Collection and Visualization) including Purpose and Methods of data collection **Software and Visualization:** Assisted in generating simulation graphs and agent-based models for Section 3. **Methodology:** Helped design the rules governing AI agents and ad interactions.
Mohammad Hossain	**Investigation:** Conducted literature review on AI-driven advertising and recommendation algorithms. **Writing – Original Draft:** Authored Section 4 (Ethical and Societal Reflections) including ethical considerations following ethical guide of CAE and societal considerations at the micro, meso and macro level. Authored Section 5 (Lesson Learned and Future Directions) including design and development reflections, model

	limitations and areas for improvement and future applications. **Formal Analysis:** Evaluated simulation results, identified emergent behaviors, and assessed ad targeting trends. **Validation:** Ensured the model aligns with real-world AI-advertising behaviors.
Saina Shishegar	**Conceptualization:** Led the development of the central phenomenon focus, specifically the exploration of AI-to-AI interactions in advertising ecosystems. **Writing – Original Draft:** Wrote Section 1 (Phenomenon Overview), including the description of the phenomenon, problem statement, academic connections, and significance of Agent-Based Modeling (ABM). Authored Section 2 (Simulation Design & Implementation), detailing system components, simulation environment, and agent behaviors. **Review & Editing:** Reviewed the entire report for consistency, clarity, and scholarly rigor. **Writing – Attestation**: Drafted and finalized the Attestation Section.

For the final report, our team collaborated closely and ensured that all sections were developed together. Each member made meaningful contributions to the writing, simulation design, data analysis, and ethical reflections. We confirm that this final report is the result of a collaborative effort, and we are committed to maintaining academic integrity and acknowledging everyone's contributions.

Signed by:
Saina Shishegar | Mohammad Hossain | Jasmin Slootweg
Date: 2025-03-31