Multi-agent system for a semi-realistic simulation of animal behavior in an educational game about ecosystems

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Abstract. Introduction: *Educational games can support environmental education by allowing players to explore ecosystems interactively, yet animal behavior in these games remains underexplored, particularly regarding responses to environmental conditions and survival needs.* ***Objective:*** *This work presents a multi-agent system for semi-realistic animal simulation in GAIA, an educational game about Brazilian ecosystems, assessing agents' survival behaviors and players' perceptions.* ***Methodology:*** *The system was developed in Unity using C#, Finite State Machines, pluggable behaviors, Unity Navigation, and A* pathfinding. Agents make decisions based on spatial perception, time cycles, and internal needs (hunger, thirst, energy). Evaluation included simulation trials and a post-test questionnaire with 18 participants.* ***Results:*** *The agents portraying the four depicted species survived more effectively than a baseline agent, with statistically significant differences between the four species and the baseline. Participants reported positive perceptions of the animals' behavior and its contribution to the game experience, indicating that the proposed system is a promising foundation for semi-realistic animal behavior in educational ecosystem games.*

Keywords *Multi-agent systems, Artificial Intelligence, Ecosystem simulation, Educational games, Serious games.*

1. Introduction

Brazil has some of the most biodiverse biomes in the world, such as the Amazon and the Atlantic Forest, with an estimated 170 to 210,000 species [Lewinsohn e Prado 2005]. The Atlantic Forest, home to high biodiversity and endemic species, is a highly threatened and deforested biome [Marques e Grelle 2021] with only 28% of its original vegetation coverage remaining, mainly in small fragmented patches [Grelle et al. 2021].

Education on sustainability and conservation can improve student awareness [Boeve-de Pauw et al. 2015]. Educational games foster knowledge and values through engaging alternative methods, especially for younger people [Boncu et al. 2022]. Games such as Sea Adventure [Veronica e Calvano 2020] and Sustainable Planet: Mission Preserve [Ferreira Bezerra et al. 2025] have reported success in teaching about marine litter and solid waste disposal, respectively.

Observing animal behavior can support learning about species and ecological relationships by encouraging learners to formulate hypotheses [Dawkins 2007]. Semi-realistic representations may therefore provide educational opportunities related to fauna [Metcalf et al. 2023]. However, animal NPCs in games such as Minecraft [Mojang Studios 2009] and Don't Starve [Klei Entertainment 2013] generally respond to immediate stimuli or scripted temporal conditions without explicitly prioritizing internal survival needs. Scientific simulations model complex behavior through approaches such as reinforcement learning [Strannegård et al. 2022] and fuzzy logic [Turan e Çetin 2019], but are not necessarily designed as interactive educational experiences.

An agent is an autonomous system capable of perceiving and acting in an environment [Wooldridge e Jennings 1995]. A multi-agent system comprises multiple interacting agents [Wooldridge 2009]. In biological contexts, animal behavior consists of responses to environmental conditions and survival demands, including resource acquisition and threat avoidance [Davies et al. 2012].

In this context, a multi-agent system for semi-realistic simulation of animal behavior was developed using Unity and C# as part of GAIA, an educational game developed in parallel to teach players about Brazilian ecosystems, initially focusing on the Atlantic Forest. A Finite State Machine was implemented via pluggable behaviors, where decisions consider an animal's surroundings and needs. Animal movement uses Unity Navigation with A* pathfinding. The system performs essential survival actions: searching for food and water, sleeping, and defending itself. The game and systems followed the COMBO methodology [Luccas e Branco 2023]. The study was guided by two research questions:

- (RQ1) How well can agents survive through a game cycle in different Atlantic Forest-based ecosystems?
- (RQ2) How are agents' actions perceived by players?

To answer RQ1, the system samples attributes from all agents over multiple cycles. To answer RQ2, data were collected from participants (N=18) using a post-test 5-point Likert-scale questionnaire [Joshi et al. 2015]. The proposed system shows promise for semi-realistic animal behavior: agents survived significantly better than a baseline control and were well received in an initial test. The modular architecture allows future expansion of GAIA's content and behaviors.

2. Related Work

The related works discussed in this section were identified through an exploratory search conducted on Google Scholar in April 2026. The search strings included "virtual simulation games," "ecosystem model games," "multi-agent ecosystems," "multi-agent animal simulation," "ecological model artificial intelligence," and "animal behavior artificial intelligence." We prioritized studies that modeled animals or ecosystems using artificial intelligence and that described mechanisms related to spatial perception, temporal information, internal states, or survival behavior. Commercial games were included as design references because they informed the development of the proposed system, rather than as scientific evidence. Therefore, this section presents a focused comparison of directly relevant approaches and is not a systematic literature review.

Ecosystem models can take many forms, ranging from mathematical formulas [Wangersky 1978] to fully interactive virtual environments. In some cases, these models function as digital twins of real-world ecosystems, while in others they serve as experimental testbeds for exploring complex behaviors in which their environment may not always resemble natural biomes or real ecological scenarios [Sunehag et al. 2019].

In entertainment games such as *Minecraft* [Mojang Studios 2009], animals inspired by real-world counterparts are typically controlled by simple reflex-based AI systems, where behavior is driven by immediate stimuli rather than internal state. Although some games, such as *Don't Starve* [Klei Entertainment 2013], feature animal agents capable of responding to spatiotemporal cues (e.g. consuming nearby food or sleeping at night), these agents generally lack mechanisms for explicitly tracking internal needs over time. In contrast, life simulation games such as *The Sims 4* [Maxis 2014] employ utility-based AI systems, in which agents maintain internal need variables and select actions based on their relative urgency, allowing for more coherent and adaptive behavior.

[Strannegård et al. 2022] models a terrestrial ecosystem based on the island of Lilla Amundön off the west coast of Sweden and uses Unity3D to represent a realistic geography inhabited by hares, whose behavior and intelligence were trained using Reinforcement Learning (RL) in two different environments for testing: the first an environment with abundant food and the second directly on the simulated island. The hares learned to prefer open fields, similar to reality.

[Turan e Çetin 2019] develop an artificial intelligence agent system based on fuzzy logic, in which the threat responses of rabbits and deer are determined by an analysis of three factors: Health, Confidence Level, and Behavior Type. Similarly, this study also models a realistic representation of an island in Unity3D, the Island of Chios.

Within this context, there remains an opportunity to develop interactive educational ecosystem games in which animal agents integrate spatial perception, temporal awareness, and internal need states to select appropriate survival behaviors. Table 1 compares the proposed system with related scientific simulations and entertainment games. Unlike the systems examined, the proposed approach combines interactive player responses, spatial awareness, day–night awareness, and explicit internal survival needs within an educational ecosystem game.

Table 1. Comparative analysis of ecosystem models with animal behavior AI agents

Work	Interactive	Semi-Realistic	Spatial Awareness	Time Awareness	Needs Awareness
[Strannegård et al. 2022]	×	✓	✓	×	✓
[Turan e Çetin 2019]	✓	✓	✓	×	×
Don't Starve	✓	×	✓	✓	×
Minecraft	✓	×	✓	×	×
Our Work	✓	✓	✓	✓	✓

Note: Semi-realistic indicates behavior intended to resemble real animals; the awareness columns indicate whether agents use spatial information, time cycles, and internal needs.

3. Multi-Agent System Design

In this work, semi-realistic animal behavior refers to the ability of agents to perform survival-related actions such as moving, sleeping, eating, drinking, and defending themselves in response to spatiotemporal cues and internal needs. The following subsections describe agent perception, time and need representation, and behavior selection through an FSM.

3.1. Agent Awareness

Agent perception was implemented through 16 equidistant raycasts and two circular trigger colliders centered on each animal agent, as illustrated in Figure 1. Raycasts are used during Food Search and Water Search states to detect tiles in the corresponding food or water layers. Food layers vary by species and are configured in each species prefab through the Unity Inspector.

The trigger colliders are used for player detection. When the player enters the outer collider, the animal perceives a threat and reacts accordingly. When the player enters the inner collider, the animal transitions to a defensive response. Additionally, agents are implemented as NavMeshAgents, allowing them to use Unity Navigation and A* pathfinding to move through the generated terrain [Cui e Shi 2011].

In-game time is tracked by animal agents through access to a World Time component within a central time controller object. This allows all agents to be aware of the current time and determine whether they are within their active periods. Each in-game day was set to last two minutes in real time.

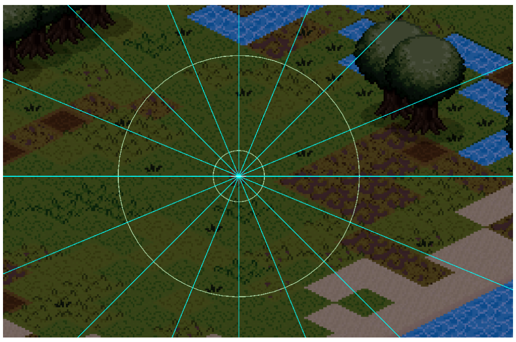

Figure 1. Perception: resource-detection rays and player threat and defense radii.

Agents within the game have two primary needs, Hunger and Thirst. These needs are represented as continuous variables ranging from 0 to 100, where a value of 100 denotes complete satisfaction and 0 corresponds to starvation or dehydration, respectively. Both needs diminish linearly over time, slower during sleep, and with Thirst decreasing at a faster rate than Hunger.

A secondary need is Energy, which steadily decreases during an agent's active period and replenishes at a slightly faster rate during sleep, both changes to this need are linear. It is considered secondary because, in the system's current version, it does not influence an agent's decision-making process but does influence Health, an attribute discussed further in the study.

3.2. Finite State Machine

The FSM illustrated in Figure 2 controls the agents' behavior. Each state represents an action, while transitions respond to internal needs, in-game time, environmental resources, or player proximity. States were implemented through Pluggable Behaviors, with each state script inheriting shared methods and attributes from a base class. This modular structure allows behaviors to be modified or extended independently.

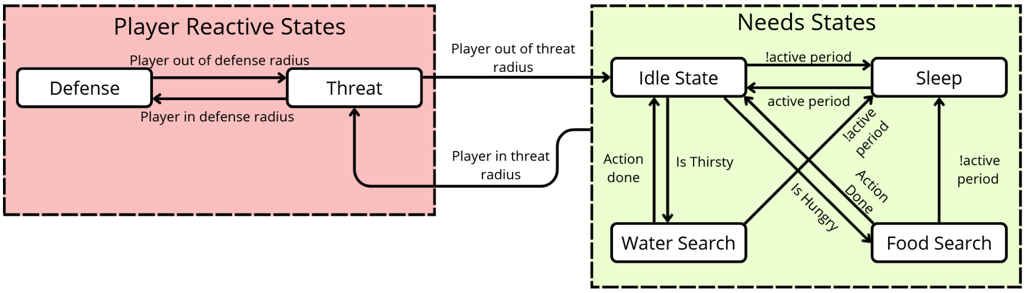

Figure 2. FSM controlling animal-agent behavior.

The Idle State is the default active behavior. While idle, the agent periodically evaluates Hunger and Thirst and converts their deficits into desire values, similar to Utility-Based AI. When a desire exceeds a threshold, the agent may enter the corresponding search state with a probability proportional to that desire. This utility-inspired mechanism introduces behavioral variation while retaining explicit FSM transitions.

All States portrayed in-game are described in the following itemized list:

- ***Idle State***: During its active period, the agent wanders randomly and evaluates its needs and player proximity.
- ***Resource Search States***: In the Food Search and Water Search states, the agent seeks the resource associated with its current need. A target is set when a raycast detects a valid Food or Water layer; otherwise, the agent wanders randomly until the resource is found. After eating or drinking, the agent transitions back to the Idle State.
- ***Sleep State***: Outside its active period, the agent remains asleep until its active period begins or the player triggers a threat response.
- ***Threat State***: The agent enters this state from Idle, Sleep, Food Search, or Water Search when the player is detected inside its Threat trigger collider. Two variants were implemented: Run Away, in which the agent moves away from the player, and Wait, in which it remains still while observing the player. If the player leaves the Threat radius, the agent returns to Idle.
- ***Defense State***: When the player enters the inner radius, the agent reduces the player's score and loses Health. It returns to the Threat State when the player moves away.

Agents continue monitoring player-detection colliders while sleeping, representing the possibility that auditory or olfactory cues may awaken them. A sleeping agent can therefore transition directly to the Threat State when the player enters its threat radius. Once the player leaves, the agent returns to Idle rather than Sleep, although future work should examine whether this transition should vary by species, time of day, disturbance duration, or remaining Energy.

4. Game Design

The developed multi-agent system was integrated as one of the main systems of an educational game, GAIA, which was developed in parallel with the work on this project. GAIA is an educational game designed to teach players about ecosystems, biomes, and fauna native to Brazil, with an initial emphasis on the Atlantic Forest. The game takes place on an island designed to resemble this biome and includes four animal species selected with support from an ecology expert: the hoary fox (*Lycalopex vetulus*) (Species 1), the capybara (*Hydrochoerus hydrochaeris*) (Species 2), the broad-snouted caiman (*Caiman latirostris*) (Species 3) and the giant anteater (*Myrmecophaga tridactyla*) (Species 4). By observing when animals are active, which resources they seek, and how they respond to player proximity, players are expected to formulate hypotheses about the animals' real-life ecology.

In the game, players collect resources, plant vegetation, avoid unnecessary harm to animals and trees, and interact with NPCs that present information about the biome. The game lasts eight in-game days, approximately sixteen minutes in real time. Screenshots and additional study materials are available in our OSF repository [1].

5. Methods

5.1. Study Design

Through a script, data were collected from all individual agents across the environment's population over ten trials. At the end of each trial, the population was reset, with each individual returning to its initial conditions and spatial configuration, after which a new trial commenced. Each trial had a varying number of individuals for each species and spanned eight in-game days and was conducted within one of five similar ecosystems (with small differences but following Atlantic Forest characteristics), all without player interaction, this allows for an analysis of the agents' survival in ecosystems with no player intervention.

As no player interaction was present in this experimental setup, transitions to the Threat and Defense states did not occur. To qualitatively evaluate the system in a way that incorporates these behaviors, a exploratory user study was conducted in which voluntary participants interacted with the system and subsequently reported their perceptions of the agents (RQ2) by answering a questionnaire containing three 5-point Likert-scale questions related to the system.

5.2. Material

The primary material for the study was the educational game designed and developed in parallel to the proposed system, which intends to teach multiple topics related to the brazilian biome of the Atlantic Forest, such as information on its soil, fauna, flora and conservation. The game also allowed the collection of data regarding the system's performance, this data is analyzed and discussed in further sections.

[1] https://osf.io/a7x9g/overview?view_only=67b277fdb8324ab7b4e21767ef780431

Additionally, a self-administered questionnaire was created using the Google Forms platform, in which participants were provided with instructions on how to download and play GAIA. Participants were given an ad hoc post-test set of questions related to the agent system.

5.3. Procedure

For 10 trials, the Health attribute of every agent was recorded every four in-game hours. At each time step, the mean Health was first computed across all individuals belonging to the same species within a trial. These per-trial species-level time series were then averaged across trials, producing a single representative trajectory of mean Health over time for each species.

This process was repeated for all five ecosystems, and the resulting trajectories were further averaged to obtain an overall estimate of species-level health dynamics under varying environmental conditions. Agents were instantiated in an ecosystem using a version of the procedural enemy generator from Project Overlord [Viana et al. 2022], adapted to instantiate animal agents, therefore all ecosystems vary in number of individuals, further data on the ecosystems and individuals can be found in our OSF repository. The resulting curves therefore represent the expected temporal evolution of species health in the absence of player intervention, allowing direct assessment of agent survivability and system stability (RQ1).

Participants accessed the study through a questionnaire link shared on social media (*Instagram*, *LinkedIn*, and *Discord*), with no time constraints imposed. The first section presented the Informed Consent Form, describing the study's purpose, voluntary participation, anonymization guarantees, and right to withdraw. After consenting, participants answered demographic and context questions, including 5-point Likert-scale self-perception items, and were then instructed on how to download and play the game. After playing, they returned to the questionnaire to answer Likert-scale items about their perceptions of the game's agents. All responses were recorded anonymously.

After removing incomplete responses and responses that failed attention checks ($N = 2$ out of 20 initial answers), following established recommendations [Pei et al. 2020, Kung et al. 2018, Silber et al. 2022], the final sample consisted of 18 valid participants. Most participants were cisgender men (77.8%, $n = 14$), aged between 19 and 22 years old (77.8%, $n = 14$), and had incomplete higher education (61.1%, $n = 11$). Monthly household income varied, with the most frequent ranges being three to five and five to ten minimum wages.

5.4. Data Analysis

To answer the research questions posed for this work, several measures were used. To address RQ1, the four FSM-controlled species were compared with a baseline agent that moves randomly but cannot intentionally seek or consume resources. All agents were evaluated using the same Health measure. Survival efficacy was assessed comparatively through end-of-cycle Health distributions and statistical tests, rather than against a predefined survival threshold. The median and mean of participants' responses to the 3 ad hoc questions posed to players in the post-test were analyzed, where higher values indicate a more positive experience in relation to the agents (RQ2). Data collected and used to answer both research questions were processed through python language scripts.

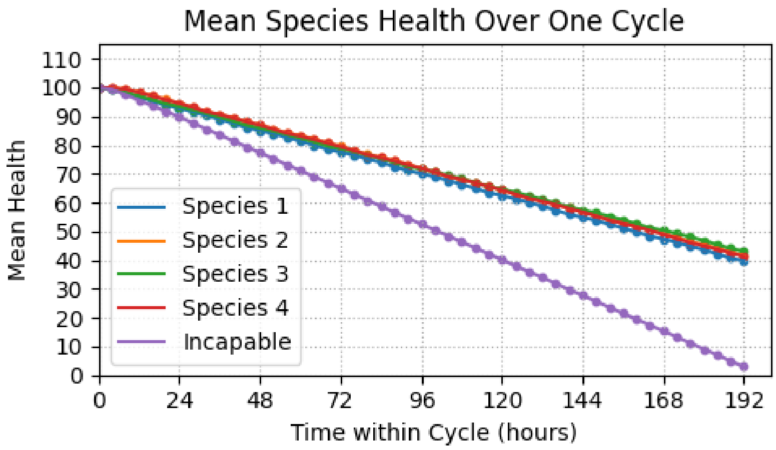

Figure 3. Mean species health over a game's cycle, averaging from 50 executions.

The Health (H) attribute is initially 100 for all individuals, and at each time step, it decreases according to a weighted average of normalized deficits in hunger (Hu), thirst (Th), and energy (En), where each variable is expressed relative to its maximum value. Said maximum values, $Hu_{\max}$, $Th_{\max}$, and $En_{\max}$ are set to 100 in our tests. The resulting penalty is scaled by the agent's maximum Health ($H_{\max}$) and normalized over the total cycle duration T, see Equation 1, producing a consistent decay rate in which larger resource deficits lead to faster reductions in Health. Consequently, a higher Health value at the end of a cycle indicates that an agent is more effectively able to satisfy its needs and, therefore, has improved survival capacity.

$$H_{t+1} = H_t - \left(\frac{(1 - \frac{Hu}{Hu_{\max}}) + 1.5\left(1 - \frac{Th}{Th_{\max}}\right) + 0.5\left(1 - \frac{En}{En_{\max}}\right)}{3} \right) \cdot \frac{H_{\max}}{T} \tag{1}$$

6. Results

6.1. RQ1 - How well can the agents survive?

The data presented in Figure 3 highlight the difference in mean health at the end of a cycle between the four species represented in the game and a control Incapable species, which is unable to satisfy any of their needs. While all four agent species finish the cycle with mean health values above one third of their initial health, the Incapable species reaches a value close to zero, indicating death or near-death. Species 3 has the highest final mean health, with an average of 43.138, followed by Species 2, with an average of 41.523, Species 4, with an average of 41.317, and Species 1, with an average of 39.750. In contrast, the Incapable species ended with an average health of only 2.940. The sample standard deviation among the regular species varied between 3.572 and 7.893, while the Incapable species showed a much smaller standard deviation of 0.193, indicating that its poor survival outcome was highly consistent across executions.

To understand if the state machine behaviors influenced survival, we further compared the mean health using a hypothesis test. A Shapiro-Wilk Normality test showed that Species 1 and Species 3 possibly followed a normal distribution, while Species 2, Species 4, and the Incapable species did not [Shapiro e Wilk 1965]. Therefore, we conducted a Kruskal-Wallis test [Kruskal e Wallis 1952]. The power analysis, using ANOVA as the closest comparable test, indicated a very large effect size, with $\eta^2 = 0.906$ and Cohen's $f = 3.106$ for a total sample size of 250 across 5 groups. This resulted in statistical power close to 1.00, indicating a very low chance of a Type II error. The Kruskal-Wallis test produced $p < 0.001$ and $H = 126.311$, so a significant difference between groups was found.

Then, a Dunn post-hoc test was conducted with Bonferroni correction [Dunn 1964]. It found a significant difference between each regular species and the Incapable species: Species 1 versus Incapable ($p = 5.569 \times 10^{-12}$), Species 2 versus Incapable ($p = 1.543 \times 10^{-18}$), Species 3 versus Incapable ($p = 2.300 \times 10^{-21}$), and Species 4 versus Incapable ($p = 8.430 \times 10^{-17}$). However, no significant differences were found among the four regular species after correction. Therefore, the state machine was able to strongly influence survival when compared with the incapable control species, but the differences among the regular species were not statistically significant under the post-hoc analysis.

6.2. RQ2: Player Perceptions of Animal Agents

A total of 18 participants completed the post-game questionnaire. Data cleaning removed incomplete responses and those failing attention checks (2 out of 20 initial answers), following established recommendations [Pei et al. 2020, Kung et al. 2018, Silber et al. 2022]. The sample was predominantly male (77.8% cisgender men, n=14), aged 19–22 years (77.8%, n=14), with incomplete higher education (61.1%, n=11), residing in São Paulo state (83.3%, n=15). Monthly household income varied, with the most common ranges being 3–5 and 5–10 minimum wages (22.2%, n=4 and 27.8%, n=5, respectively). Half of the participants played digital games daily (50.0%, n=9).

After playing GAIA, participants rated three statements on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The first statement, "I found the animals' behavior to be pleasant," obtained a mean of 4.00 (median = 4, SD = 1.08). The second statement, "I found the animals' behavior to be a good representation of the real world," yielded a mean of 3.67 (median = 4, SD = 1.14). The third statement, "I believe that the animals and changes in vegetation contributed to my experience in the game," produced a mean of 4.56 (median = 5, SD = 0.70).

A one-sample Wilcoxon signed-rank test was performed against the neutral value of 3. Due to the presence of zero differences (responses equal to 3), the normal approximation was used as recommended by SciPy. All three items showed statistically significant deviations from neutrality: Q1 (W = 7.0, p = 0.003), Q2 (W = 22.0, p = 0.025), and Q3 (W = 0.0, p = 0.000). These results indicate that players positively evaluated the animal agents' behavior, perceived it as a reasonably realistic representation of real-world counterparts, and strongly agreed that the dynamic animals and vegetation enhanced their gameplay experience.

Internal consistency of the three-item scale was assessed using Cronbach's α and McDonald's ω. Cronbach's α was 0.807 (95% CI: 0.575–0.922) and McDonald's ω was 0.892, indicating good reliability. Post-hoc power analysis via bootstrap (1000 resamples) showed high observed power for Q1 (0.968) and Q3 (1.000), and moderate power for Q2 (0.658), consistent with the larger variance and some neutral or disagree responses for that item. Nevertheless, the effect remained statistically significant. Overall, the user study provides an affirmative answer to RQ2: players perceived the semi-realistic animal behaviors positively across all measured dimensions.

6.3. Implications

The system developed in this work provides a solid foundation for future research on semi-realistic animal agents in games. It allows developers participating in the GAIA project to explore the implementation of new and more complex behaviors, variations of existing behaviors, or alternative approaches to simulating animal perception.

For players, the system offers an opportunity to observe virtual animals attempting to survive in an interactive environment. Through this observation, players may formulate hypotheses about the animals' behavior and become curious to learn more about their real-life counterparts.

6.4. Threats to Validity and Limitations

This study has two main limitations related to (RQ1) and one to (RQ2). First, the proposed system was not compared with alternative decision-making approaches, such as fuzzy logic, utility-based AI, or machine learning, therefore, although the results indicate that the agents are capable of producing coherent survival behavior, it is not possible to determine whether this approach performs better than other possible models. Second, some biological processes were simplified, since eating and drinking fully restore Hunger and Thirst rather than modeling gradual satiety, hydration, digestion, or metabolism.

In relation to (RQ2), the user study was exploratory, with a small sample (N = 18) and no control condition that compares the proposed agents with simpler agents. Future studies should include larger samples, controlled comparisons, and more detailed educational measures.

7. Conclusion

This work presented a multi-agent system for semi-realistic animal behavior in GAIA, an educational game about ecosystems. The agents respond to spatial cues, time cycles, player proximity, and internal needs such as hunger, thirst, and energy. Simulation results showed that the proposed agents survived significantly better than an incapable baseline, while the exploratory user study indicated positive player perceptions of the animals' behavior and their contribution to the game experience.

The modular structure also provides a foundation for future extensions in GAIA, including new species, additional behaviors, and alternative models of perception or decision-making. Future work should compare the proposed approach with other AI techniques and evaluate the game's educational impact with larger and controlled studies.

Declaration of Generative AI and AI-assisted technologies

We used LLMs such as DeepSeek and ChatGPT to improve the article's overall quality. We take full responsibility for all content produced with AI assistance.

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