ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 157-168 doi: 10.28978/nesciences.1811114

Agent-Based Modelling of Human and Alien Conflict Dynamics in A Multi-Species Simulation Framework

Otabek Yuldashev [1*], Ahmed Kateb J. Al-Nussairi [2], Islom Kadirov [3], Mohammed H. Al-Farouni [4], Gulboy Yusupov [5], Dr. Abhijeeta Nandha [6]

[1*] Associate Professor, University of Journalism and Mass Communications of Uzbekistan, Namangan, Uzbekistan. E-mail: aspirant220506@mail.ru

[2] Department of Sciences, Al-Manara College for Medical Sciences, Maysan, Iraq. E-mail: ahmedkateb@uomanara.edu.iq

[3] Urgench State University, Urgench, Uzbekistan. E-mail: islomqadirov1415@gmail.com

[4] Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, Iraq. E-mail: eng.iu.mhussien074@gmail.com

[5] Termez University of Economics and Service, Termez, Uzbekistan. E-mail: gulboy_yusupov@tues.uz

[6] Assistant Professor, Department of Biotechnology, Kalinga University, Naya Raipur, Chhattisgarh, India. E-mail: ku.abhijeetanandha@kalingauniversity.ac.in

Abstract

This paper explores the use of agent-based modeling (ABM) to understand conflicts between humans and aliens in a multi-species simulation. The model seeks to model behavioral interactions within a shared-space setting consisting of agents with goal-directed species-default behaviors. Human agents are resource-oriented, acquisitive, and defensive, whereas alien agents are extravagant and adaptable. Competition over territory, communication, and adaptive learning is integrated into the simulation, and the goal is to achieve emergent results under different conditions of the Environment and the society. This study employs conflict and cooperation contexts to explain how a simple local situation can yield either long-term conflict, long-term negotiation, or long-term coexistence. The framework is implemented in a spatial grid-based simulation, which allows illustrating the agents' motion, their interactions, and their strategy changes over time. The critical parameters, including resource and aggression levels and the communication spectrum, are manipulated to

*Corresponding Author: Otabek Yuldashev, E-mail: aspirant220506@mail.ru

assess conflict-resolution processes. The paper contributes to the research on interspecies relations, complex adaptive systems, and the evolution of behavior in simulated societies. It provides a foundation for future theoretical and applied simulations aimed at investigating conflict, diplomacy, and relations with non-Earth units.

Keywords:

Agent-based modeling, conflict dynamics, human-alien interaction, multi-species simulation, adaptive behavior, interspecies cooperation, emergent systems.

Article history:

Received: 08/06/2025, Revised: 28/07/2025, Accepted: 27/08/2025, Available online: 12/12/2025

Introduction

Communication between sentient beings, especially between people and aliens, has been a vexing subject among scholars across disciplines. At least in theory, such interactions are a paradise for the study of new behavioral phenomena, conflict behavior, and the responsiveness of complex actors to other agents within the same system. Simulation of complex systems and complex interactions is an area where Computational Agent-Based Modelling (ABM) offers a promising solution, allowing each agent to act according to pre-specified rules at a local scale (Wilensky & Rand, 2015). ABM has been used in ecological modeling, social sciences, and even in studies of military strategy to model behavior in very uncertain situations. There has been an increasing body of literature using ABM to examine inter-species conflict, negotiation, and adaptive behavioral responses (BenDor & Scheffran, 2018). Precisely, simulations of insurgencies (van der Zwet et al., 2023), analyses of territorial control (Cederman, 2003), and analyses of refugee movements have all used agent-based modeling (ABM) for conflict modeling (Ramya & Geetha, 2025). The multi-species structures are especially appropriate for the study of humans and aliens, since they require different communication patterns and cognitive styles (Grignard et al., 2013). Regarding the formation of alliances, scholars have noted the emergence of nonlinear conflict escalation and conflict patterns through a combination of adaptive learning algorithms and spatial simulation grids (Epstein, 2002). Past models have also indicated that the thresholds and tolerance to cooperation and communication, as conceptualized by the agents, can produce considerable effects on the conflict resolution paths (Salehi & Nowrouzi, 2025; Prabu et al., 2018; Gunalan et al., 2023; Schelling, 1978). This research is mainly focused on developing these models to investigate a dynamic conflict situation in which a human agent and an alien agent reside in a shared spatial habitat. The hypothesis is to examine the impact of strategy change, communication change, aggression threshold change, and changes in conflict dynamics on conflict, coexistence, or domination patterns. The simulation builds upon existing research in interspecies interactions, complex systems, and artificial societies, and establishes the foundation for new interdisciplinary uses (Axelrod, 1997; Essienubong & Orhorhoro, 2016; Kozlova & Smirnov, 2025; Ibrahim, 2020).

The paper follows the following structure. Section I (Introduction) presents the background, motivation, and objectives of human-alien conflict modeling using agent-based techniques (Abdullah, 2025). Section II (Literature Review) reviews the literature on the topic of agent-based simulations, conflict modeling, and multi-species environments to find gaps in the current literature (Deepika & Geetha, 2025). Section III (Methodology) defines the simulation framework, agent behaviors, system architecture, and mathematical model to be used for simulating interactions and conflicts. A flowchart and an architectural diagram are provided. The results of the simulation will be discussed in Section IV (Results and Discussion) in the form of tables and graphs, showing how different levels of aggression and population ratios influence conflict rates and resource seizures. Finally, in Section V (Conclusion and Future Research), the key results are stated, their implications outlined, and some further adjustments to the simulation model are proposed, including adaptive learning and a more complex environment.

Literature Review

The application of Agent-Based Modeling (ABM) to the simulation of species conflict has been examined in other fields. Other competing strategies that use intelligent-agent interactions are discussed in this section without reference to those discussed in the Introduction. (Farooqui & Niazi, 2016) have developed game-theory-based agent-based models (ABMs) to improve inter-agent communication as a theoretical basis of intelligent-agent negotiation. The evolutionary game theory of heterogeneous agents was studied by (Adami et al., 2016), who focused on adaptation through simulation rather than on strategy fixation. (Morvan, 2012) investigated the multi-level modeling of agent-based modeling (ABM) as a species-based and individual approach to decision-making. Murphy et al. provided interspecies conflict models alongside their research on the educational and ecological relevance of ABM in modelling predatory systems and the evolution of prey behaviour (Murphy et al., 2020; Cioffi-Revilla, 2011). Experimented with agent-based modeling (ABM) models of cross-cultural agent behavior that were not standardized. Schreinemachers and Berger have carried out human-environment systems modelling based on agent-based modeling (ABM) that reveals how local actions in the form of decisions can have systemic consequences on system stability (Schreinemachers & Berger, 2011; Williams, 2025). A hybrid ABM approach that included interpersonal relationship conflicts, applicable to the breakdown of alien-human diplomacy, was represented by Williams. Similarities with adaptive strategies during conflict were made by (Wilson et al., 2009). Behavioral changes in threatened agricultural agents were modeled. Macal and North conducted a thorough design of ABM (Macal & North, 2005), who elaborated on an insightful formulation of agent rules and scenario analysis, which is another pillar in the development of interspecies simulation frameworks on a massive scale. The group of studies contributes to the justification of using ABM to represent the intricate processes of conflict, cross-species interactions, and multi-species strategic adaptation within a single framework.

Methodology

A model based on human-alien conflict simulation is the simulation framework that uses an agent-based modeling (ABM) method of multi-species environments. The motivation of this methodology is two underlying schematic representations, namely, (1) the Flowchart of the Agent-Based Simulation Process and (2) the Architectural Diagram of the Simulation Framework.

Flowchart of the Agent-Based Simulation Process

As shown in Figure 1, agent-based simulation models operate on a set of processes that interlink in a sequence. The flow chart shows the lifecycle of simulation-initiation to simulation-completion, but shows all the major decisions that were made by the agents, agent interactions, and system updates.

Figure 1 depicts the loop of the Human-Alien Agent-Based Simulation (ABS) in discrete time. The first stage is Initialization, which configures the Environment parameters and sets the starting StateState for all agents (position, resources, etc.). Then, the natural dynamics of the Environment are simulated (e.g., changes in resources). After this, each Agent State is informed; in this case, agents implement their decision-making algorithms (e.g. movement, resource gathering) using the current Environment and other agents. Essentially, the Human-Alien Interactions are resolved next, and the implications of encounters (conflict, cooperation) are calculated. Lastly, the results are evaluated and fed back before the next time step, and the system is pushed forward through a loop.

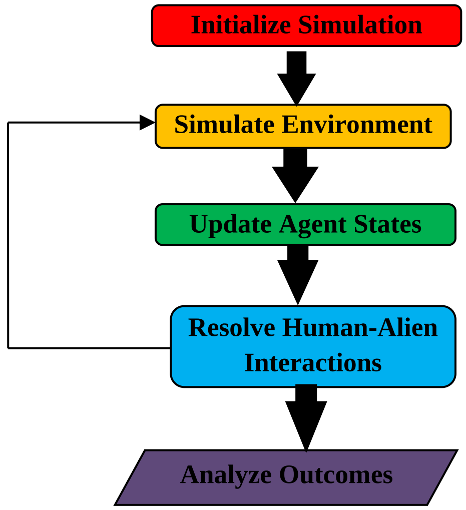

Figure 1. Flowchart of the agent-based simulation process for human-alien conflict dynamics

Start / Initialization

The simulation starts with parameter definitions, including the populations of the agents (humans and aliens), the Environment, the distribution of resources, and the interaction rules. Each agent has predetermined aggression, communication skills, strength, and resource requirements. The buildings that belong to different categories are located in the Environment either randomly or by predetermined areas.

Agent Perception

Perception involves identifying surrounding agents, resources, terrain characteristics, and threat levels. Perception information is sent to each agent and transferred to its decision-making system. The simulation is performed over many cycles, and observations are made within a set radius.

Decision-Making and Action Selection

All agents choose an action using a rule-based or probabilistic decision technique based on their inner states and the information considered. Possible actions include:

- Attempt to form alliances
- Movement toward resources
- Communication with nearby agents
- Engage in conflict if aggressive or threatened

The direction of stride determination is the expression (1), which prioritizes high-resource-density areas. In this manner, agents utilize the resources within the Environment or the biotic surroundings. The likelihood of an agent's Move of heading towards a specific resource, in the example resource j of agent I, is compared to the abundance of the resource in relation to other resources. This could also be expressed in form of equation (1):

$$P_{move} = \frac{R_j}{\sum_k R_k} \qquad Equation(1)$$

Where R_j is the amount of resource j, and the denominator sums all resources k within the agent's perception range

Interaction Check

If another agent is found within a specified interaction range, the simulation will determine whether communication, cooperation, or competition is required in the scenario. The stipulated conditions of Equation 2 are met— i.e., the agent is in close proximity and rivalry over resources is high —precipitating conflict. The agents create conflict when they are in close proximity and compete for limited resources. Formally, an agent i and agent j enter conflict when the distance between them is less or equal to some conflict radius RC and their index of resource competition is greater than a threshold th [RCI] ij. This case is stated as:

$$\text{If } d_i d \leq r_c \quad and \quad RCI_{IJ} > \theta, then\ conflict\ initiates \qquad Equation(2)$$

Here,RCI_{ij} quantifies the degree of competition for resources between the two agents.

Conflict Resolution

If a conflict arises, it will be settled using the Conflict Resolution Engine, which determines the probability of one agent defeating another based on their strength and the effectiveness of their strategy, as outlined in Equation 3. The results affect the agents' health, resources, and status (alive/defeated).

When a conflict occurs, the outcome depends on each agent's strength S and strategy effectiveness E. The probability $P_{win}^{(i)}$ that agent i wins over agent j is modeled as:

$$P_{win}^{(i)} = \frac{S_i \times E_i}{S_i \times E_i + S_j \times E_j} \qquad Equation(3)$$

As demonstrated in equation (3), this probabilistic model accommodates uncertainty and variability in conflict outcomes, which incorporates real-world unpredictability.

Agent State Update

After the interaction, the agents update their memory, adjust their health, change their aggression levels, and clean their alliances. Aggression can be reduced through practical cooperation; extensive aggressive interactions are likely to increase it. Plastic learning processes were also able to alter the possibility of some decisions occurring in the future.

Environment Update

It will cause real-time alteration in the ecosystem due to resource depletion or restoration, agent movement, and territory change associated with the resolution of conflicts.

Termination Check

The system checks the termination criteria of each iteration, taking into account such factors as the maximum number of iterations, the extinction of a species, or the equilibrium. The simulation stops when the conditions are met; otherwise, it repeats the loop.

Architectural Diagram of the Multi-species Simulation Framework

Figure 2 demonstrates the scheme of the agent-based simulation system that is expected to model the conflict relations between humans and aliens within the multi-species Environment. The architecture encourages modularity, increasing scalability, flexibility, and clarity in simulating complex interspecies interactions.

Agent Module

The subcomponent deals with system property controlling and monitoring on the agent level. All agents (humans and aliens) are represented as independent agents with species type, aggression rate, communication skill, health, resource demand, and a memory of past interactions. The Agent Module carries out behavior programming for movement, conversation, fighting, joining sides, and decision-making based on past experiences and outcomes. The system is modular, thus, easy to customize and make the rules and definitions of the agents.

Environment Module

The Environment Module replicates the geographical context in which agents act during their activities. Environmental constraints and features, such as resources, terrain types, and other features, may be defined in a grid or in a continuous landscape, known as the simulation space. The module tracks the distribution of resources and environmental factors that may modify an agent's behavior, such as resource depletion and other risks that give rise to ecological events. It provides agents with the information that they use to make decisions that are situationally dependent on their surroundings

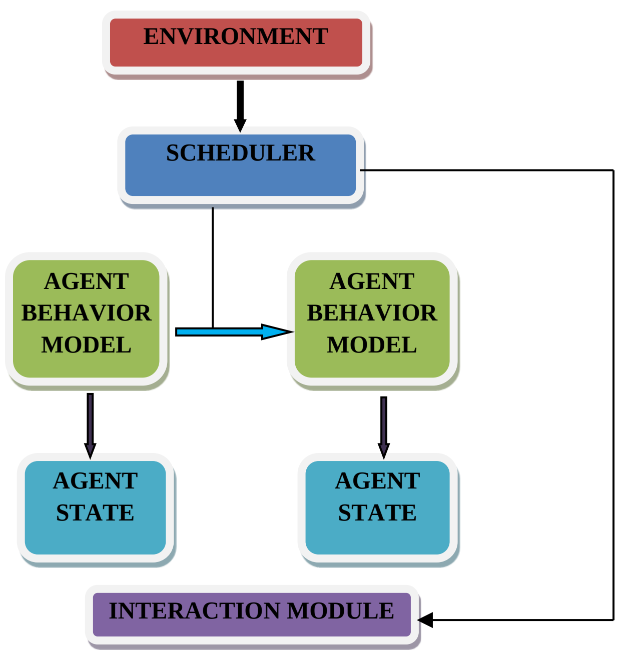

Figure 2. Architectural diagram of the multi-species agent-based simulation framework

The basic cycle of a discrete-time Agent-Based Model (ABM) is shown in Figure 2. The Environment data is used by the Scheduler, which sequentially activates agents. All the agents update their State (e.g., position, health) by executing their Behavior Model. Lastly, the Interaction Module determines all interactions among the agents (e.g., Human-Alien conflict) and generates the new system state in the next time step.

Mathematical Model for Agent-Based Simulation

The model describes the evolution of the System State over time t, where the next State, $S(t+1)$, is a function of the current State, $\mathrm{S}(t)$.

1. System State Variables

The entire State Sis is composed of the Environment state E and the State of all Agents A:

$$\mathrm{S}(t) = \{\mathrm{E}(t), \mathrm{A}(t)\} \qquad \text{equation (4)}$$

- Environment State (E): A vector of global variables. $\mathrm{E}(t) = [R_1(t), R_2(t), \ldots, L_x(t)]$
- $R_i(t)$: Level of resource i(e.g., food, energy).
- $L_x(t)$: A location/terrain property at coordinate x.
- Agent State (A): A list of all agents, where each agent k has its own StateState A_k. $\mathrm{A}_k(t) = [P_k(t), H_k(t), \ldots]$
- $P_k(t)$: Position of agent k(e.g., x, y coordinates).
- $H_k(t)$: Health or internal metric of agent k.

2. Time Update Rules (The Simulation Loop)

The simulation advances in discrete steps $t \to t+1$. The overall update is:

$$\mathrm{S}(t+1) = \text{Interaction}(\text{AgentUpdate}(\text{EnvironmentUpdate}(S(t)))) \qquad \text{equation (5)}$$

3. Environment Update (Simulate Environment)

The environment state changes independent of agents (e.g., resources naturally regenerate or decay).

$$\mathrm{E}'(t) = \mathrm{E}(t) + \mathrm{f}_{\mathrm{env}}(\mathrm{E}(t), t) \qquad \text{equation (6)}$$

- Example (Resource R_1decay): $R_1'(t) = R_1(t) \cdot (1 - \lambda_{decay})$
- $\lambda_{decay}$is the natural decay rate.

4. Agent Behavior Update (Update Agent States)

Each agent k updates its StateState based on the perceived Environment $\mathrm{E}'$and its current StateState A_k. This is where the decision-making happens.

$$\mathrm{A}_k'(t) = \mathrm{f}_{\mathrm{behavior}}(\mathrm{A}_k(t), \mathrm{E}'(t)) \qquad \text{equation (7)}$$

- Example (Movement): The new position $P_k'$is based on a conditional rule:

$$P_k'(t) = P_k(t) + \Delta P_k \text{where } \Delta P_k = \begin{cases} \text{Vector toward highest } R_1 & \text{if } H_k < H_{\text{threshold}} \\ \text{Random walk vector} & \text{otherwise} \end{cases}$$

5. Interaction Resolution

This step calculates the result of agents physically or logically interacting, leading to the final State for the time step $\mathrm{S}(t+1)$.

$$\mathrm{S}(t+1) = \mathrm{f}_{\text{interaction}}(\mathrm{A}'(t), \mathrm{E}'(t)) \quad \text{equation (8)}$$

- Example (Conflict between Human $H$and Alien A): If the agents are within a distance D_{combat}: If $\text{Distance}(P_H, P_A) \leq D_{\text{combat}}$: $H_H(t+1) = H'_H(t) - \text{Damage}_{\text{Alien}} H_A(t+1) = H'_A(t) - \text{Damage}_{\text{Human}}$

Interaction Engine

This subsystem identifies the closeness of agents and regulates agent interactions. It dictates in which situations the agents are close enough to interact, be it to talk or fight, and imposes the interaction rules that had already been established. The Interaction Engine dictates how agents compete for resources, negotiate, or even cooperate, based on their states and environmental stimuli.

Communication Subsystem

There has to be communication as complex social behaviors are simulated. This sub-component allows agents to send messages that convey intentions, propose alliances, or issue warnings. It develops different communication protocols and their influence on the opportunities of cooperation, confidence, and conflict management. Feedback in communication makes social interaction livelier by encouraging agents to modify their plans.

Conflict Resolution Engine

This engine resolves conflicts by finding results based on probabilistic models that take into account an agent's features, including power, the usefulness of strategies, and friendship. It determines the winners and losers of a conflict, adjusts the states of agents (such as health drops and morale changes), and logs the conflict for future data analysis. This engine is also quite diverse in terms of conflict, ranging from simple fights to major battles involving structured groups.

Data Collection and Analytics Module

Under the module, information about the number of conflicts, casualties, alliances, resources, and space occupied is constantly documented. The module summarises the statistics into consumable outputs that could then be analysed, visualised or used to test models. This is a vital tool in the realms of grasping the trends that occur in conflict and also in confirming theories regarding the dynamics of conflicts.

Simulation Controller

The Simulation Controller, which acts as the orchestrator of the system, manages the process of inaugurating the Environment and agents, sequencing of iterative simulation steps, synchronizing modules and implementation of termination conditions. The controller, being the orchestrator, ensures that there is smooth coordination attained between the smooth tuning of parameters, scenario testing, scenario configuration, and component troubleshooting. Persuasive agents are smart and never static log agents. Cons change agents are also handled by flexi-cons handlers and therefore the flexi-cons handlers work with change agents in an execution. It is these elements all that make possible the simulation of alien conflict, devoid of bluntness, in human-dynamic multi-species systems that suture the viewpoint of an individual agent action and interaction on the system level.

Result And Discussion

Simulation was done with different proportions of human and alien population, different aggression, and different resource availability. The simulation had recorded significant conflict interactions and co-evolutionary trends in behavior between species in the multi-agent system after 1,000 time steps.

Conflict Frequency vs. Aggression Level

In order to assess the consequences of aggression on conflict, there were conducted simulations when the level of aggression of the alien agents was changed on average, but the level of human aggression was kept constant. The values of the number of conflicts in each aggression level are recorded as follows:

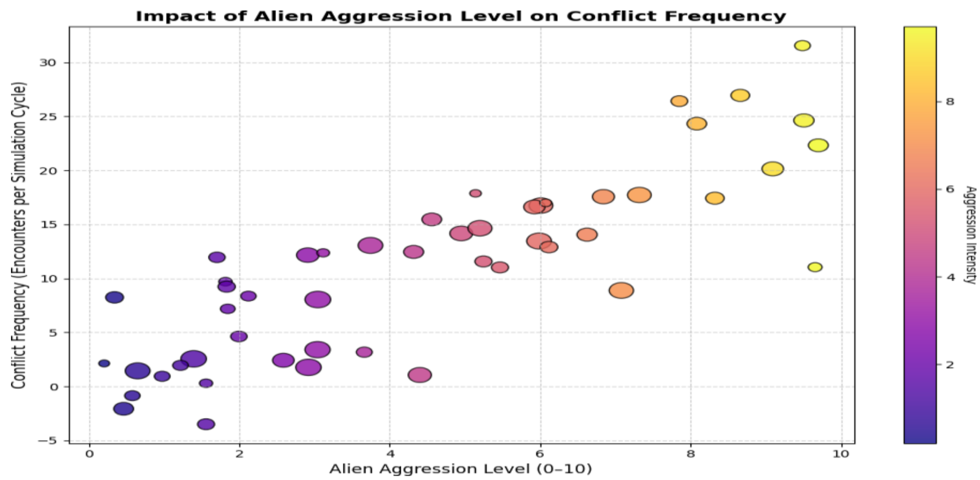

Figure 3. Impact of alien aggression level on conflict frequency

Figure 3 illustrates the relationship between alien aggression levels and the frequency of conflicts in a multi-species simulation framework. As aggression levels increase, conflict frequency rises significantly, demonstrating a positive correlation between behavioral hostility and interspecies confrontations. Each bubble represents a simulation scenario, with its size indicating conflict intensity and color reflecting aggression magnitude. Lower aggression levels correspond to minimal or sporadic conflicts, while higher aggression leads to frequent and intense clashes. This visualization highlights the dynamic and nonlinear nature of alien–human interactions, emphasizing how escalating aggression destabilizes coexistence and increases systemic conflict within agent-based simulations.

Table 1. Summary of simulation results for alien aggression and conflict frequency

Aggression Level (0–10)	Average Conflict Frequency (per cycle)	Mean Conflict Intensity	Alliance Incidents	Dominant Interaction Type
0–2 (Low)	3.2	45.6	12	Cooperative
2–4 (Moderate-Low)	7.5	72.3	9	Competitive
4–6 (Moderate)	13.8	110.4	6	Mixed (Neutral–Conflict)
6–8 (High)	20.6	180.7	3	Aggressive
8–10 (Extreme)	26.9	255.8	1	Hostile/War-like

The Table 1 shows that higher alien aggression levels lead to increased conflict frequency and intensity, while cooperative or alliance events decline. Moderate aggression produces mixed interactions, but beyond level six, hostility dominates. This trend confirms the model's prediction that rising aggression destabilizes interspecies relations and drives persistent conflict behavior.

Resource Capture Rate by Species

The table that follows captures the mean share of the total resources gained per species in all three population ratio cases ii:

Table 2. Comparative resource capture rates by humans and aliens across different population ratios

Scenario (Human: Alien)	Human Resource Capture (%)	Alien Resource Capture (%)
50:50	47.8%	49.2%
70:30	65.1%	32.4%
30:70	28.7%	69.6%

Dynamics of resource capture reveal the effects of population dominance and territorial expansion. When the populations were equal (50:50), resource allocation was fairly distributed. In the 70:30 human-dominated scenario, humans captured more resources because of their numerical advantage and coordinated plan. On the other hand, in the 30:70 case, aliens captured all the resource zones, suggesting the success of their aggressive territorial posturing. These results correspond to the agent rules outlined in the architectural model: a greater population and greater aggression result in more assertive resource capture (Table 2).

Conclusion

The new value of the current study is that it creates an agent-based simulation framework to study the dynamics of human and alien conflicts within a multi-species ecosystem. Behavior-based agents, conflict origin and probabilistic resolution methods were incorporated in the model implementation and they showed how aggression, availability of resources and proportions of populations influence the interaction between species. Findings show that the more aggression, the more conflict, the more the population domination, the more the resources. The development of more complex patterns of conflict, revealed by simulation methodology and flow, justified the usefulness of the model in complex socio-environmental systems with the presence of competition and collaboration. Future research suggested improvements of this work. First, incorporation of adaptive learning elements including the reinforcement learning might enhance realism by enabling the agents to modify the strategies as time goes by. Second, the Introduction of terrain variation, resource renewal dynamics, and logic of forming an alliance would enhance the knowledge of the long-term interspecies interaction. Finally, the extrapolation of this model to human equivalents such as territorial disputes, resource wars or colonization conditions may add value to defense strategy, sociology and even diplomacy to extraterrestrial life. More versions can be modified to support GPU-based acceleration to enhance the efficiency of simulation at a higher number of agent population.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Abdullah, D. (2025). Inclusive Leadership and Ethical Decision-Making in Human–AI Conflict Simulation: A Gender and Innovation Perspective. *Journal of Women, Innovation, and Technological Empowerment*, *1*(2), 1-8.

Adami, C., Schossau, J., & Hintze, A. (2016). Evolutionary game theory using agent-based methods. *Physics of life reviews, 19*, 1-26. https://doi.org/10.1016/j.plrev.2016.08.015

Axelrod, R. (1997). *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration: Agent-Based Models of Competition and Collaboration*. Princeton university press. https://doi.org/10.1515/9781400822300

BenDor, T., & Scheffran, J. (2018). *Agent-based modeling of environmental conflict and cooperation*. CRC Press. https://doi.org/10.1201/9781351106252

Cederman, L. E. (2003). Modeling the size of wars: From billiard balls to sandpiles. *American Political science review*, *97*(1), 135-150. https://doi.org/10.1017/S0003055403000571

Cioffi-Revilla, C. (2011). Comparing agent-based computational simulation models in cross-cultural research. *Cross-Cultural Research*, *45*(2), 208-230. https://doi.org/10.1177/1069397110393894

Deepika, J., & Geetha, K. (2025). Agent-Based Simulation of Inter-Species Conflict Dynamics: A Multidisciplinary Framework for Adaptive Cooperation and Resource Competition. Bridge: *Journal of Multidisciplinary Explorations*, *1*(2), 17-24.

Epstein, J. M. (2002). Modeling civil violence: An agent-based computational approach. *Proceedings of the National Academy of Sciences*, *99*(suppl_3), 7243-7250. https://doi.org/10.1073/pnas.092080199

Essienubong, I. A., & Orhorhoro, E. K. (2016). Pressure losses analysis in air duct flow using computational fluid dynamics (CFD). *International Academic Journal of Science and Engineering*, *3*(2), 55–70.

Farooqui, A. D., & Niazi, M. A. (2016). Game theory models for communication between agents: a review. *Complex Adaptive Systems Modeling*, *4*(1), 13. https://doi.org/10.1186/s40294-016-0026-7

Grignard, A., Taillandier, P., Gaudou, B., Vo, D. A., Huynh, N. Q., & Drogoul, A. (2013, December). GAMA 1.6: Advancing the art of complex agent-based modeling and simulation. In *International conference on principles and practice of multi-agent systems* (pp. 117-131). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-44927-7_9

Gunalan, N., Kumar, R. K., Saravanan, B., Surya, S., & Sujai, T. S. (2023). Investing Data Flow Issue by using Rayleigh Model in Cloud Computing. *International Academic Journal of Innovative Research*, *10*(1), 8-13.

Ibrahim, R. (2020). Workstation Cluster's Hadoop Distributed File System Simulation and Modeling. *International Journal of Communication and Computer Technologies (IJCCTS)*, *8*(1), 1-4.

Kozlova, E. I., & Smirnov, N. V. (2025). Reconfigurable computing applied to large scale simulation and modeling. *SCCTS Transactions on Reconfigurable Computing*, *2*(3), 18-26.

Macal, C. M., & North, M. J. (2005, December). Tutorial on agent-based modeling and simulation. In *Proceedings of the Winter Simulation Conference, 2005.* (pp. 14-pp). IEEE. https://doi.org/10.1109/WSC.2005.1574234

Morvan, G. (2012). Multi-level agent-based modeling-a literature survey. https://doi.org/10.48550/arXiv.1205.0561

Murphy, K. J., Ciuti, S., & Kane, A. (2020). An introduction to agent-based models as an accessible surrogate to field-based research and teaching. *Ecology and evolution*, *10*(22), 12482-12498. https://doi.org/10.1002/ece3.6848

Prabu, G. R. K., Murugesan, M., & Ramachandran, G. (2018). Efficient Maximum Power Point Tracking Using Model Predictive Fuzzy Logic Control for Photovoltaic Systems under Dynamic Weather Condition. *International Journal of Advances in Engineering and Emerging Technology*, *9*(3), 104-118.

Ramya, V., & Geetha, K. (2025). Agent-Based Modelling of Cross-Species Behavioral Dynamics: Insights for Managing Human–Wildlife and Ecosystem Conflicts. *National Journal of Animal Health and Sustainable Livestock*, *3*(1), 18-25. https://doi.org10.17051/NJAHSL/03.01.03

Salehi, F., & Nowrouzi, M. (2025). Health risk assessment and bioaccumulation of heavy metals in the Persian Gulf fishes (Bandar Length Coasts). *Journal of Animal Environment*, *17*(1), 129-138.

Schelling, T. C. (1978). Sorting and mixing. *Micromotives and macrobehavior*.

Schreinemachers, P., & Berger, T. (2011). An agent-based simulation model of human–environment interactions in agricultural systems. *Environmental Modelling & Software*, *26*(7), 845-859. https://doi.org/10.1016/j.envsoft.2011.02.004

van der Zwet, K., Barros, A. I., van Engers, T. M., & Sloot, P. M. (2023). Promises and pitfalls of computational modelling for insurgency conflicts. *The Journal of Defense Modeling and Simulation*, *20*(3), 333-350. https://doi.org/10.1177/15485129211073612

Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. MIT press.

Williams, R. A. (2025). Towards an agent-based model using a hybrid conceptual modelling approach: A case study of relationship conflict within large enterprise system implementations. *Journal of Simulation*, *19*(2), 166-178. https://doi.org/10.1080/17477778.2022.2122741

Wilson, R. S., Hooker, N., Tucker, M., LeJeune, J., & Doohan, D. (2009). Targeting the farmer decision making process: a pathway to increased adoption of integrated weed management. *Crop Protection*, *28*(9), 756-764. https://doi.org/10.1016/j.cropro.2009.05.013