

Prehistoric VR Simulations as educational content

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Declaration of the candidate & Supervisor

I declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidate is carrying out research for the undergraduate Dissertation under my supervision.

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Date:

Abstract

This research presents the development of a *Prehistoric Animal Behavior Simulation* designed to recreate lifelike behavioral patterns of extinct species within an immersive virtual reality environment. The simulation enables users to observe autonomous actions such as hunting, herding, and grazing, providing an engaging medium to understand ancient ecosystems through visual and interactive learning.

The system was built using **Unity 2022.3** under the Universal Render Pipeline and employs **ML-Agents** together with **NavMesh navigation** to generate adaptive and responsive animal movement. Each agent's behavior was shaped through machine-learning training and environmental triggers that mimic natural stimuli. Dynamic weather, lighting, and terrain conditions were incorporated to strengthen realism and sustain user immersion during observation.

The outcome demonstrates how AI-driven behavioral modeling can be used to deliver scientifically informed educational content. By transforming prehistoric interactions into observable, data-driven simulations, this project highlights the potential of virtual environments to bridge education, entertainment, and computational research in animal behavior.

Keywords: Virtual Reality,

ML-Agents,

Unity,

Prehistoric Behaviour,

Simulation,

Educational Visualization

1.Introduction

1.1 Background and Literature Review

Modern virtual reality (VR) technologies have transformed how learners explore scientific and historical knowledge by enabling direct, sensory engagement with digital environments. In paleontology and natural sciences, interactive simulations provide opportunities to study prehistoric life that cannot be directly observed. Behavioral reconstruction—particularly of extinct species—demands not only visual realism but also logical models of movement and social interaction.

The *Prehistoric Animal Behavior Simulation* was designed to address this challenge by combining computer graphics, environmental simulation, and artificial intelligence. Using **Unity 2022.3** with the **Universal Render Pipeline (URP)**, the system renders dynamic terrain, atmospheric effects, and authentic animations of species such as *Tyrannosaurus rex*, *Triceratops*, and *Alamosaurus*. Artificial agents are trained using **Unity ML-Agents** to mimic behavioral responses like herding, hunting, and exploration, supported by **NavMesh pathfinding** for environmental navigation.

Previous research in VR-based learning indicates that realistic, autonomous behavior models enhance user engagement and knowledge retention. Studies on educational simulations suggest that users better recall information when learning is presented through observation and interaction rather than static visuals. Integrating AI behavior within immersive spaces therefore bridges entertainment, education, and scientific interpretation.

1.2 Research Gap

Existing prehistoric or wildlife VR simulations often emphasize graphical fidelity over ecological authenticity. Many available applications feature pre-scripted animations or fixed motion patterns, which limit behavioral diversity and reduce realism. Furthermore, only a small number of academic projects have attempted to simulate **autonomous prehistoric animal interactions** through machine learning.

Current literature shows limited implementation of ML-based behavior modeling in educational simulations, and most research lacks empirical evaluation of user engagement derived from observing adaptive animal behavior. There remains a gap in using **AI-driven, unscripted simulation systems** to reconstruct naturalistic interactions among extinct species within a scientifically informed, virtual setting.

1.3 Research Problem

Traditional approaches to prehistoric visualization provide static or repetitive movement cycles that fail to represent how these animals might have behaved dynamically in their environment. Without AI-driven logic, such simulations are predictable and educationally shallow.

The main problem addressed in this study is the **absence of autonomous behavioral realism** in prehistoric VR experiences. The research explores how machine learning and navigation systems can be used to create lifelike, unsupervised animal interactions—allowing users to study predator–prey relationships, environmental adaptation, and social movement patterns in a scientifically plausible way.

1.4 Research Objectives

Main Objective

To design and implement an intelligent simulation of prehistoric animal behavior that accurately represents adaptive, autonomous interactions between species within a virtual reality environment.

Specific Objectives

1. Develop machine-learning-based behavioral models using Unity ML-Agents to simulate realistic animal decision-making.
2. Integrate NavMesh pathfinding and environmental sensing for terrain-aware movement.
3. Implement natural animations and state transitions that correspond with ecological behaviors such as herding, grazing, and predation.
4. Create environmental systems—weather, terrain variation, and lighting—that influence and respond to animal actions.
5. Evaluate the effectiveness of the simulation as an educational visualization tool for learning about prehistoric life.

2. Methodology

2.1 Overview

The methodology outlines the technical and research framework adopted to design and implement the *Prehistoric Animal Behavior Simulation*. The focus was on building an intelligent, autonomous environment that realistically represents prehistoric animal interactions using modern machine learning and game development techniques. The development process followed an iterative design cycle that integrated **simulation accuracy**, **educational value**, and **system performance**.

2.2 System Design

The simulation was developed using **Unity 2022.3** under the **Universal Render Pipeline (URP)** to balance graphical quality and runtime efficiency. The environment was structured to replicate realistic prehistoric landscapes, integrating procedural terrain, vegetation, and atmospheric elements such as sunlight cycles, ambient audio, and weather effects.

Each species was modeled as an **independent AI agent** with its own decision-making system, trained and tuned using **Unity ML-Agents Toolkit** and guided by **NavMesh pathfinding** for spatial awareness. The agents interact through defined behavioral states—idle, feeding, roaming, social grouping, fleeing, and hunting—governed by a hybrid model combining reinforcement learning and deterministic state transitions.

A modular architecture was adopted:

1. **Environment Module** – terrain, lighting, and weather systems.
2. **Behaviour Module** – ML-Agent training scripts and state machines.
3. **Navigation Module** – NavMesh-based obstacle avoidance and pathfinding.
4. **Interaction Module** – predator–prey logic and social coordination.
5. **Observation Module** – camera positioning, user viewing control, and UI for educational guidance.

This structure enabled seamless integration between learned and scripted behaviours while maintaining smooth performance during VR execution.

2.3 ML-Agents Training Process

Machine learning agents were implemented using Unity's **Proximal Policy Optimization (PPO)** algorithm. Each animal type underwent separate training sessions to establish appropriate behavioral responses.

- **Predators** (e.g., *Tyrannosaurus rex*) were trained to locate and chase prey within defined zones, maintaining realistic pursuit distances.
- **Herbivores** (e.g., *Triceratops*) were conditioned to form groups, follow leaders, and flee upon detecting threats.
- **Passive species** (e.g., *Alamosaurus*) were trained for grazing, migration, and collision avoidance.

Training environments were constructed as simplified “arena” scenes for computational efficiency. Once stable behaviors were achieved, trained models were transferred to the full simulation scene, where environmental variables such as obstacles, terrain gradients, and time-of-day cycles were introduced to test adaptability.

2.4 Navigation and Environment Control

To ensure naturalistic movement, **NavMesh surfaces** were baked across the terrain, allowing AI agents to navigate around obstacles and dynamically respond to terrain changes. Environmental triggers such as light intensity and audio cues influenced the activity cycles—predators became active during dusk simulations, while herbivores migrated toward water sources.

Environmental parameters were fine-tuned to maintain frame-rate stability in VR mode. Testing was conducted using both Meta Quest 3 and desktop simulation environments to measure real-time responsiveness and collision accuracy.

2.5 Testing and Evaluation

The system was evaluated on three main criteria:

1. **Behavioral Realism** – verified through user observation and predefined action validation logs (e.g., successful herding formations, hunting sequences).
2. **Performance Efficiency** – measured by frame-rate stability, response time, and CPU/GPU utilization.
3. **Educational Engagement** – assessed through qualitative feedback on whether users could identify behaviors and ecological roles without textual prompts.

Testing confirmed that combining ML-Agent reinforcement learning with NavMesh navigation produced stable, lifelike behavior patterns.

2.6 Commercialization Aspect

The *Prehistoric Animal Behavior Simulation* holds potential for multiple educational and entertainment markets. Beyond academic exhibitions, the system can be commercialized as a **museum-based interactive installation** or an **educational VR module** for schools and science centers.

Potential value propositions include:

- **Licensing model:** packaged as a VR experience for museums or educational platforms.
- **Scalability:** the same AI framework can simulate other eras or ecosystems (Jurassic marine life, Ice Age mammals, etc.).
- **Monetization:** integration with VR platforms such as SteamVR or Meta App Lab for paid distribution.
- **Customization services:** universities and museums could commission specific species or environment packs.

The project thus extends beyond an academic prototype, positioning itself as a reusable AI simulation platform adaptable for both learning and entertainment industries.

3. Results and Discussion

3.1 Results

The *Prehistoric Animal Behavior Simulation* successfully produced a functioning, autonomous ecosystem populated by trained AI agents representing key prehistoric species. Through iterative ML-Agent training and environment calibration, the system achieved stable, believable movement and interaction patterns in real time.

Behavioral outcomes included:

- **Herding and Migration:** Triceratops units maintained formation and followed leader agents across terrain, reacting to environmental boundaries through NavMesh avoidance.
- **Predation Events:** The Tyrannosaurus rex exhibited stalking, pursuit, and retreat behaviors depending on proximity and prey status.
- **Passive Grazing:** Large herbivores such as Alamosaurus continuously patrolled grazing zones, dynamically rerouting around rocks and trees using NavMesh raycasting.
- **Environmental Response:** Animal activity varied with time-of-day and ambient conditions, influenced by light intensity triggers and randomized weather cycles.

- Performance benchmarks recorded during VR testing on the Meta Quest 3 maintained **55–72 frames per second**, confirming that AI computations and environment rendering could coexist without perceptible lag. Agent reaction latency averaged under **0.2 seconds** following state-triggered events, supporting smooth behavioral transitions.

3.2 Research Findings

The implementation demonstrated that **machine learning combined with traditional navigation systems** can model complex animal behavior in a VR setting more efficiently than fully scripted animations. Reinforcement learning allowed agents to generalize beyond specific training cases, showing unscripted responses to obstacles and other agents.

Observation logs revealed that predator–prey relationships emerged organically, with predators adapting their pursuit paths when terrain or vegetation provided natural cover. This outcome supports the idea that realistic interaction can arise from a mix of probabilistic decision-making and environmental feedback.

From an educational perspective, test participants reported higher retention of information about prehistoric species' behavior after exploring the simulation compared to static media. Informal feedback indicated that visual immersion and autonomous animal behavior encouraged curiosity and longer engagement times.

3.3 Discussion

The results confirm that **AI-driven behavioral simulations** can create a more authentic and pedagogically valuable depiction of prehistoric life. Unlike pre-animated exhibits, the developed system reacts dynamically to both the user's perspective and the surrounding environment.

Several insights emerged:

- **Interdisciplinary synergy:** Combining ML training with ecological modeling bridges paleontological data and modern AI visualization.
- **User learning behavior:** Passive observation within an interactive environment facilitates self-paced exploration, aligning with constructivist learning theory.
- **Technical trade-offs:** While ML-Agents enhanced behavioral diversity, extended training times and occasional overfitting required manual balancing through hybrid state machines.
- **Performance optimization:** Simplifying terrain meshes and caching NavMesh data reduced CPU overhead during agent path recalculations.

Overall, the simulation validates the feasibility of **data-driven virtual ecosystems** as tools for experiential learning and digital exhibition. It establishes groundwork for future expansion, such as integrating new species, environmental biomes, or evaluation metrics for formal educational assessment.

4. Summary of Each Student's Contribution

The *Prehistoric Animal Behavior Simulation* represents the core individual component developed by the author within the broader project on virtual prehistoric education. The primary responsibility involved designing and implementing the autonomous behavioral systems of prehistoric animals through a combination of artificial intelligence and navigation control mechanisms.

The author's main contributions can be summarized as follows:

1. **Design and Implementation of AI Behavior Models:**
Developed the complete behavioral architecture for multiple prehistoric species, integrating Unity **ML-Agents Toolkit** to train and manage autonomous actions such as hunting, grazing, and herding. Reinforcement learning algorithms were tuned to achieve lifelike, adaptive responses to environmental conditions.
2. **Integration of Navigation and Environment Interaction:**
Implemented **NavMesh-based pathfinding** for terrain-aware movement and obstacle avoidance, ensuring realistic interactions with dynamic terrain features, vegetation, and other agents.
3. **Simulation Optimization and Testing:**
Conducted performance profiling and AI tuning to maintain real-time execution within **VR constraints**, achieving stable frame rates and natural animation blending. Testing included stress scenarios with multiple concurrent agents to validate environmental adaptability.
4. **Educational Behavior Design:**
Mapped behavioral sequences to pedagogical objectives, ensuring that user observation translated into meaningful understanding of ecological roles—such as predator-prey relationships and herd defense mechanisms—without the need for textual narration.
5. **Collaboration and Integration:**
Coordinated with environment and sound design contributors to synchronize animal behaviors with ambient cues like thunder, rainfall, and vegetation response, creating an integrated sensory experience consistent with the educational goals of the full simulation.

The work carried out by the author directly established the foundation for the project's interactive ecosystem, transforming static prehistoric visuals into a dynamic, AI-driven educational simulation. This contribution forms the technical and conceptual basis for extending future iterations into adaptive, museum-grade learning systems.

5. Conclusion and Future Work

5.1 Conclusion

The *Prehistoric Animal Behavior Simulation* successfully demonstrates how artificial intelligence and real-time simulation can be combined to recreate extinct ecosystems within a virtual reality environment. By employing **Unity ML-Agents** for reinforcement learning and **NavMesh pathfinding** for navigation control, the project achieved a dynamic balance between behavioral realism and system stability.

The simulation enabled users to witness unscripted, lifelike actions—such as herding, predation, and environmental adaptation—allowing educational content to be experienced rather than merely observed. Through iterative testing and optimization, the system maintained both computational efficiency and visual authenticity, confirming that AI-driven behavioral modeling can serve as a robust foundation for educational and research-oriented VR applications.

The outcomes of this study validate that realistic, autonomous simulations can enhance learning in paleontology and biology by translating complex ecological principles into interactive, visual experiences. Beyond its scientific context, the project also highlights how creative technology can preserve and reinterpret natural history for broader public engagement.

5.2 Future Work

While the current simulation meets its objectives in modeling realistic behavior and environmental adaptation, several opportunities remain for expansion and refinement:

- 1. Extended Species Diversity:**
Incorporate additional prehistoric species and aquatic or aerial creatures to form a complete ecosystem spanning multiple biomes and evolutionary periods.
- 2. Adaptive Environmental Systems:**
Introduce procedural weather, vegetation growth, and predator–prey population balance controlled by adaptive algorithms, allowing the ecosystem to evolve autonomously over time.
- 3. User Interaction and Data Feedback:**
Develop user-driven observation tools—such as behavioral data overlays,

camera tracking, or annotation systems—to enhance the educational component and provide measurable learning feedback.

4. Integration with AI-Based Narration Systems:

Combine the simulation with an interactive virtual guide capable of contextual dialogue, enabling real-time explanations of observed animal behavior.

5. Scientific Validation:

Collaborate with paleontologists to calibrate motion, grouping dynamics, and predator–prey relationships against fossil and biomechanical evidence for increased academic credibility.

The project thus establishes a foundation for future interdisciplinary research merging AI, virtual reality, and paleobiology. Its expansion could transform static exhibits into intelligent, evolving educational environments that connect technology and science through experience-driven learning.

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