Exploring the Role of Generative AI in Advancing Agent-Based Model Design and Implementation

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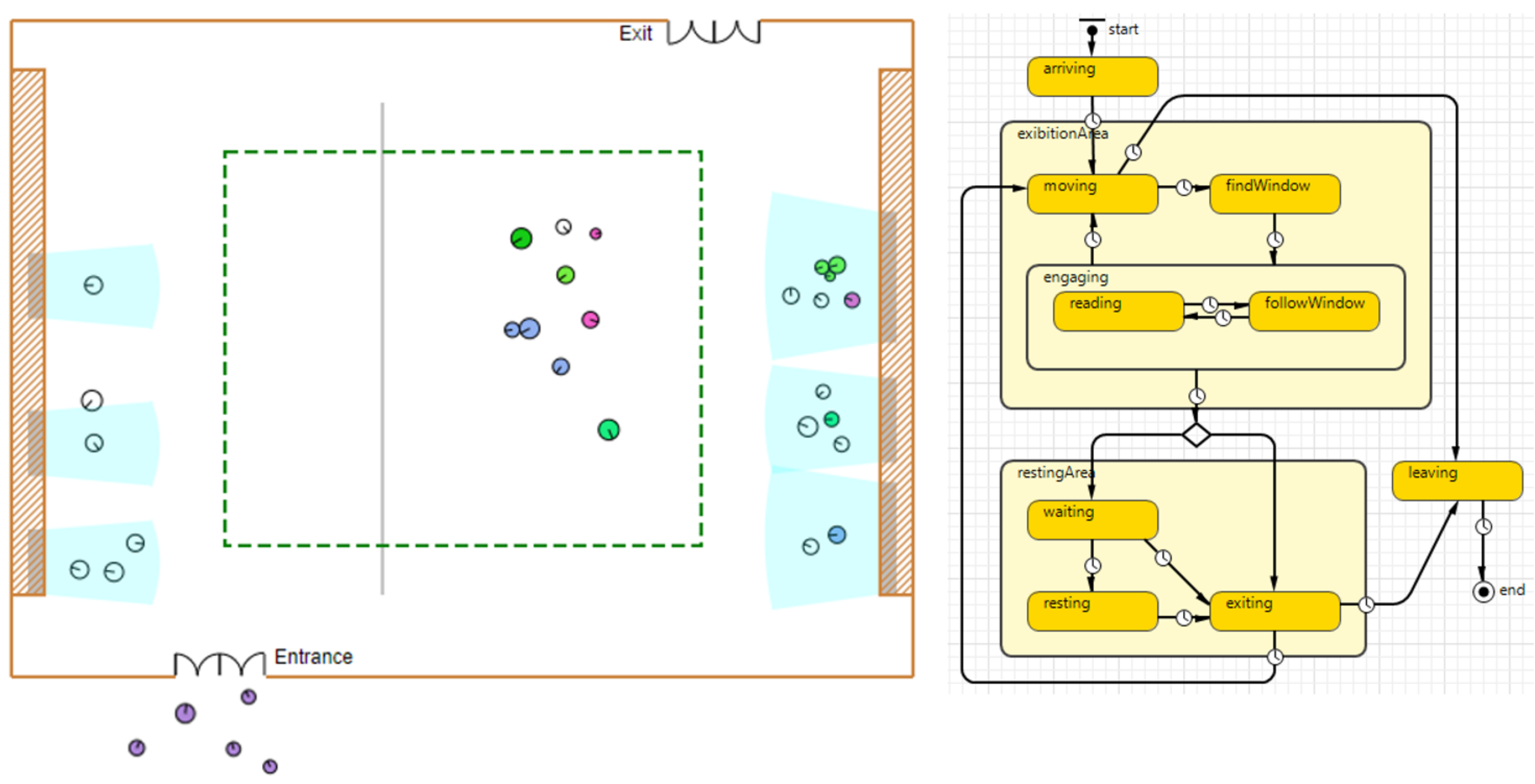
Agent-Based Modelling and Simulation

Simulation modelling refers to the process of creating virtual worlds that mimic real-world systems. It can be thought of as a digital laboratory where experiments can be conducted without any risk. In Agent-Based Modelling (ABM), a complex system is represented by a collection of agents programmed to follow often very simple behaviour rules. These agents interact with each other and their environment, producing complex collective behaviour patterns. Agents can represent individuals or groups; for example, a household agent may contain individual household member agents. ABM is widely used in fields such as economics, biology, operations research, and social sciences to model phenomena like market dynamics, predator-prey interactions, traffic flow, or disease spread. It typically utilises diverse data, including behavioural, demographic, and spatial information, to create simulations that reflect real-world scenarios and offer insights into how individual actions lead to collective outcomes.



Understanding GAI Terminology

To effectively use *Generative AI*, it is essential to understand the terminology surrounding this emerging subfield of AI. As of June 2024, no reliable glossaries were available, so we developed our own.

Application Layer

APIs and SDKs provide easy access to generative AI models for developers (e.g. OpenAI API; Gemini API)
Application Development Tools help developers to build the user interface (e.g. Flask)
End User Applications are the final products that users interact with (Chatbots (e.g. ChatGPT UI; Gemini UI); Content Creation (e.g. Midjourney; Synthesia); Virtual Assistants (e.g.Amazon Alexa; Google Assistant) Legal Apps (e.g. LexMachina); Financial Apps (e.g. AlphaSense) Code Generation Apps (e.g. GitHub Copilot))

Model Layer

Foundation Models are trained on massive amounts of heterogeneous data (e.g. GPT-4; Gemini)
Specific Models result from training foundation models on large datasets of specific content types (e.g. ChatGPT (conversation); DALL-E2 (text-to-image))
Specialised Models are tailored to specific domains, use cases or customers (ClaraHealth (healthcare domain); LegalSifter (contract review use case))
Model Hubs act as a central repository for accessing pre-trained models developed by various organisations or researchers (e.g. HuggingFace)

Infrastructure Layer

Hardware Platforms equipped with optimised chipsets (Graphics Processing Units (GPUs) from Nvidia or AMD, Tensor Processing Units (TPUs) from Google)
- **Cloud Platforms** as remote delivery systems for computing resources (e.g. Google Cloud TPUs, Amazon Elastic Compute Cloud (EC2), Microsoft Azure)
- **Storage Platforms**: High-performance storage systems from companies like NetApp, Dell EMC

Connectivity Platforms (wired and unwired) providing access to the cloud (e.g. BT, Virgin Media, Sky Broadband, TalkTalk)

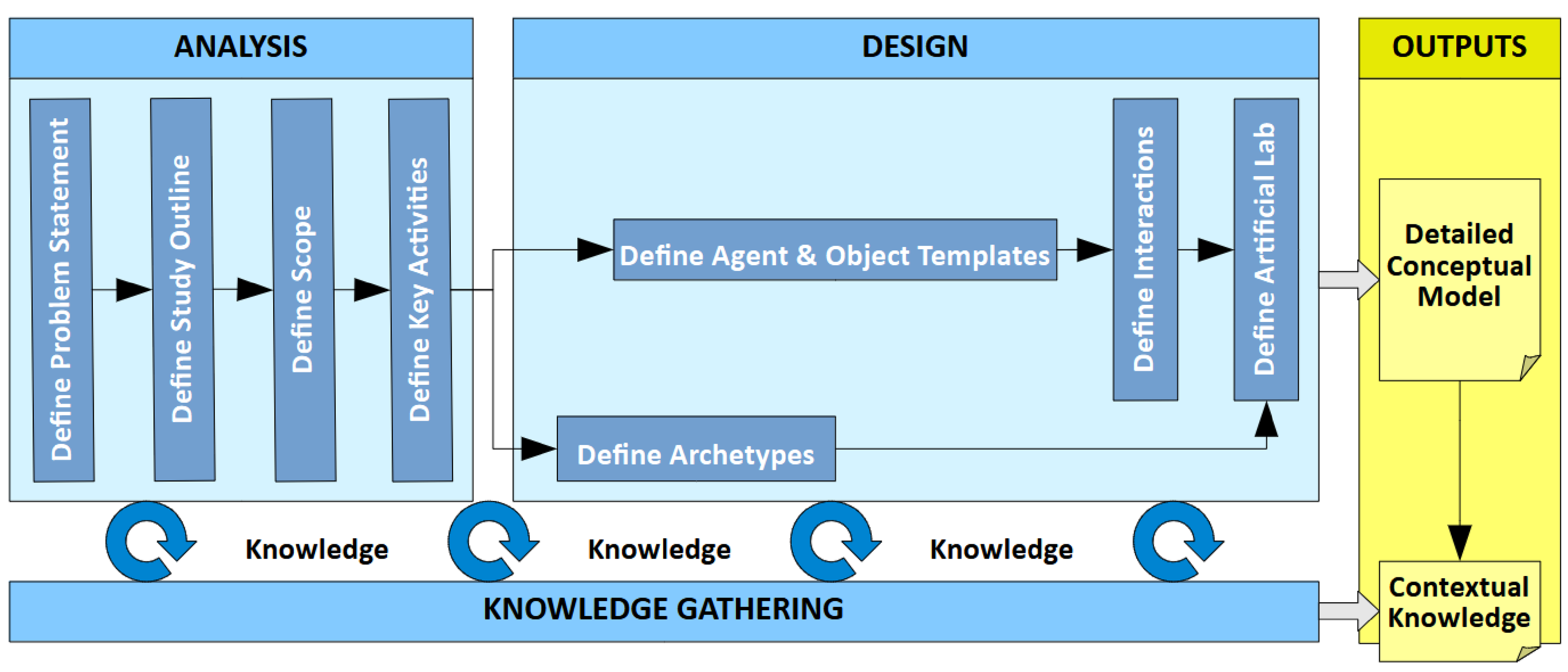
From Qualitative Evidence to Rules with the Help of GAI

Incorporating *Generative AI* into the analysis of qualitative data, such as interviews, reports, or news articles, enables the automatic extraction of patterns to derive behavioural personas or decision rules. This process allows for more accurate modelling of human behaviour, providing a solid foundation for agent-based simulations. Through advanced natural language processing techniques, *Generative AI* offers a novel approach to data-driven rule creation.

Our current research aims to develop a robust methodology for converting qualitative evidence into actionable rules that can be effectively integrated into ABMs, enhancing the realism and predictive power of these models. This project is a collaborative effort within the research community. Our objectives include developing a systematic, automated approach for extracting rules from qualitative sources, investigating how to integrate these rules into ABM design to inform agent behaviour and interactions, and establishing benchmarks for evaluating rule quality. We also aim to validate the rules against manually derived ones and apply the methodology to diverse case studies to demonstrate its effectiveness across different domains.

Model Co-Creation with GAI and the EABSS Framework

The Engineering Agent-Based Social Simulation (EABSS) framework allows the co-creation of conceptual ABMs in a structured way. We have developed a concept that demonstrates how *Generative AI* can facilitate the development of innovative ABMs in a concise timeframe and with minimal required upfront case-based knowledge. By employing advanced prompt engineering techniques and adhering to the EABSS framework, we have constructed a comprehensive prompt script that enables the design of ABMs with or by the *Generative AI*.



Reference: Siebers (2024) Exploring the Potential of Conversational AI Support for Agent-Based Social Simulation Model Design. https://arxiv.org/pdf/2405.08032

From Conceptual Model to Implementation with GAI

Traditional approaches to implementing ABMs often rely on extensive manual coding, which creates a major bottleneck in the development process. However, the recent advancements in *Generative AI* technology present an exciting opportunity to improve this workflow.

Our current research involves fine tuning an LLM for the use in the field of Social Simulation, designing prompts that translate UML diagrams derived from the previously generated conceptual ABM into executable GAML code for the Gama platform, a modelling and simulation environment for creating and running spatially explicit agent-based simulations, and evaluating the quality of the derived scripts.

Generating Synthetic Populations for Simulations Using GAI

Generating synthetic populations involves creating realistic, representative datasets of individuals or households to simulate real-world populations in models. These synthetic populations are built using demographic, geographic, and behavioural data, often drawn from census or survey sources. By reflecting key characteristics of real populations, synthetic populations allow for more accurate, scalable simulations.

Our current research focuses on creating synthetic populations for cases in which real-world data is missing or has gaps, combining the power of *Generative AI* and machine learning to improve the quality of the generated synthetic population. This approach enhances the ability to model complex systems where data scarcity or inconsistency would otherwise limit the credibility of the simulation results.

The Future

Utopian Dreams about AI

- AI Assistants: AI assistants seamlessly integrated into our lives, managing schedules, personalising healthcare, and providing real-time education
- Supercharged Science: AI could accelerate scientific discovery, leading to breakthroughs in medicine, materials science, and clean energy
- Enhanced Creativity: AI could collaborate with artists and designers, leading to new forms of artistic expression and innovation
- Personalised Learning: AI tutors could tailor education to individual students' needs, maximising learning potential
- Robotic Workforce: Advanced robots could handle dangerous or repetitive tasks, freeing up humans for more creative and strategic work

Dystopian Fears about AI

- Fear of Being Replaced: This is the worry that AI will automate jobs and make human skills obsolete
- Misinformation and Deepfakes: Generative AI could be used to create very realistic but fake videos or text, making it difficult to distinguish truth from fiction
- Loss of Control: As AI gets more complex, some fear we might not understand how it works or be able to control its decision-making

Where are we going to be in 10 years?