Github URL: https://github.com/jasminSlootweg/AdCeption.git

§1: Phenomenon Overview:

Description

In recent times, people engage more with digital media compared to the traditional media outlets. As a consequence of this transition, advertising also had to undergo various changes. Modern advertisements focus more, if not solely, on digital advertising. Our main purpose of the research is to investigate the digital marketing space and how AI integration has further changed the advertising space.

Our phenomenon of interest is the relationship between AI creating advertisements, and these advertisements being promoted by AI recommendation tools to target specific groups of people. AI in advertising has changed how businesses create, distribute, and target ads to certain audiences. These ads can be text based, image based, or video based that are tailored to specific audiences based on data analysis. How this is executed in Instagram advertisement space is our focus for the research.

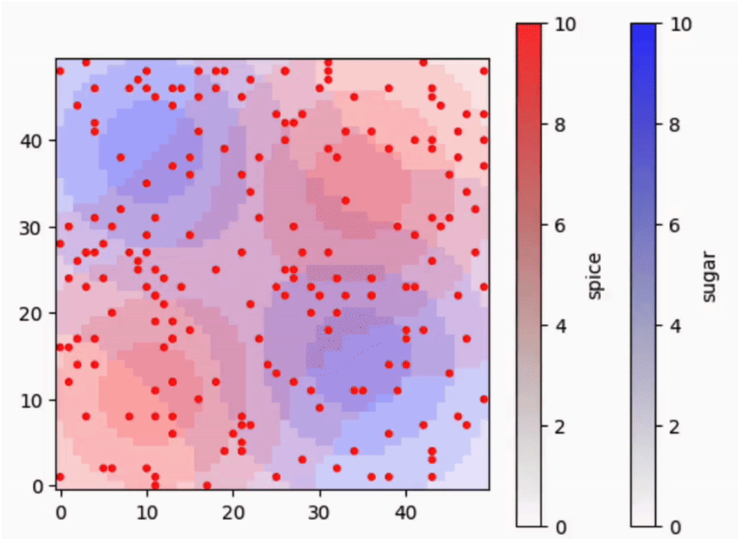
Problem Statement

Instagram extracts customer insights by analyzing user search preferences and engagement patterns. This data can be then sold by them to major corporations in the form of targeted advertisements, presenting these advertisements only to customer profiles who are most likely to engage with the marketing messages. (Marr, 2021, para. 3) While AI-enhanced targeting improves advertising efficiency, it also creates risks of algorithmic biases that may lead to unfair targeting, privacy concerns, and potential manipulation of consumer behavior. "Because targeting means different ads are shown to different people, the advertising system becomes less transparent, and it is therefore more difficult for civil society or government to hold companies accountable. It is, in the most literal sense, 'systemic racism.' " (Rogoff, 2023, para. 5)

Significance of Agent-Based Modelling (ABM)

Agent-based modeling (ABM) is an effective method for examining the complexities of AI-driven advertising, as it facilitates the simulation of individual agents—such as advertisers, consumers, and recommendation algorithms—within a digital media environment. Through ABM, researchers can explore emergent behaviors arising from AI-to-AI interactions, including how ad distribution patterns change over time and how users react to AI-personalized content. By modeling various scenarios, ABM can reveal unintended outcomes, such as the amplification of biases or reduced user engagement due to excessive personalization.

Significance of Agent-Based Modelling (ABM)



(figure 1: GIF of the simulation running for 10 seconds)

As can be seen from the GIF above, the simulation begins with a grid overview that shows the distribution of sugar (which represent users), spice (which represent AI Advertisements), and traders as red dots (which represent AI Recommendation systems). The grid displays the hotspots where the resources Spice and Sugar are clustered, showing areas of high concentration which mirrors real-world digital ecosystems where algorithms will concentrate recommendations around user interests. We see in the GIF that the traders are moving, searching for resources that match user interests. They will only trade advertisements for user attention when the advertisement matches the users preference, mirroring real life recommendation systems that recommend content to users based on their preferences. Over time, as traders move, we see hotspots be created, mirroring the clustering of preferences we see on social media platforms, where users interact with other users or content of the same interest types, illustrating how algorithms evolve and refine their recommendations to serve users more relevant content as they learn user preferences.

§2: Simulation Design & Implementation

System Overview

The simulation models AI-driven advertising with three main agents: AI content generation bots, AI recommendation bots, and human users. Each entity is assigned attributes that determine their interactions with each other. Users and AI advertisements as the resources, AI recommendation bots as the traders. The simulation will showcase the interactions in a preference system, where traders only match users with ads that align with the users assigned value. The simulation aims to replicate how AI driven recommendation systems operate, and how they ensure users receive personalized content.

Simulation Environment

The simulation is built on the Sugarscape Model with Trading, where user attention works like a resource. Just as traders in the Sugarscape model compete for sugar, ads in this system compete for user engagement. In this simulation, traders will ensure the right content is traded for the right user, changing their placements in the grid to match where their user base is located. AI recommendation bots constantly adjust ad placements in real time to prioritize the ones that are getting clicks and interactions. This is similar to how social media algorithms optimize ad reach by tracking user behavior.

Agent Design

There are three main agents that operate within the simulation:

- Traders (AI recommendation systems): These traders move throughout the grid harvesting sugar and spice. Their goal is to distribute relevant content, which mimics real world recommendation algorithms.
- Sugar (Users): This resource represents users in a media ecosystem. Each user is assigned a number, representing the type of content they prefer.
- Spice (AI Advertisements): This resource represents the different advertisements that come out of media content, which is also assigned a number according to which user base it aims to reach.

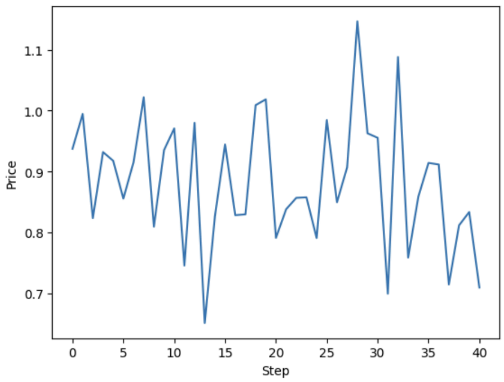
Traders in this model make rule-based decisions. Mainly, only interacting with a resource that matches their preferences. If a trader comes across an unmatched resource, they continue searching until they find the resource that matches their need. This constraint models algorithmic filtering, where recommendation systems only deliver advertisements to users who have a perceived interest in its value.

Early on in development, we made adjustments to the traders behavior to ensure they continue to move even if no matches are found for the resource it is looking for, which helps prevent the traders from being static and still in the simulation.

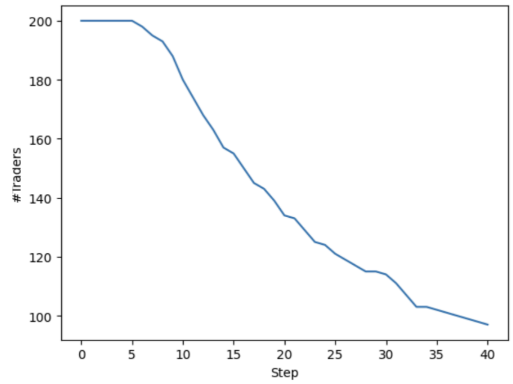
Interaction Dynamics

This model uses a RandomActivation scheduler. Agents take turns in a randomized order to interact with the environment. This allows us to prevent predictable behavior and simulate organic digital interactions. Bot-to-bot interactions emerge when multiple traders are competing for the same content, or when traders influence each other's movements by deleting resources in one area by harvesting them, forcing other traders to go elsewhere. Over time, we can see groups form in the simulation, demonstrating how recommendation algorithms create bubbles in which users repeatedly engage with similar types of content.

Data Collection & Visualization



(Figure 2: Price per Step graph of simulation)



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

Our simulation currently collects data on the resource prices per step, and the number of traders in the simulation per step. Resource prices fluctuate based on availability and demand, which mimics real world trends in AI driven marketplaces. The number of traders helps track system efficiency. These trends are visualized using line graphs as seen in figures 2 and 3, so that we can easily see the fluctuations of price and decrease of traders in the simulation over time.

In the future, we aim to improve the main simulation model as seen in the earlier figure 1 by assigning traders a color based on the content preference they aim to match to better illustrate the bubbles that emerge with this type of interaction. In the future, it also might be beneficial to add different ai recommendation strategies to the traders, such as aggressive targeting or balanced recommendations.

§3: Preliminary Observations & Results

In the early simulation results, we saw through the visualized graph as seen in figure 3 that the number of traders in the simulation decreases exponentially until it eventually stabilizes. This is likely to be caused by the removal or deactivation of traders based on a few specific conditions, such as failing to meet their trade minimum threshold. In our system, this is done because recommendation systems that perform poorly or are unable to secure enough engagement are deactivated (in the code this condition is checked through the method maybe_die). This is what likely leads to the decrease in the number of traders, or AI recommendation systems. As the simulation progresses and fewer traders remain, the trader population stabilizes. These remaining traders are those who have established sustainable interactions by finding their resources that align with the content type they aimed to trade for, leading to the observed stabilization in the graph.

Another observation is the formation of groups. As the simulation runs, some traders group together around resource hotspots, and with the implemented functionality of content preferences, we can assume that the clustering is being done by the types of content the traders prefer to trade with. This is an emergent behavior that is consistent with real AI recommendation systems adapting to local conditions, interests, and forming networks of traders that share similar behaviors. This clustering however, does have a major limitation in the way that it is visualized by our simulation. Since traders are not differentiated by color based on their content preferences, it's difficult to see the clustering behavior explicitly. This limitation in the models visualization makes it harder to track and analyze the specific groupings that occur due to content based trading preferences. A simple solution we could try to implement in the next iteration of the model would be to assign traders a color based on their content preference. By coloring based on preference, we should be able to more easily observe how these content preferences influence how the traders interact with each other and the resources they are trading. It would also allow us to see the emerging clustering behavior more easily, giving us a better understanding of how these grouping behaviours emerge in the simulation.

§4: Challenges and Next Steps:

Development Challenges:

- Initialization: The source code for the agent based modelling simulation for the sugarscape model had to be manually extracted from their website. So, after extracting the code, our team faced many difficulties just starting up the base simulation. There were different kinds of errors popping up in the terminal when we tried running the server as recommended in the MESA website. In order to successfully run the server we had to download a list of packages. Some of the required packages that had to be additionally downloaded include Solara, Mesa, Urlib3, NetworkX, FuzzyTM, Matplotlib, DefusedXML, Clyent, Altair, Conda-repo-cli and Requests. Once these packages were downloaded we were successfully able to run the server running on Solara.

- Changing the code: We wanted to change various aspects of the code provided for the base simulation model. We wanted to change the overall layout of the interface and change the graphs that were displayed as well. However, making even a small change in the base code resulted in various errors in re-running the server. Understanding which errors were being caused by these changes were also very difficult as there were no clear indications in which part of the code was generating that error. Our team tried to figure out the errors and fix the code appropriately which took a lot of effort and time as well. Then we had to change our plans on how to modify the simulation and decided to focus more on the actions of the agents instead. We divided the agents into preference groups and changed the code so that traders will only trade for resources that align with their personal preference group.

Planned Refinements:

In this deliverable we focussed more on the behaviour of the agents and how they trade with each other. In the future deliverable, we intend to focus even further on this aspect of the simulation. We aim to change the color and visualization of the agents based on their content preference. For example, if a trader has a color blue, then that specific trader will only trade for resources that are also colored blue. This will help to better portray our chosen phenomenon as we can visually see the bubbles that emerge and how, in real-life situations, users interact within certain advertisements bubbles that are created.

We also wanted to incorporate different AI recommendation strategies to the traders, such as aggressive targeting, collaborative filtering systems etc. This is primarily because every large platform today comes with a built-in recommendation system. These recommendation systems, also called recommender systems, are a lucrative alternative to traditional search algorithms and offer personalized recommendations based on user preferences. (Takyar, 2023, para. 6)

We also wanted to work on changing the layout of the simulation server. We want to incorporate more graphs into the server as well. We want to add a graph which measures the user satisfaction over time. This would provide a quantifiable measure of how content and trading interactions affect agent well-being, engagement, or success within the system. Another graph we want to incorporate is based on the total number of trades over time. This will provide valuable insights into the activity level of the market, the effectiveness of agent interactions, and whether trade dynamics are improving or declining over time.

§6: References:

1. Marr, B. (2021, July 2). The Amazing Ways Instagram Uses Big Data And Artificial Intelligence. Bernard Marr. https://bernardmarr.com/the-amazing-ways-instagram-uses-big-data-and-artificial-intelligence/
2. Rogoff, Z. (2023, May 16). Generative AI's Overlooked Risk: Ads. Democracy Journal. https://democracyjournal.org/arguments/generative-ais-overlooked-risk-ads/
3. Akash Takyar. (2023, April 7). How to Build an AI-based Recommendation System. LeewayHertz - AI Development Company; Leewayhertz. https://www.leewayhertz.com/build-recommendation-system/#What-is-an-AI-powered-recommendation-system

§7: Attestation:

We all confirm that all group members actively contributed to the development and writing of this draft report. The table below details each member's specific contributions based on CRediT.

Group Member Contributions

Name	Del3
Jasmin Slootweg	**Conceptualization:** Defined research focus and aligned the stimulation with AI advertising. **Writing - Original Draft:** Wrote sections on Significance of Agent Modeling (ABM), Interaction Dynamics, and Data Collection and Visualization. **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 (Challenges & Next Steps) and contributed to Section 1 (Description, Problem Statement, and ABM Significance). **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	**Methodology & System Development:** Developed System Overview, Simulation Environment, and Agent Design (Section 2). **Writing – Original Draft:** Authored Section 2 (Simulation Design & Implementation). **Writing – Attestation**: Drafted and finalized the Attestation Section.

Planned Contributions for Final Report (DEL 4.B)

For the final report, our team will expand on ethics, societal implications, and long-term impacts of AI-driven advertising. Each member will contribute as follows:

Jasmin Slootweg (Software, Data Visualization, Writing – Original Draft): Enhancing the simulation model, improving agent interactions, and visualizing AI-driven ad targeting.

Mohammad Hossain (Investigation, Writing – Original Draft, Formal Analysis): Conducting further research on AI advertising case studies and refining data analysis for final results

Saina Shishegar (Writing – Review & Editing, Ethics, Data Curation): Expanding discussions on AI ethics, algorithmic bias, and privacy concerns in AI-driven advertising.

We confirm that this draft report is the result of a collaborative effort, and we are committed to refining and improving it for the final submission.

Signed by:
Saina Shishegar | Mohammad Hossain | Jasmin Slootweg

2025-03-16