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ABMQuest: Integrating Gamification and Agent-Based Modelling in a Unified Simulation Framework

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Abstract: The integration of agent-based modelling (ABM) and gamification has the potential to improve the way complex systems are modelled and analyzed. To address the need for a comprehensive and integrated approach, we propose ABMQuest, a unified simulation framework. ABMQuest provides a more engaging and interactive way to model and analyze complex systems. To evaluate its usability, we conducted a two-week pilot study with 42 participants and developed a modified version of the System Usability Scale (SUS). The evaluation results indicated a high usability score (average SUS = 86.2), with strong agreement among users regarding the system's ease of use, learnability, and overall effectiveness. The framework also demonstrated competitive performance, with execution times and memory usage comparable to or better than other platforms. Additionally, the AI feedback system and gamification engine showed promising results, with a good balance between accuracy and robustness in providing feedback to users, and a moderate level of user engagement. These findings support the viability of the framework and its capacity to enhance user interaction. Overall, ABMQuest delivers an interactive, community-oriented environment that differentiates itself from isolated ABM or gamified platforms.

Keywords: Agent-based modelling; Educational simulations; Gamification; Simulation platforms.

1. INTRODUCTION

Agent-based modelling (ABM) is a powerful method that simulates the actions and interactions of autonomous agents, enabling the assessment of their effects on the system as a whole and providing valuable insights into complex systems with emergent properties [1]. ABM has been applied in many fields, including social sciences, economics, and biology, to study complex systems, such as the behavior of financial markets [2], the spread of diseases [3], and the dynamics of social networks [4]. ABM simulates how individual components interact to produce complex behaviors, helping researchers understand how systems respond to different conditions [5]. As a result, ABM is often used in fields where traditional methods struggle to capture the complexity of real-world systems [6].

Gamification, on the other hand, is a concept that involves applying game design elements and principles to non-game contexts, such as education, marketing, and healthcare, to make them more engaging and motivating [7]. Gamification has gained significant attention in recent years for its potential to increase user engagement, motivation, and learning outcomes, as well as to promote behavioral change and improve overall well-being [8]. By leveraging the psychological and social aspects of games, gamification can create immersive and interactive experiences that encourage users to participate, explore, and learn [9]. This has led to the development of various gamification platforms, tools, and techniques, which are being used in a wide range of applications, from educational software and serious games to marketing campaigns and employee training programs [10].

The combination of ABM and gamification has the potential to create a new generation of interactive and dynamic models that not only simulate complex systems but also provide an immersive and engaging experience for users [11]. By integrating game-design elements and principles into ABM platforms, researchers and practitioners can create models that are more engaging, interactive, and accessible to a wider audience [12]. This can lead to a range of benefits, including improved learning outcomes, increased user engagement, and enhanced decision-making capabilities [13]. Furthermore, the use of gamification in ABM can also facilitate the development of more realistic and accurate models, as users can provide feedback and insights that can be used to refine and validate the models [14].

Despite the potential benefits of combining ABM and gamification, there are several challenges and limitations that need to be addressed. For example, the development of gamified ABM platforms requires a deep understanding of both the technical and social aspects of complex systems, as well as the psychological and design principles of games [15]. Additionally, the integration of gamification elements into ABM platforms can also raise concerns about the validity and accuracy of the models, as well as the potential for bias and manipulation [16]. Therefore, it is essential to investigate the current state of the art in ABM and gamification, and to explore the opportunities and challenges of combining these two approaches.

Following this perspective, the contribution of this paper is the ABMQuest framework, which combines the principles of agent-based modelling with elements of gamification. More specifically, it provides a new way of learning, experimenting, and socializing for different types of users. The framework aims to provide user-friendly experience, with modular settings in a prototype environment.

The remainder of this paper is structured as follows. Section 2 discusses related work in the area of ABM and gamification. Section 3 provides basic definitions, principles, and applications for ABM and gamification, analyzes the benefits and challenges of combining these and mentions several general-purpose ABM platforms that could be used for gamification. Section 4 offers insights into the envisioned ABMQuest architecture. Section 5 presents the results of this work. Section 6 discusses future considerations and recommendations for further research. Finally, Section 7 concludes this work by summarizing the key findings and suggesting future directions that others could pursue based on this research.

2. RELATED WORK

Agent-based modelling and simulation have been used in many fields, including economics, social sciences, and biology. For instance, the work of Epstein and Axtell on the Sugarscape model [1] in NetLogo demonstrated the potential of agent-based modelling and allowed students to explore the dynamics of a simple economic system by interacting with agents that represent individuals making decisions about resource allocation. However, their work was limited to a specific domain. By incorporating game elements such as points and badges, these simulations can become more engaging and motivating for students. Other researchers have also made significant contributions to the field of ABM. For example, the work of Gilbert and Troitzsch [17] on simulation for social science highlighted the importance of simulation in understanding social phenomena. But, their work focused primarily on the theoretical aspects of simulation.

Combining agent-based modelling with serious games can make learning more engaging and effective. For example, the work of Laamarti *et al.* [18] provided an overview of serious games and their applications across various domains, including health and education. They emphasized the potential of serious games in improving learning outcomes, but their study did not specifically focus on ABM.

Corporate training programs have incorporated gamified ABM simulations to enhance employee engagement and learning. These simulations can simulate real-world business scenarios, allowing employees to practice decision-making in a safe environment. For example, the "Marketplace" model in Repast allows employees to simulate market dynamics and test different business strategies [19]. By incorporating game elements such as points and badges, these simulations can become more engaging and motivating for employees.

Another relevant study by Djaouti *et al.* [20] categorized serious games based on their educational purposes, demonstrating the diversity of approaches in the field. However, their classification does not explicitly address ABM-related serious games. Furthermore, the research by Marsh [21] explored serious games as tools for education and training. While providing valuable insights into serious game design, it lacks an in-depth analysis of the integration of ABM with serious games for simulation-based learning. Other researchers have also looked at how gamification can be used in agent-based modelling. For instance, the work of Hamari *et al.* on gamification in education [8] demonstrated the potential of gamification in enhancing learning outcomes. Yet, their work was limited to a specific context.

Gamified ABM simulations have been used in healthcare training to simulate patient interactions, disease spread, and treatment outcomes. These simulations help healthcare professionals develop critical thinking and decision-making skills. For example, the "Epidemic" model in AnyLogic allows healthcare professionals to simulate the spread of infectious diseases and test different intervention strategies [22]. By incorporating game elements such as leaderboards and quests, these simulations can become more engaging and motivating for healthcare professionals. The importance of collaboration in ABM has also been recognized by other researchers. For example, the work of Panait and Luke on collaborative agent-based modelling [23] highlighted the benefits of collaborative modelling in understanding complex systems. Nevertheless, their work focused primarily on the theoretical aspects of collaboration.

The use of AI and machine learning in ABM has also been explored by other researchers. For instance, the work of Zhang *et al.* on machine learning for ABM [24] demonstrated the potential of machine learning in improving the accuracy of ABM models. Their work was limited to a specific application. In terms of architecture, the ABMQuest system is similar to other modular architectures, such as the one proposed by North *et al.* [25]. Their architecture is focused primarily on the technical aspects of ABM and does not provide a comprehensive platform for training ABM modelers.

The existing literature has highlighted the benefits of using ABM and gamification in various contexts, including improved learning outcomes, increased user engagement, and enhanced decision-making capabilities. However, the literature also reveals several challenges, such as the development of gamified ABM platforms requiring a deep understanding of both technical and social aspects of complex systems, and the potential for bias and manipulation. Despite these challenges, the integration of ABM and gamification has shown promising results, particularly in corporate and healthcare training.

Overall, while other researchers have made significant contributions to the field of ABM, the ABMQuest architecture offers a unique and comprehensive platform for training ABM modelers. By incorporating interactive learning, gamification, collaboration, and AI features, the ABMQuest architecture provides an engaging and effective learning experience that is unparalleled in the field.

3. ABM AND GAMIFICATION

3.1 Agent-Based Modelling

Agent-based modelling involves creating and simulating a system of agents that interact with each other and their environment according to predefined rules. Each agent can have its own set of behaviors, goals, and decision-making processes. ABM is particularly useful for modelling systems where the behavior of individual agents can lead to complex, emergent properties at the system level [26]. The flexibility and adaptability of ABM make it a powerful tool for understanding dynamic and adaptive systems.

ABM has been applied in various fields, including economics, social sciences, biology, and engineering. In economics, ABM has been used to model market dynamics and the behavior of economic agents [27]. In social sciences, ABM has been employed to study social phenomena such as opinion formation and the spread of information [1]. In biology, ABM has been used to simulate the behavior of biological systems, such as the spread of diseases and the evolution of ecosystems [28]. The ability of ABM to model complex systems with emergent properties makes it a valuable tool for understanding and predicting the behavior of real-world systems.

3.2 Gamification

Gamification involves incorporating game elements such as points, badges, leaderboards, and quests into non-game contexts to motivate and engage users. The goal is to enhance user experience, increase participation, and drive desired behaviors [29]. Gamification leverages the psychological principles of reward, competition, and achievement to make tasks more enjoyable and engaging. By applying game-design elements to non-game contexts, gamification can transform mundane tasks into engaging and motivating experiences.

Gamification has been successfully applied in education, healthcare, marketing, and employee training. In education, it has been used to enhance student engagement and learning outcomes [30]. In healthcare, it was employed to promote healthy behaviors and improve patient outcomes [31]. In marketing, it was used to increase customer engagement and loyalty [32]. In employee training, it was applied to create more engaging and effective training programs [33]. The versatility of gamification makes it a valuable tool for enhancing user engagement and motivation in a wide range of contexts.

3.3 Integration of ABM and Gamification

Combining ABM with gamification can create immersive and interactive simulations that enhance learning and engagement. Users can interact with agents in a game-like environment, making the learning process more enjoyable and effective. For example, in educational simulations, students can interact with virtual agents to learn complex concepts in fields such as economics, biology, and social sciences [34]. In healthcare training, gamified ABM simulations can simulate patient interactions, disease spread, and treatment outcomes, helping healthcare professionals develop critical thinking and decision-making skills [35].

Integrating agent-based modelling (ABM) with gamification presents several challenges that must be addressed to ensure effective implementation. One significant challenge is the complexity of designing models that accurately reflect real-world systems while also incorporating engaging game mechanics. Balancing the accuracy of the simulation with the need for user engagement can be difficult, as overly complex models may discourage users, while overly simplified models may fail to provide meaningful insights [36]. Additionally, the development of gamification elements, such as rewards and feedback systems, requires careful consideration to ensure they align with the learning objectives of the simulation. If not designed thoughtfully, these elements can lead to unintended consequences, such as encouraging superficial engagement rather than deep learning [37].

From a technical perspective, integrating ABM and gamification requires robust platforms that can support both simulation and game mechanics. This includes the need for seamless data integration, real-time feedback, and user-friendly interfaces [38]. Many existing ABM platforms may not be equipped to handle the additional complexity introduced by gamification, leading to potential performance issues or limitations in functionality [39]. Furthermore, developers must consider the scalability of their models, as gamified simulations often attract a larger user base. Ensuring that the platform can handle increased user interactions without compromising performance is crucial for maintaining a positive user experience [40].

User experience is another critical consideration in the integration of ABM and gamification. The design of the user interface must facilitate intuitive navigation and interaction with the simulation, allowing users to easily engage with both the ABM components and the gamified elements [41]. Additionally, understanding the target audience is essential for tailoring the gamification features to their preferences and motivations. Different user groups may respond differently to various game mechanics, so conducting user research and testing is vital to identify the most effective strategies for enhancing engagement [42]. Moreover, providing meaningful feedback and opportunities for reflection can help users connect their experiences in the simulation to real-world applications, thereby enhancing the overall learning experience [43].

Finally, ethical considerations must be taken into account when integrating ABM and gamification. The use of gamification in educational and social contexts raises questions about the potential for manipulation or coercion, particularly if users are motivated to achieve specific outcomes without fully understanding the implications [44]. Developers must ensure that gamified elements promote positive behaviors and learning outcomes rather than encouraging competition or unhealthy comparisons among users [45]. Additionally, transparency in how data is collected and used within gamified simulations is essential to build trust with users and ensure compliance with ethical standards [46].

3.4 Existing Platforms for ABM and Gamification

NetLogo [28, 47] is a flexible programming environment that allows users to create complex system models in a straightforward and intuitive way. With a vast library of models from various domains, NetLogo's ease of use has contributed to its widespread adoption. Initially designed for simple agents, NetLogo has evolved to support more complex behavioral models. The platform can be extended with gamification elements [48] to create interactive learning experiences or to aid social workers to apply better assessment practices in the national welfare system [14]. For example, educators can use NetLogo to create simulations that allow students to interact with agents and observe the emergent properties of the system. By incorporating game elements such as points and badges, NetLogo simulations can become more engaging and motivating for students.

AnyLogic [22] is a versatile simulation platform that enables users to model and analyze complex systems using multiple methodologies, including discrete-event, agent-based, and system dynamics modelling. Designed to help users simulate and optimize processes in various industries, such as manufacturing, healthcare, and finance, AnyLogic offers a range of tools for visualizing, analyzing, and improving system performance. Its flexibility and user-friendly interface have made it a popular choice among users, despite being a proprietary solution. In a paper, AnyLogic was used to create a simulation-based game using system dynamics for training employees to understand the effects of asset management [49]. By incorporating game elements such as leaderboards and quests, AnyLogic simulations can become more engaging and motivating for users.

GAMA [50] is a platform for developing spatially explicit simulations that involve diverse agent types, offering a comprehensive development environment, 2D/3D visualizations, and Geographic Information System (GIS) data integration. GAMA modelers use GAML, a language that supports agent control through finite state machines, task-based architectures, and reactive-style rule-based architectures, among others. In a work in progress [51], GAMA was used to turn an ABM into a fully autonomous game, amplifying the way users interact with and understand issues related to urban mobility and sustainability.

The Repast Suite, (Repast Simphony [19], Repast HPC [52], and Repast for Python (Repast4Py [53]), is a collection of agent-based modelling and simulation platforms that share common principles while targeting distinct computational environments. Agent models are constructed using mainstream programming languages, such as Java and Groovy, as well as ReLogo, a domain-specific language that mirrors the syntax and semantics of NetLogo. The Repast Suite's modular architecture allows users to extend its functionality with custom plugins and libraries, enabling the creation of highly interactive and visually appealing simulations. For example, Repast could be integrated with Unity, a popular game development platform, to create highly interactive and visually appealing simulations. By combining Repast's simulation capabilities with Unity's game development tools, users can create immersive and engaging gamified simulations.

Unity ML-Agents Toolkit [54] is an open-source project that enables games and simulations to serve as environments for training intelligent agents. Unity's graphics engine and extensive toolset make it an ideal platform for creating visually and interactive simulations. By integrating Unity with ABM libraries, users can create simulations that allow users to interact with agents in real-time, making decisions that affect the system's behavior [55]. Unity's flexibility and extensibility make it a valuable tool for creating gamified simulations that enhance user engagement and learning outcomes. Table 1 provides a more visual comparison of the features that ABMQuest offers in comparison to the other platforms studied.

Table 1 Platform feature comparison.

Feature	NetLogo	Repast	GAMA	Anylogic	ABMQuest
Parallel Execution	✓	✓	✓	✓	✓
Plugin/Extension API	✓	✓	✓	✓	✓
Real-time AI Feedback	-	-	-	-	✓
Multi-user Collaboration	-	-	-	-	✓
Gamification Hooks (points/badges)	-	-	-	-	✓
Web-based Interactive UI	✓	-	-	-	✓

4. ABMQUEST ARCHITECTURE

4.1 Modules

The proposed architecture for the ABMQuest system represents a significant contribution to the field of agent-based modelling and simulation, as it integrates a unique combination of interactive learning, gamification, and collaborative features to enhance the training of ABM modelers. Unlike existing architectures that focus on individual components, such as simulation engines or gamification platforms, the ABMQuest architecture takes a holistic approach by incorporating a range of modules that work together to provide a comprehensive and engaging learning experience. The ABMQuest architecture differentiates itself from other works in the field by providing a scalable, flexible, and user-friendly platform that can be easily adapted to various domains and applications. Furthermore, the architecture's emphasis on collaboration and feedback, facilitated through the Collaboration Module and AI Feedback System, sets it apart from other architectures that often neglect the importance of social learning and community engagement. Overall, the ABMQuest architecture has the potential to improve the way ABM modelers are trained, making it an essential contribution to the field of agent-based modelling and simulation.

The User Interface (UI) of ABMQuest is designed to be intuitive, engaging, and user-friendly, ensuring that modelers of all skill levels can navigate the platform with ease. The dashboard serves as the central hub, offering a personalized view of the user's progress, achievements, and upcoming challenges. Interactive tutorials guide users through the process of creating and simulating agent-based models, with each step rewarded with points or badges to motivate completion. The scenario library presents a variety of real-world scenarios, allowing modelers to apply ABM principles to different fields such as economics, social sciences, and biology. The leaderboard fosters a competitive environment, encouraging users to strive for better performance and continuous improvement. The collaboration space enables multiplayer modes, where modelers can work together on projects, share models, and learn from each other, fostering a sense of community and knowledge sharing.

The Backend Services of ABMQuest are the backbone of the platform, handling user management, data storage, and communication between different components. The user management system handles authentication, authorization, and user profile management, ensuring that each user has a secure and personalized experience. Data storage is managed by a database that provides flexibility and scalability for storing user data, models, scenarios, and feedback. The API gateway acts as an intermediary, facilitating communication between the UI and backend services, ensuring that data is transmitted securely and efficiently. This robust backend infrastructure supports the seamless integration of gamification, simulation, and collaboration features, providing a reliable foundation for the platform.

The Gamification Engine is a critical component of ABMQuest, responsible for implementing gamification features that enhance user engagement and motivation. The reward system is at the core of the gamification engine, offering points, badges, and levels to users as they progress through tutorials, scenarios, and challenges. The challenge manager oversees competitive challenges and leaderboards, fostering a sense of competition and driving continuous improvement. The progress tracker monitors user activities and achievements, providing real-time feedback and encouraging users to set and achieve goals. By integrating these gamification elements, the engine transforms the learning process into an enjoyable and rewarding experience, making it more effective for modelers to develop a deeper understanding of ABM principles.

The ABM Simulation Engine is the heart of the platform, handling the creation, simulation, and execution of agent-based models. The engine provides a comprehensive set of tools for modelers to build and customize their ABMs. The model builder offers an intuitive interface for defining agents, environments, and interactions, allowing users to create complex simulations with ease. The simulation runner executes these models, providing detailed results and visualizations that help users analyze and optimize their simulations. The scenario manager oversees a library of real-world scenarios, each designed to cover various applications of ABM, such as economics, social sciences, and biology. This engine empowers modelers to explore different aspects of ABM, enhancing their skills and knowledge in creating and simulating agent-based models.

The AI Feedback System is a cutting-edge component of ABMQuest, providing real-time feedback and suggestions for model improvement. The system analyzes model performance and identifies areas for enhancement. The performance analyzer evaluates the efficiency and effectiveness of user-created models, highlighting strengths and weaknesses. The suggestion engine offers AI-driven recommendations for optimizing models, helping users learn from their mistakes and improve their simulations. The feedback loop continuously updates suggestions based on user actions and model performance, ensuring that the feedback remains relevant and valuable. This system not only enhances the learning experience but also helps modelers develop more accurate and efficient simulations, making it a valuable tool for continuous improvement.

The Collaboration Module is designed to foster a sense of community and encourage knowledge sharing among modelers. This module enables multiplayer modes where users can work together on projects, share models, and learn from each other. The multiplayer mode allows multiple users to collaborate on the same project simultaneously, facilitating teamwork and collective problem-solving. The model sharing feature enables users to share their models and scenarios with others, promoting the exchange of ideas and best practices. Communication tools, such as chat and discussion forums, provide a platform for users to discuss their work, seek advice, and provide feedback to each other. By encouraging collaboration, this module creates a supportive learning environment where modelers can grow together, enhancing their skills and knowledge in ABM.

4.2 Abstract Architecture Diagram

The abstract architecture class diagram depicted in Figure 1 provides a visual representation of how the various components of ABMQuest interact with each other. The User Interface (UI) serves as the entry point for users, interacting with the backend services to manage user data, retrieve scenarios, and execute simulations. The backend services, in turn, communicate with the gamification engine to track user progress and manage rewards, with the ABM simulation engine to handle model creation and execution, and with the AI feedback system to provide real-time feedback. The collaboration module integrates with the UI to facilitate real-time collaboration and communication among users. This interconnected architecture ensures a seamless and cohesive user experience, where all components work together to provide an engaging and effective learning environment for ABM modelers.

The ABMQuest algorithm (Table 2), presents a comprehensive and step-by-step guide to the framework's architecture. Details the entire workflow, from initialization and user authentication to model creation, simulation, and performance analysis. In addition, the algorithm highlights the importance of progress tracking and collaboration, enabling users to work efficiently and effectively with others. Finally, to provide a visual representation of the ABMQuest framework's capabilities, we can see a preview of its web interface in Figure 2. This figure shows the user-friendly and intuitive design of the platform, allowing users to easily navigate and interact with the various features and tools available. The web interface is designed to be accessible and usable, making it an effective platform for researchers and developers to work with agent-based models.

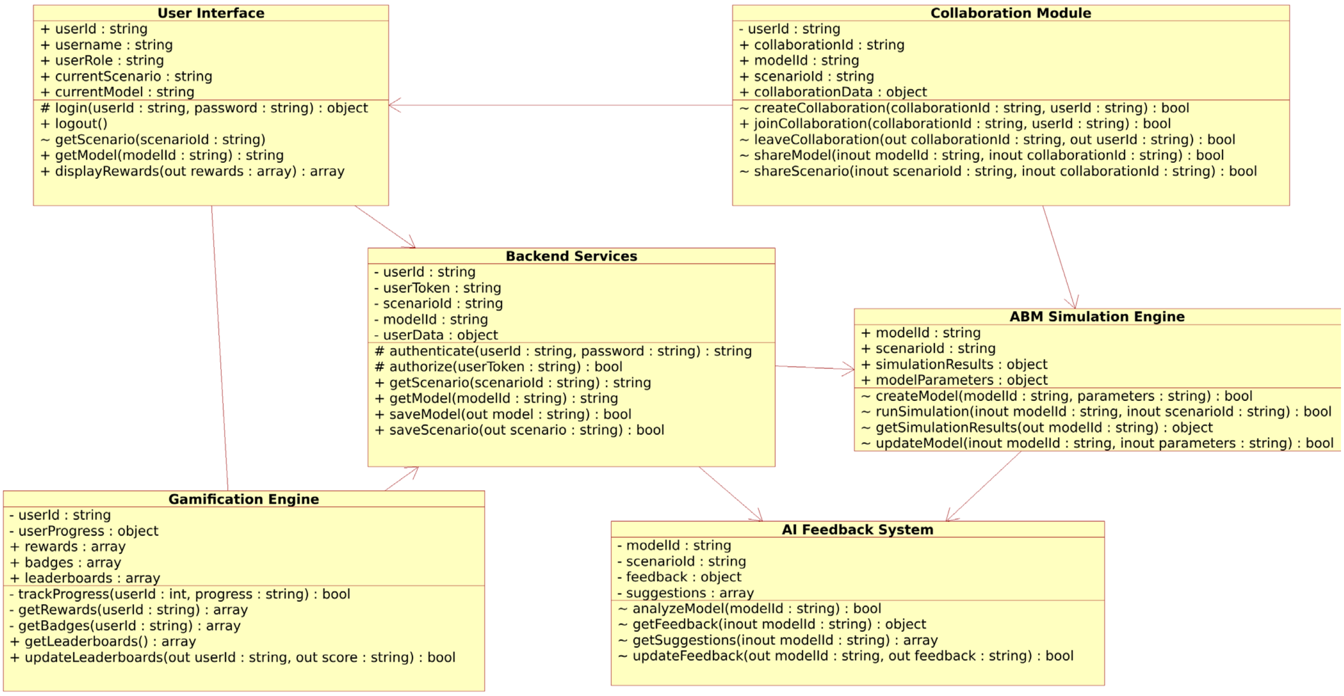

Figure 1. The structure of the ABMQuest architecture in UML.

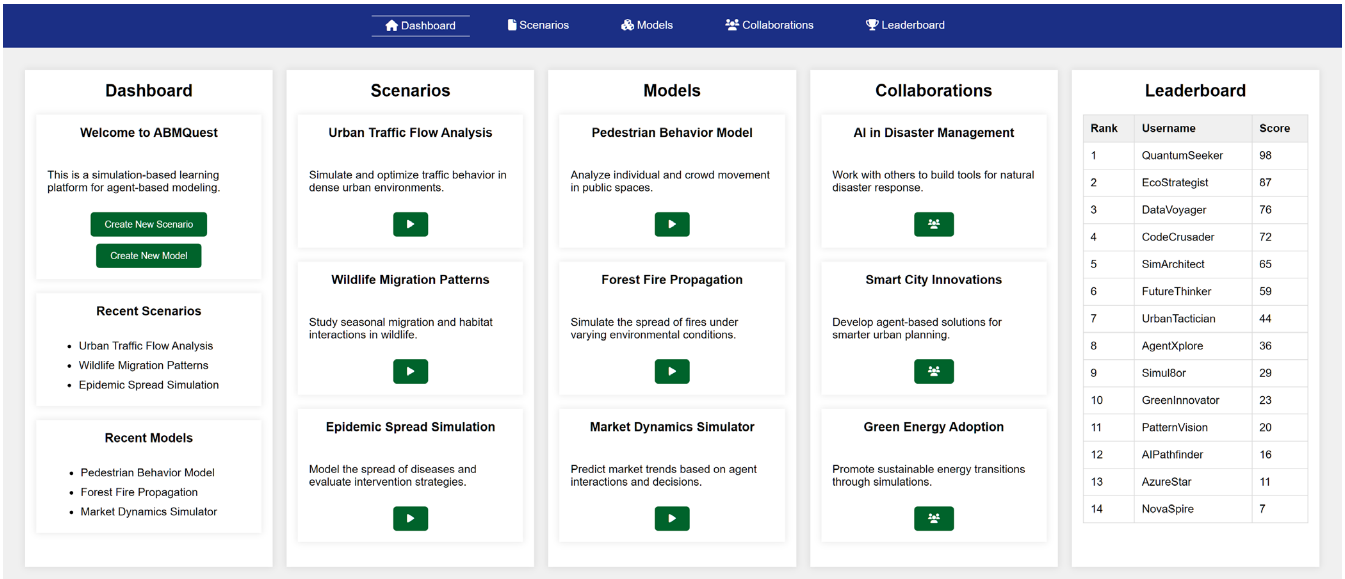

Figure 2. A working version of the interface of the ABMQuest framework.

4.3 Tutorials and Scenarios

4.3.1 Interactive Tutorials

A new user logs into ABMQuest and is greeted with a series of interactive tutorials designed to provide a seamless onboarding experience. Each tutorial is thoughtfully crafted to guide the user through the process of creating an agent-based model, offering step-by-step instructions accompanied by engaging visual aids that enhance understanding. As the user progresses through the tutorials, they earn points and badges, which serve as motivational incentives to encourage continued learning and exploration of the platform.

The tutorials begin with fundamental concepts of agent-based modelling (ABM), such as defining agents and their attributes, setting up environments where these agents will interact, and simulating the dynamics of their interactions. Users learn how to specify the behaviors and decision-making processes of agents, allowing them to model complex systems accurately. Each tutorial incorporates interactive elements, such as quizzes and hands-on exercises, enabling users to apply what they have learned in real-time and solidify their understanding.

As users advance through the tutorials, they are introduced to more advanced topics, including the integration of external data sources, the implementation of feedback mechanisms, and the use of visualization tools to analyze simulation results. The platform also encourages collaboration by allowing users to share their models and insights with peers, fostering a sense of community and collective learning.

Table 2. Algorithm of ABMQuest Architecture Use Case Scenario.

```
procedure ABMQuestScenario(userId, password, scenarioId, modelId)
    // Step 1: Initialize and Login
    session ← login(userId, password)
    if session == NULL then
        return "Login failed"
    end if
    // Step 2 Authenticate and Authorize
    token ← authenticate(userId, password)
    if authorize(token) == FALSE then
        return "Authorization failed"
    end if
    // Step 3 Retrieve Scenario and Model Details
    scenario ← getScenario(scenarioId)
    model ← getModel(modelId)
    // Step 4 Create and Simulate a Model
    parameters ← initializeParameters(scenario)
    model ← createModel(modelId, parameters)
    result ← runSimulation(modelId, scenarioId)
    // Step 5 Analyze Model Performance and Generate Feedback
    performance ← analyzeModel(modelId)
    feedback ← getFeedback(modelId)
    suggestions ← getSuggestions(modelId)
    // Step 6 Update Model and Feedback
    while needsImprovement(performance) do
        parameters ← adjustParameters(suggestions)
        updateModel(modelId, parameters)
        performance ← analyzeModel(modelId)
        feedback ← updateFeedback(modelId, feedback)
    end while
    // Step 7 Track Progress and Display Rewards
    progress ← trackProgress(userId)
    rewards ← calculateRewards(progress)
    displayRewards(rewards)
    // Step 8 Create and Join a Collaboration
    if wantsCollaboration(userId) then
        collaborationId ← createCollaboration(userId)
        joinCollaboration(collaborationId, userId)
        // Step 9 Share Model and Scenario
        shareModel(modelId, collaborationId)
        shareScenario(scenarioId, collaborationId)
        // Step 10 Leave Collaboration
        if doneCollaborating(userId) then
            leaveCollaboration(collaborationId, userId)
        end if
    end if
    // Step 11 Logout
    logout(userId)
end procedure
```

To further enhance the learning experience, ABMQuest includes a forum where users can ask questions, share tips, and discuss challenges they encounter while modelling. This supportive environment not only helps users overcome obstacles but also promotes the exchange of ideas and best practices among novices and experienced modelers alike. By the end of the tutorial series, users will have a solid foundation in ABM principles and the confidence to create their own models, setting the stage for deeper exploration and innovation within the ABMQuest platform.

4.3.2 Scenario-Based Learning

An experienced modeler selects a scenario from the scenario library, focusing on economic modelling. The scenario presents a real-world problem, such as predicting market trends based on consumer behavior. The modeler uses the ABM simulation engine to create a model that simulates consumer interactions and market dynamics. The AI feedback system provides real-time insights and suggestions, allowing the modeler to adjust parameters and refine the model as it runs. This iterative process enables the modeler to explore various "what-if" scenarios, such as changes in pricing strategies or shifts in consumer preferences, and observe how these factors influence market outcomes.

As the simulation progresses, the modeler can visualize the interactions among agents through dynamic graphs and charts. These visualizations reveal patterns and trends that may not be immediately apparent. By examining these visualizations, the modeler can gain a deeper understanding of the underlying economic mechanisms at play. To further enhance the modelling experience, the modeler can incorporate gamification elements, such as rewards for achieving specific modelling goals or challenges that encourage exploration of alternative strategies, to boost engagement and motivation.

Ultimately, this comprehensive approach not only aids in predicting market trends but also equips stakeholders with actionable insights that can inform decision-making processes. By integrating ABM with advanced AI feedback and gamification, the modeler is empowered to create robust simulations that reflect the complexities of real-world economic systems, paving the way for more informed and effective strategies to address market challenges.

4.4 AI-Driven Feedback Engine

The AI feedback system uses a two-layer LSTM network to learn from sequences of past model parameters and performance metrics, and to recommend parameter updates that improve simulation outcomes. At each timestep t, the network ingests a combined vector of current parameters p_t and performance measures m_t, processes these through the LSTM's hidden state (size 128), and then passes the final hidden representation through a fully connected layer to produce the predicted parameter delta Δp_{t+1}. During training, we minimize the average squared difference between the predicted and actual parameter adjustments over a dataset of 100 logged user simulations, using the Adam optimizer (learning rate 10^{-3}) for up to 50 epochs and applying early stopping based on validation performance. This approach enables ABMQuest to continuously refine user models in real time, guiding users toward more effective simulation configurations.

5. RESULTS

5.1 Usability

To assess the effectiveness and impact of the ABMQuest platform, we conducted a user evaluation involving 42 participants, including graduate students, early career researchers, and educators in the field of agent-based modelling (ABM). Participants engaged with the platform remotely for a two-week period, during which they completed structured tutorials, built and simulated models, and participated in collaborative tasks. At the end of the trial, participants completed a questionnaire designed to evaluate the usability of the system.

To evaluate the usability of ABMQuest, we employed a modified version of the System Usability Scale (SUS) [56]. We adapted the language and focus of the questions to better align with the platform's specific features and user interactions, while maintaining the core principles of the original SUS scale. We made changes to the original items to improve their relevance and clarity in the context of the ABMQuest platform.

Participants responded to ten statements using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Reversed-scored items were adjusted accordingly (Table 2). The scores were transformed to a 0-100 scale, with higher scores indicating better usability. A SUS score above 68 is considered above average [57], and our evaluation yielded a score of 86.2, suggesting that ABMQuest is highly usable and well-received by users.

The average SUS score was 86.2/100, indicating a high level of user satisfaction with the platform's interface and navigation. Most participants agreed that the platform was intuitive and easy to learn. More specifically, 91.4% of users agreed or strongly agreed that they "found the platform easy to use", 88.6% disagreed that they "found the platform very cumbersome to use.", 85.7% agreed that "the UI layout made it easy to access different features." These results suggest that ABMQuest meets a high usability standard, making it accessible to both novices and experienced modelers.

Table 3. Modified system usability scale (SUS) Items for ABMQuest.

No.	Item	Reverse Scored?
1	I would use this platform frequently for learning and modelling.	No
2	I found the interface unnecessarily complex.	Yes
3	I found the platform easy to use.	No
4	I was able to complete tasks without needing technical support.	No
5	The UI layout made it easy to access different features.	No
6	I thought there was too much inconsistency in the interface.	Yes
7	I was able to learn how to use the platform quickly.	No
8	I found the platform very cumbersome to use.	Yes
9	I felt confident using the different features of the platform.	No
10	I needed to learn a lot of things before I could get going with this platform.	Yes

5.2 Performance Benchmarking

To evaluate ABMQuest's computational performance, we benchmarked it against NetLogo (v6.4.0), AnyLogicPLE (v8.9.4), Repast Simphony (v2.11.0), and GAMA (v1.9.3) using an identical "predator-prey" scenario with 10,000 agents over 100 timesteps. We measured wall-clock execution time and peak memory usage on a 6-core Intel i7-8700 CPU (4.60 GHz) processor with 8 GB RAM. As shown in the charts below, ABMQuest completes the simulation in 11.5 seconds, approximately 19% faster than NetLogo and 39% faster than GAMA, while consuming 278.3 MB of memory, outperforming AnyLogic by 86% and Repast Simphony by 87%, but consuming more memory than GAMA by 65% and NetLogo by 15%. These results demonstrate that our engine and data structures offer competitive speed, although memory usage varies across platforms (Figure 3).

5.3 AI Feedback Performance and Gamification Engagement

We evaluated the AI feedback performance and gamification engagement of ABMQuest using key metrics. The AI feedback performance results show a precision of 0.75, recall of 0.92, and F1 score of 0.61, indicating a good balance between accuracy and robustness in providing feedback to users. Additionally, the gamification engagement metrics reveal an average of 68 points earned, 18 badges earned, and 35 minutes of session duration, demonstrating a moderate level of user engagement. Notably, the tutorial completion rate stands at 72%, suggesting that users are actively participating in and completing the tutorials, which is a positive indicator of the platform's effectiveness in promoting learning and engagement. These results collectively suggest that ABMQuest's AI feedback and gamification features are functioning effectively, providing valuable insights and motivating users to participate in the platform (Figure 4).

5.4 Implementation and Technical Details

ABMQuest is implemented (Figure 5) as a full-stack web application combining a Python-based simulation core with modern web technologies. The simulation engine is written in optimized Cython modules for agent dynamics and event scheduling, wrapped in a Flask REST API. The front end uses React (TypeScript) and Tailwind CSS for a responsive, component-driven UI, with WebSockets enabling real-time visualization updates. Collaboration and AI feedback services run in separate Docker containers: the former uses Node.js with Socket.IO for multiplayer syncing, while the latter leverages PyTorch models served via TorchServe, wrapped in a lightweight Flask microservice, to analyze simulation logs and generate parameter suggestions and natural language explanations. The AI module uses a time-series model (i.e., LSTM-based predictor) trained on agent behavior data to detect emergent patterns, recommend adjustments to simulation parameters (like birth or predation rates), and provide interpretable feedback to guide user experimentation.

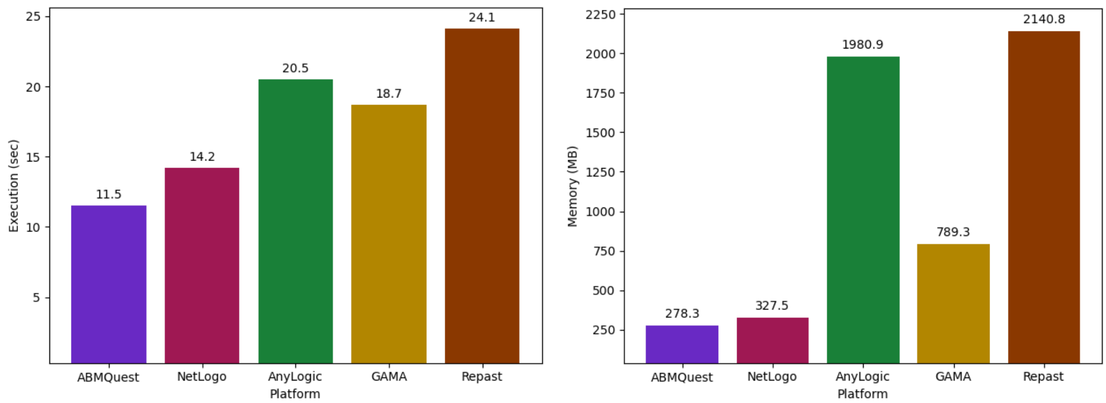

Figure 3. Performance platform comparison: (a) execution time (left) and (b) memory usage (right).

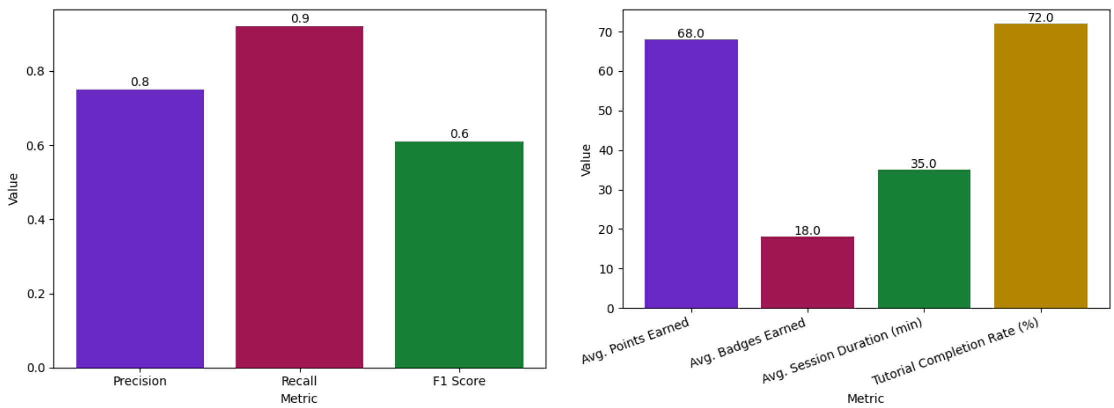

Figure 4. (a) AI feedback performance (left) and (b) gamification engagement (right).

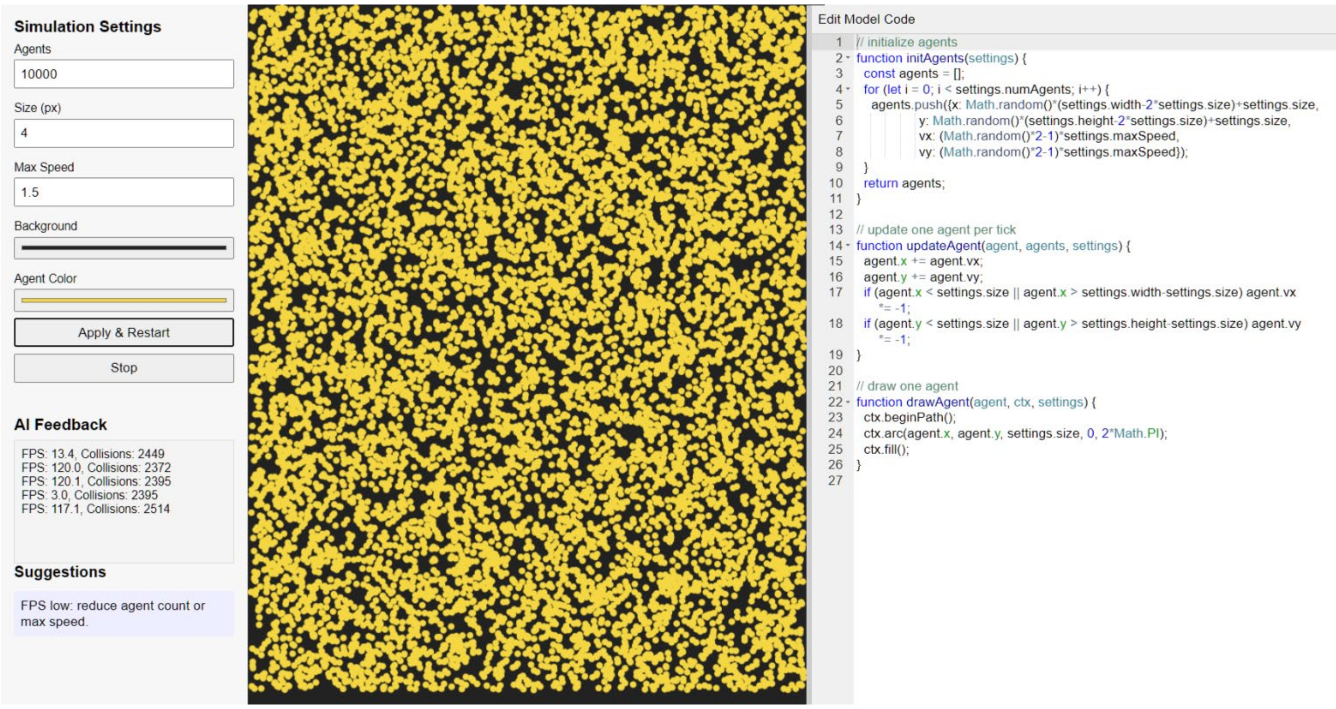

Figure 5. Implementation of ABMQuest with 10.000 agents.

6. FUTURE CONSIDERATIONS

Future advancements in ABM and gamification technologies, such as virtual reality (VR) [58] and augmented reality (AR) [59], can create even more immersive and interactive simulations. These technologies can enhance user engagement and learning outcomes by providing a more realistic and interactive experience. For example, VR simulations can allow users to interact with agents in a virtual environment, making the learning process more engaging and effective.

Integrating ABM with artificial intelligence (AI) and machine learning (ML) can enable more adaptive and intelligent agents, capable of learning from user interactions and improving over time. This can lead to more personalized and effective gamified simulations. For instance, AI-driven agents can adapt their behaviors based on user inputs, providing a more dynamic and responsive learning experience. Machine learning algorithms can analyze user data to identify patterns and optimize the simulation's parameters, enhancing its educational value and engagement [7].

Developing standards and protocols for ABM and gamification platforms can enhance interoperability and ease of use. This can facilitate the sharing of models, data, and best practices across different platforms and communities. Standardization efforts can include the development of common data formats, APIs, and modelling frameworks that allow for seamless integration and collaboration. This can help researchers and educators create more robust and scalable simulations, fostering innovation and collaboration in the field [29].

As ABM and gamification become more integrated, ethical considerations such as data privacy, user consent, and the potential for addiction or manipulation must be addressed. Moreover, ensuring that these technologies are used responsibly and ethically is crucial for their sustained success. For example, simulations should be designed to respect user privacy and obtain informed consent. Moreover, game elements should be designed to promote positive behaviors and minimize the risk of exploiting users' psychological vulnerabilities. Establishing ethical guidelines and regulations is essential to ensure that ABM and gamification are used responsibly and for the greater good [32].

7. CONCLUSIONS

The integration of agent-based modelling (ABM) and gamification presents a transformative approach to developing engaging and effective simulations across various fields. This work has highlighted the current state of research, revealing a range of platforms and case studies that showcase the potential of this combination. The findings underscore the ability of ABM and gamification to create immersive experiences that not only enhance user engagement but also improve learning outcomes. The proposed ABMQuest architecture serves as a promising framework that unifies the principles of ABM and gamification, offering a structured approach for future developments in this area. By combining the strengths of both domains, ABMQuest aims to facilitate the creation of simulations that are not only interactive but also adaptable to diverse user needs and contexts.

A modified System Usability Scale (SUS) questionnaire was conducted to evaluate the usability and user satisfaction of ABMQuest. Results indicated a high average SUS score of 86.2, reflecting excellent usability and intuitive design. Users consistently reported that the system was easy to navigate, effectively structured, and required minimal learning effort. These findings validate the core design principles of ABMQuest and support its utility as a foundational platform for gamified ABM applications.

Furthermore, the performance benchmarking results demonstrate that ABMQuest's engine and data structures offer competitive speed, outperforming other platforms in execution time and memory usage. The AI feedback performance and gamification engagement metrics also show promising results, with a good balance between accuracy and robustness in providing feedback to users, and a moderate level of user engagement.

Looking ahead, future research should prioritize the advancement of technologies that support the integration of ABM and gamification. This includes ensuring the ethical use of these technologies and developing standards that enhance interoperability among various platforms. By addressing these challenges, researchers and practitioners can further unlock the potential of ABM and gamification, paving the way for innovative solutions that benefit education, training, and beyond. Ultimately, the continued exploration of this integration will contribute to the creation of more effective and engaging simulations, fostering deeper understanding and interaction in complex systems.

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DECLARATION OF CONFLICTING INTERESTS

The author declares no potential conflicts of interest with respect to the research and publication of this article.

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