Designing Reliable Experiments with Generative

Agent-Based Modeling: A Comprehensive Guide Using

Concordia by Google DeepMind



## Alejandro Leonardo García Navarro, Nataliia Koneva, Alfonso Sánchez-Macián, José Alberto Hernández

Departamento de Ingeniería Telemática Universidad Carlos III de Madrid, Spain

{agnavarr,nkoneva}@pa.uc3m.es, {alfonsan,jahgutie}@it.uc3m.es

## Manuel Goyanes

Departamento de Comunicación Universidad Carlos III de Madrid, Spain [manuel.goyanes@uc3m.es](mailto:manuel.goyanes@uc3m.es)

# Abstract

In social sciences, researchers often face challenges when conducting large-scale experiments, particularly due to the complexity of the simulations, as well as the lack of technical expertise required to develop such frameworks. However, Generative Agent-Based Modeling (GABM) offers a solution by enabling researchers to create simulations where AI-driven agents can generate complex behaviors based on underlying rules and interactions. This paper introduces a framework for designing reliable experiments using GABM, making sophisticated simulation techniques more accessible to researchers across various fields. We provide a step-by-step guide for selecting appropriate tools, designing the ABM models, establishing experimentation protocols, and validating results.

***K*eywords** Generative ABM *·* Social Science Experiments *·* Computational Social Science *·* Artificial Intelligence *·*

Machine Learning

# Introduction

In an era where artificial intelligence is reshaping countless fields, experts need to adapt to the changes posed by these technologies. More often than not, the most affected areas of study are the social sciences, since they rely heavily on the quality and authenticity of data to make meaningful conclusions [[1].](#_heading=h.3j2qqm3)

There are many traditional ways of getting data, such as datasets and surveys, but this artificial intelligence has led to innovative approaches, like using agent-based models (ABMs). In recent years, the use of agent-based modeling (ABM) has gained significant popularity across a variety of fields, from economics and social sciences to artificial intelligence and computational biology (INCLUIR CITAS AQUÍ). ABMs allow researchers to simulate complex situations by modeling the behaviors and interactions of individual agents within a given environment. These models provide a powerful way to understand emergent phenomena—such as market dynamics, social behaviors, or ecological systems—that arise from the independent actions and interactions of individual agents, each following its own set of rules (xxxx).

In spite of their flexibility, these models face some limitations, particularly when dealing with complex environments. One of the main challenges is that the agents’ behaviors are programmed by the modeler based on assumptions or simplified rules. This rigid structure limits the ability to account for the full range of possible interactions that can emerge in real-world scenarios, failing to output results that closely resemble the reality.

However, it is in the intersection between generative modeling and agent-based modeling that we find a more complete approach: generative agent-based models (GABMs). Generative ABMs take this concept further by allowing the model

to generate and learn behaviors based on patterns in the data, rather than being rigidly defined by pre-programmed rules. Additionally, agents can have the reasoning skills of large language models (LLMs), enabling them to incorporate more human-like decision-making processes. This makes GABMs more complete and adaptable, as they can simulate not only interactions but also the complex thought processes and strategies that may emerge in day-to-day situations.

There are already many platforms designed for agent-based modeling, but Concordia, developed by Google DeepMind, stands out for its approach to GABMs [[2](#_heading=h.1y810tw)]. It is a platform that integrates artificial intelligence techniques to support the design, execution, and analysis of simulations. Thanks to its scalability and computational efficiency, users can model large-scale simulations.

Nonetheless, it is of high vitality to consider that, when designing experiments, ensuring reliability and accuracy is key. Poorly designed simulations not only risk producing misleading or unrealistic results but also interferes with the ability to draw valid conclusions from the data.

This guide aims to bridge that gap, offering best practices for researchers who wish to use Concordia to conduct accurate and reproducible simulations. With this paper, we want to make these simulation techniques more accessible to a broader audience, including those who may not have extensive technical expertise in developing agent-based models. We provide a step-by-step framework for designing reliable experiments, covering critical aspects such as selecting the right tools, designing robust GABM models, establishing experimentation protocols, and validating simulation outcomes.

The remainder of the paper is organized as follows: Section [2](#_heading=h.1fob9te) establishes the theoretical foundation for our proposed approach, explaining key concepts such as Generative Agent-Based Modeling (GABM), its role in experimentation, and the integration of AI tools within the framework. Next, Section [3](#_heading=h.17dp8vu) provides a practical guide on implementing the framework, outlining steps such as tool selection, agent design, experimentation protocols, and validation techniques. Therefore, this knowledge is used in Section [4,](#_heading=h.44sinio) in which a case study showcases the implementation process, results, and an analysis of the framework’s effectiveness and reliability. Finally, Section [5](#_heading=h.z337ya) concludes this study with a summary of its main findings, conclusions, and future work.

# Conceptual Framework

This section establishes the theoretical foundation and structure of the approach we propose for conducting reliable experiments using GABMs. To better understand how this technology fits into experimental research, we will first define the core concepts behind agent-based modeling and generative models, followed by a discussion on the framework we propose for GABM-based experimentation.

## What is Agent-Based Modeling?

At its core, as previously mentioned, Agent-Based Modeling (ABM) tries to understand the behaviour of complex systems by placing agents in an environment and studying the outcomes of the interactions between the agents and the environment [[3](#_heading=h.4i7ojhp)]. These so-called agents are rule-based entities, meaning their behaviors are predetermined by a set of static rules defined by the person carrying out the experiment. Its use is often limited by its rigidity, since it may fail to capture real-world behavior. This can result in models that are deterministic or, in other words, unable to adapt to or exhibit more human-like, context-driven decision-making.

However, more mundane results can be obtained by taking a step further. This type of modeling could incorporate generative models, ultimately allowing its agents to produce more complex behaviors, evolve, learn from their environments, and generate outcomes that reflect more realistic social dynamics.

## What is Generative Agent-Based Modeling?

Generative models are designed to create new data samples that mimic the patterns of existing data [[4](#_heading=h.4i7ojhp)]. These have the ability to learn the underlying distribution of a dataset and use this knowledge to generate new, synthetic instances.

If not familiarized with this technology, it might not ring any bells, but in the realm of language, generative models have had a transformative impact, especially through models like GPT (Generative Pretrained Transformers). GPTs have gained significant fame in recent years for allowing us to have a conversation with what looks like a human.

When integrated into ABM, generative models like these elevate the capabilities of agents, leading to Generative Agent-Based Modeling (GABM), where agents can indeed enhance more robust and unpredictable simulations, making this a powerful tool for studying complex phenomena.

## The Role of GABMs in Experimentation

The use of this modeling in experimentation opens up a new boundary for social scientists and researchers. These models allow them to conduct simulations that imitate real scenarios with a high degree of complexity, offering opportunities to explore human behavior, societal interactions, and decision-making processes in ways that traditional methodologies struggle to achieve.

For instance, in survey-based research, there might me some situations in which we do not have enough participation to draw significant conclusions. With GABMs, researchers can run virtual experiments where agents are fully customized: diverse personalities, backgrounds, and motivations. All this ensemble could provide insights into how different social groups might respond to certain situations.

Additionally, this might even be useful for deeper understanding of human beings, such as crowd behavior, collective decision-making, or the influence of social networks. Experts can simulate how individuals form opinions, influence each other, or adopt new behaviors in a social context, allowing for experimentation with variables like information dissemination, peer pressure, or leadership styles.

Besides, it is in complex systems that shows more flexibility, such as in understanding the spread of epidemics. By modeling agents as populations with varying health conditions, movement patterns, and social behaviors, researchers can simulate how diseases propagate through communities. Adjusting parameters like infections rates or even population densities could lead to multiple outcomes, all of which would allow to observe how different factors influence the spread of the disease, as well as testing various intervention strategies.

## Framework Concept Definition

In this section of the paper, we will propose a structured, adaptable approach to building simulation models. However, beforehand, it might be convenient to have clear whether your research would benefit from this framework or not. In order to know this, you might find some help in the decision workflow depicted in Fig. [1.](#_heading=h.1t3h5sf) If you reached the decision of considering GABM, the next paragraphs might be of high interest.

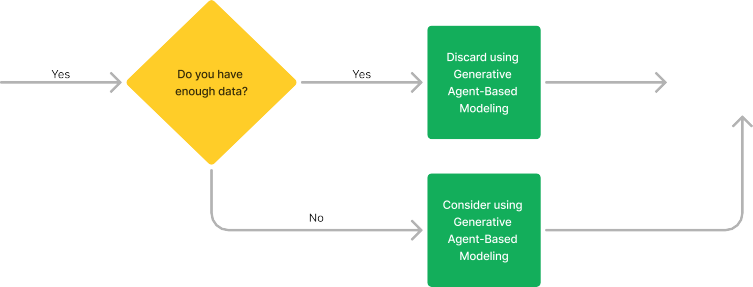
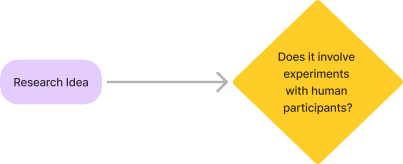


Figure 1: Workflow for determining the need for Generative Agent-Based Modeling (GABM).

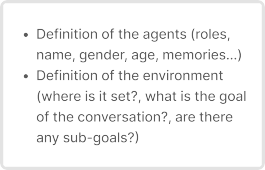
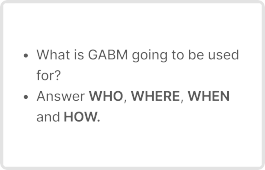
The approach for developing a Generative ABM project can be broken down into several key stages:

* + 1. **Conceptualization:** The first stage involves clearly defining the research objectives and identifying the problem that the GABM will address. The researcher might already have this clear after having used the diagram from above. In any case, this phase also requires thoughtful consideration of the simulation itself: determining who the agents will represent (individuals, groups, or organizations), when the simulation will occur (specific time periods, real-time or hypothetical scenarios), where it takes place (within a defined environment like a market, network, or geographic location), and how the agents will interact with one another and their environment. These aspects are crucial for building an effective and realistic model that will yield insightful results.
    2. **Tool Selection and Configuration:** For managing the simulations, Concordia will be used as the primary tool. However, it is equally important to choose an appropriate Large Language Model, such as Mistral or

ChatGPT. Additionally, securing an API key for the selected LLM is important to integrate its capabilities into the simulation, ensuring that it can handle the complexity of agent behaviors and environmental interactions.

* + 1. **Agent and Environment Design:** In this stage, the agents and the environment are carefully designed. Agents are defined with characteristics such as personality traits, age, gender, name, and memories, which influence their behaviors and decision-making processes. The environment is configured to replicate the setting where these interactions will take place.
    2. **Execution and Simulation:** After the design phase, the model is executed. Agents interact with each other and their environment, generating data that reflects the dynamics being studied. During this stage, researchers can observe emergent behaviors and adapt the model as necessary.

Observe in Fig. [2](#_heading=h.4d34og8) a summary of the approach for carrying out a project. This figure outlines the key steps involved, starting from the initial stage of conceptualization to the model execution and simulation stage.



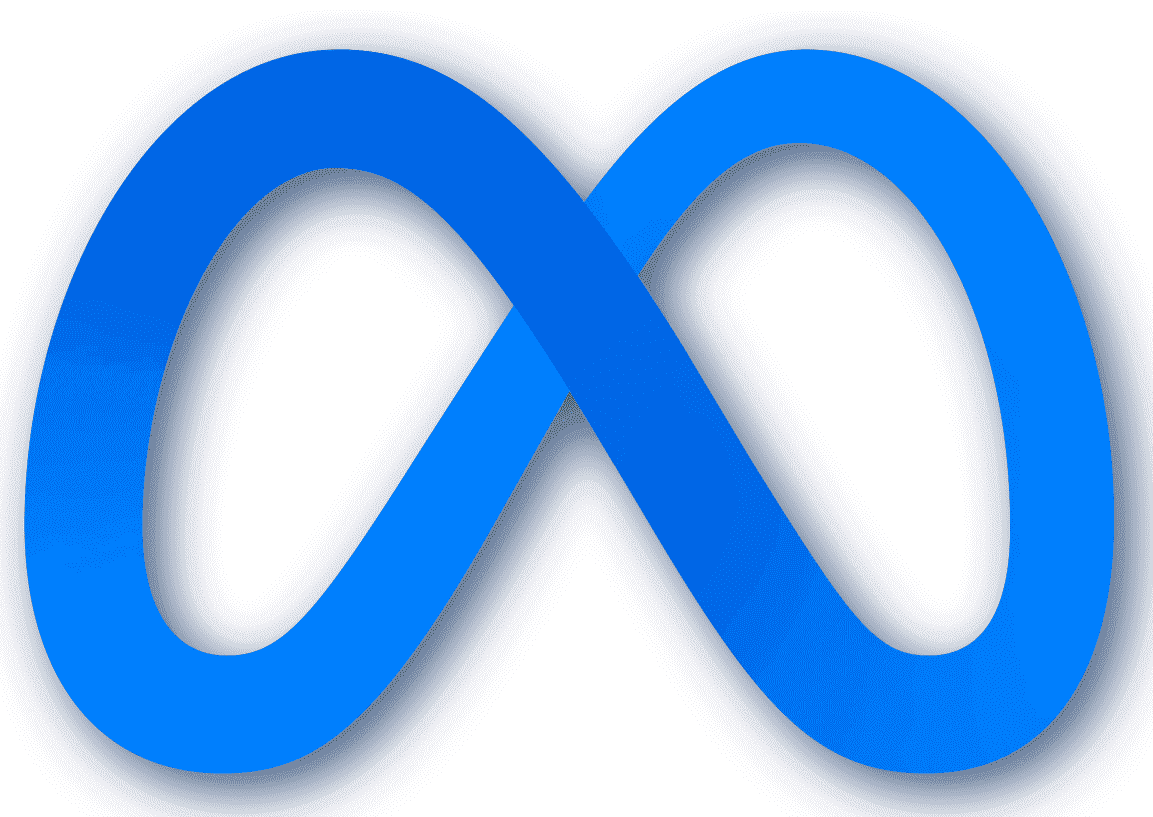
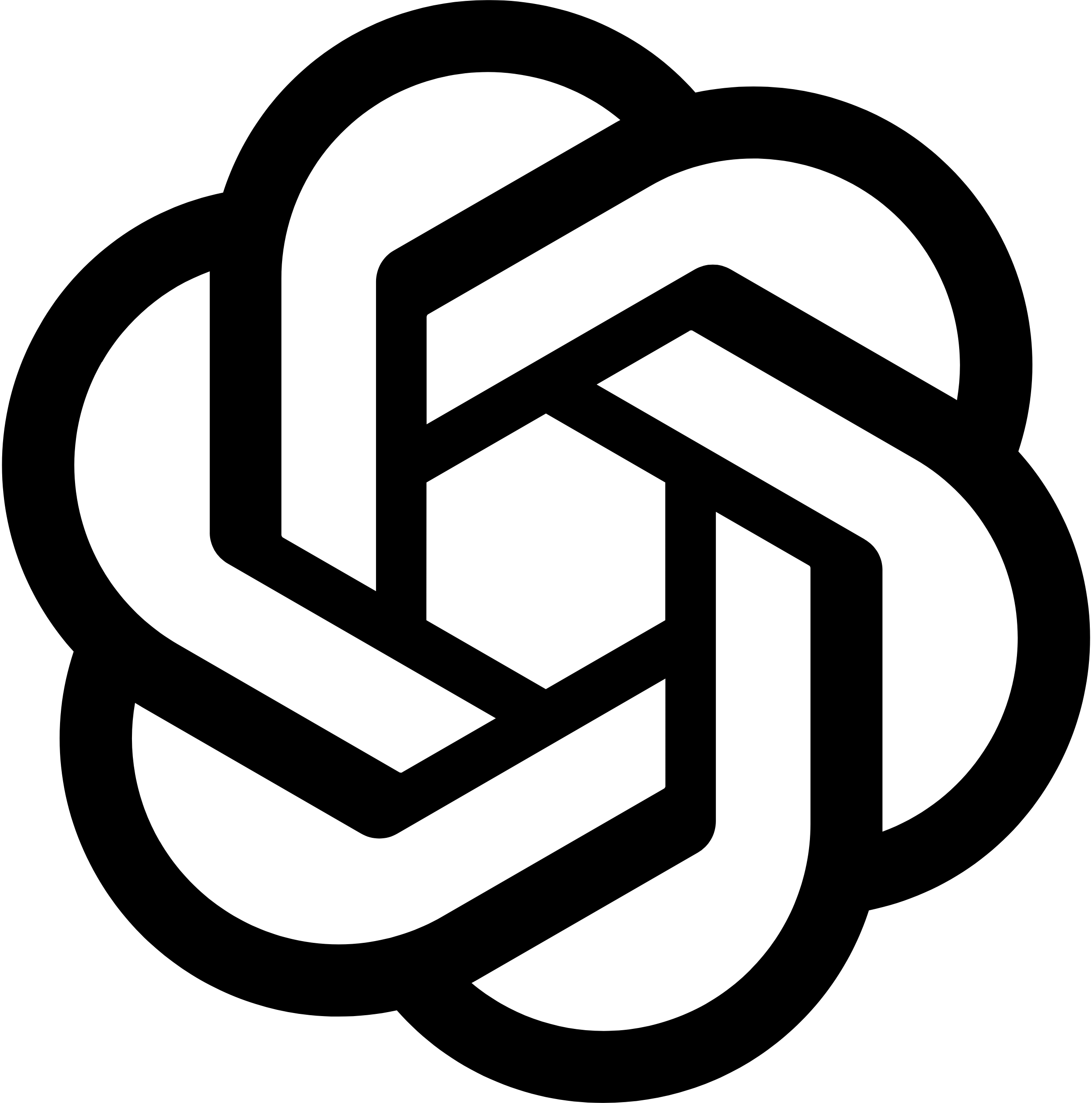
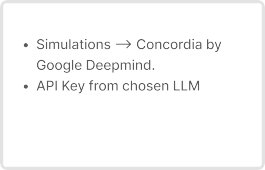


Figure 2: Summary of the steps needed to carry out a GABM project.

# Methodology

This section provides a step-by-step guide to implementing the steps outlined in Section [2.](#_heading=h.1fob9te) Unlike the previous section, which focused on theory, this one offers a practical approach, enabling the reader to carry out a project involving this type of modeling.

To illustrate this, we will use a research case of simulating the spread of information in a social network. By going through all the stages from Fig. [2,](#_heading=h.4d34og8) we will give some shape to this case, detailing the necessary actions and considerations to guarantee a reliable experiment.

## Step 1: Conceptualization

In this initial stage, the researcher defines the overall goal of the simulation. To facilitate this process, it can be helpful to pose exploratory questions, such as: “How quickly does information spread among friends on social media?” or “What role does user influence play in sharing news?”

These questions serve as a foundation for establishing a clear objective for the project. From these, we can define the objective of understanding how information spreads through a network of users when exposed to various factors, such as social influence and user engagement.

Once the target is defined, we can begin to consider the who, when, where, and how through a thought process, like the one shown below:

* **WHO:** Who are the agents in the simulation? Are they social media users, influencers, or a specific de- mographic? What age range and interests do these users have?, How are the agents connected (e.g., friend relationships, follower-following structure)?
* **WHEN:** What is the duration of the simulation (e.g., a week, a month)? Are there specific events or triggers that initiate the simulation (e.g., the release of a new story or viral content)?
* **WHERE:** What social media platform or type of network will be simulated (e.g., Twitter, Facebook, Insta- gram)? Are there specific features of the platform that need to be considered (e.g., hashtags, groups, stories)? How will the layout of the environment be structured (e.g., user profiles, news feeds)?
* **HOW:** What types of actions will agents take (e.g., likes, shares, comments)? Are there rules governing these interactions (e.g., thresholds for sharing or commenting)? How will agents’ behaviors change based on feedback or other agents’ actions?

## Step 2: Tool Selection and Configuration

The tools selected for the simulation are crucial to ensuring the project meets its objectives. For this guide, Concordia will be the platform used to manage the interactions. An important aspect of this process is selecting an appropriate LLM, as it plays a significant role in simulating realistic conversations.

When choosing an LLM, it’s essential to consider factors such as model accuracy, training data, and cost. A well-trained model can provide more accurate and contextually relevant responses, enhancing the realism of user behavior in the simulation. Additionally, evaluating pricing options is important to ensure that the selected model aligns with the project’s budget while still meeting the required performance standards.

The LLM is integrated into the Concordia platform using an API key and the model name, and it is adapted to support a range of models, including not only ChatGPT but also Mistral or Gemma.

## Step 3: Agent and Environment Design

In this third stage, we are going to incorporate the characteristics of the agents with the library. These are designed using the many components that are available with Concordia, allowing us to define not only the age or the name of the agent, but also an entire memory full of information.

We can include attributes such as age, interests, friend connections, and political ideologies. In the example we have been working on, it might be useful to consider traits like trustworthiness, susceptibility to influence, emotional state, and engagement level, which can affect how likely users are to share or engage with information.

The final step of this stage would be to give a full context of the environment where the simulation is set. The environment is provided as a common context that all agents interact with. In our case, the social media platform acts as the shared environment where users navigate and engage. For instance, we will specify that all agents (representing users) have access to a generic platform where they can view a news feed, like posts, share content, and comment on discussions.

The shared context might include information such as, "The platform allows users to post updates, follow others, and engage with trending topics," or "Influential users have more followers, which increases the spread of their posts." For example, in a simulation, users could share knowledge like, "Posts with images are more likely to be shared," or "Comments from verified accounts receive more engagement." This contextual setup ensures that each agent uses the platform in a manner that reflects real-world user behaviors.

## Step 4: Execution and Simulation

Once the agents and the environment are defined, it is time to generate the simulations. This is done by means of a Game Master (GM). It balances LLM calls and associative memory retrieval, overseeing the simulation of the environment where the agents interact. When agents decide on actions, they express their intentions in natural language, and the GM interprets these actions, translating them into appropriate implementations within the simulation.

In Concordia, we can simulate conversations and interactions between agents by setting up structured rounds of exchanges. Throughout these rounds, agents can generate observations and respond based on the evolving scenario. These interactions are monitored and plotted using various metrics, such as how agents’ opinions of others evolve over time or how their behaviors shift during the simulation. The system allows us to visualize these metrics through detailed plots.

At the end of the simulation, we can generate summaries of the episode by compiling all the interactions and memories of the GM. These summaries can be structured as a news report, capturing the sequence of events in a narrative format. We can also produce a personalized summary for each agent, giving a perspective of what happened to them during the simulation.

Finally, we can build a comprehensive HTML log of the entire experiment. This log can display the complete sequence of events, the GM’s memory, and the perspectives of each player. This allows for easy analysis and visualization of how the simulation progressed, giving insight into the social dynamics at play.

# Demonstration

1. **Conclusion and Future Work Acknowledgments**

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