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# DEVELOPMENT OF AN INTELLIGENT TUTOR BASED ON GAMIFICATION AND IMMERSIVE VIRTUAL REALITY. USE CASE: AGRICULTURE IN TEOTIHUACAN HISTORY

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*Abstract:* Learning history as a simple memorization of events does not guarantee learning that allows one to use what has been assimilated for the benefit of oneself and society. Therefore, new learning methods must be developed that transcend passive memorization to achieve meaningful and lasting assimilation. This article presents the formal development of an Intelligent Tutoring System (ITS) for teaching agriculture in the Teotihuacan culture, implemented in an immersive Virtual Reality (VR) environment. The system integrates a virtual tutor based on Artificial Intelligence (AI) that guides the student through a gamified maize cultivation process. The main contribution of this work is the proposal of a mathematical formalism that models the gamified learning process. This model, based on Automata Theory and Markov Decision Processes (MDPs), defines the student's progress states, available actions, and transitions, which are influenced by both the user's decisions and the tutor's evaluation. Formalism allows for the systematic implementation and quantitative evaluation of the impact of gamification and AI tutoring on the acquisition of historical knowledge. The resulting virtual environment simulates the Valley of Teotihuacan, where the user interacts with pre-Hispanic tools (coa, uictli) and confronts natural phenomena, aiming to achieve a successful harvest. The final result is evaluated through an adaptive questionnaire. This approach demonstrates how the mathematical formalization of pedagogy in virtual environments can optimize the design of immersive, effective educational experiences.

***Keywords:*** Virtual Reality, Artificial Intelligence, Gamification, Mathematical Model, Markov Decision Process, Teotihuacan History, Immersive Education.

## I. INTRODUCTION

The integration of Artificial Intelligence (AI) and Virtual Reality (VR) in education has opened new frontiers for creating immersive and personalized learning experiences. While disciplines like history are often taught using traditional memorization-based methods, VR offers the possibility of "experiencing" the past, while AI can provide adaptive guidance, like that of a human teacher. However, the literature lacks formal methodologies for constructing and evaluating these systems in a structured manner. This work addresses this gap by proposing a formal framework for designing an educational environment that merges AI and VR, using the agriculture of the Teotihuacan civilization—a pivotal culture in Mesoamerican history—as a case study. The main objective is to mathematically model the gamified learning process to ensure that knowledge acquisition is not only engaging but also systematic and assessable.

## II. VIRTUAL REALITY AND ARTIFICIAL INTELLIGENCE IN EDUCATION

VR allows the construction of virtual environments where users can interact and perform actions, facilitating experiential learning [1]. AI enhances these environments through intelligent agents or "virtual tutors" that guide the user, adapt tasks, and provide feedback. These tutors can detect user difficulties and propose alternative activities to support knowledge assimilation, acting as virtual cognitive scaffolds. When users accomplish the objectives and tasks, it can be inferred that they are prepared to face challenges that may arise in real-world situations [2].

One of the subjects in which students experience greater difficulty in acquiring knowledge is history. Historical content generally consists of large volumes of text that often generate apathy and boredom among students. For this reason, historians propose the use of resources such as videos, monographs, and practical activities that stimulate students' interest in acquiring knowledge that they can apply both in the classroom and in their daily lives.

Olabe et al. [3] seek to change students' perception of history as a tedious subject by transforming it into an engaging and enjoyable experience through the use of Virtual Reality (VR). Their approach uses the Mexican Ministry of Education (SEP) textbook "La entidad donde vivo". For their study, the authors selected the history of Guanajuato as the case study. Their proposal consists of guiding students through different historical periods using virtual environments and narrative elements such as storytelling, through which a story is created in which the student interacts with the environment, thereby reinforcing the learning process.

### A. *Gamification in Learning*

Gamification is a new concept created by video game developers to keep users engaged in a game for longer. It enables interaction among users who collaborate within the virtual environment to accomplish tasks or simply for recreational purposes, resulting in a simulation that more closely resembles real-world situations. This interaction promotes empathy among users, making the experience more engaging and consequently enhancing the learning process [4], [5].

This principle applies mechanics and dynamics within the environment, motivating users to achieve objectives and progress through levels (see Figure 1). These characteristics can be applied to non-game contexts to motivate action, encourage learning, and facilitate problem-solving [6]. It is not limited to creating rewards but seeks to improve the user experience, fostering voluntary participation and immersion in a world with its own rules (learning) [4]. In the educational context, gamification can transform the perception of complex subjects like history, making them more engaging.

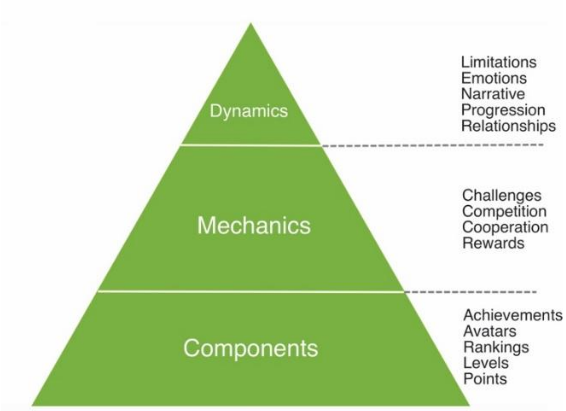


Figure 1. Basic concepts of gamification.

Based on the principles of gamification, a methodology is proposed consisting of five phases, as shown in Figure 2. This includes the transitions between levels, the tasks to be completed, and the relationships that enable the student to acquire knowledge. The proposed methodology allows the validation of gamification concepts using traditional processes and mathematical formalisms such as Markov models.

### B. *Historical Context: Agriculture in Teotihuacan*

The archaeological zone of Teotihuacan is located approximately 45 km from what is now Mexico City [7]. One of the most important activities of the Teotihuacan culture was agriculture. Their diet consisted mainly of products derived from maize, such as tortillas, tamales, atole, and pozole. Maize was the primary food of Mesoamerican peoples and was even associated with religious beliefs [8].

Archaeological evidence suggests that the Teotihuacanos developed various agricultural techniques. Among these were artificial irrigation systems that allowed them to retain water, reduce the resting time of the land, cultivate intensively, and farm in arid areas [8]. Likewise, records have been found of rainfed agriculture, trenches used to store floodwater, and systems designed to collect torrential runoff for irrigation [9].

Another technique used by Teotihuacan farmers was terrace farming, in which the land on mountainous areas was cultivated in stepped formations to retain moisture and control soil erosion. Among the tools used by the inhabitants of Teotihuacan were axes, planting sticks known as coa or uictli, and shovels (uictli axoquen) [8].

### C. *Mathematical Modeling in Adaptive Systems*

The use of mathematical formalisms such as **Markov Decision Processes (MDPs)** is common in intelligent recommendation systems. An MDP is defined by the tuple *(S, A, P, R)* [10], where:

- $S$ is a finite set of states.
- $A$ is a finite set of actions.
- $P$ is the transition probability matrix, where $P(s' \mid s, a)$ is the probability of transitioning to state $s'$ from state $s$ by taking action $a$.
- $R$ is the reward function, $R(s, a, s')$, which quantifies the immediate benefit of a transition.

This model can be adapted to represent and ensure the learning process, in which the student's decisions (actions) and the tutor's interventions (which can modify the transition probabilities) lead to different states of knowledge (rewards).

### D. *Proposed Mathematical Formalism for the Gamified Learning System*

To provide the system with a solid theoretical foundation, agents are proposed in conjunction with a mathematical model that represents the student's journey through the virtual environment. This model integrates phased progression (gamification) with the AI tutor's adaptability.

*[Student State Space]* Let $S = \{S_{phase,\ state}\}$ be the set of all possible states in which a student can find themselves. This set is the union of all states defined in the five phases of the system (see image Gamification). Each state $s \in S$ is characterized by a set of knowledge and progress variables.

*[Learning Process as a Markov Decision Process]* The student's learning process is modeled as a *(MDP)* $M = (S, A, P, R)$, where:

- $S$: Is the finite state space defined above.
- $A$: Is the finite set of actions that the student can perform. These actions can be of two types:
  - $A_u$: User actions (e.g., clear_land, plant_seed, build_wall, ignore_task).
  - $A_t$: AI tutor actions (e.g., explain_task, offer_help, assess_knowledge), which are activated in response to the user's state or inaction.
- $P$: State Transition Function. Defines the probability of transitioning from state $s$ to state $s'$ by taking action $a$.

$$P(s' \mid s, a) = p_{s,a,s'} \in [0, 1] \qquad (1)$$

Example: From state Phase 3_WaitingForRain, if the user performs the secondary action build_wall ($a_u$), the probability of transitioning to state Phase 4_ProtectedCrop is high (p = 0.95). If the task ($a_u$) is ignored, the probability of transitioning to Phase 4_Vulnerable is high (p = 0.9).

- *R*: Reward Function. It quantifies the value of a transition and reflects learning progress. It is not a grade, but a measure of knowledge acquisition and goal achievement.

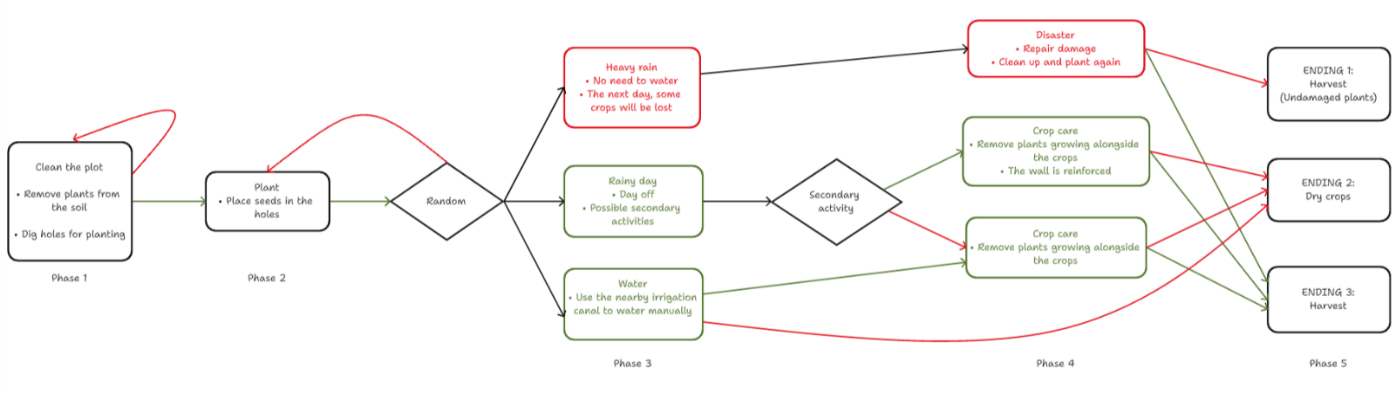


Figure 2. Proposed methodology based on gamification for learning Teotihuacan history

*R(s, a, s′)* = {+10, if s′ is a progress state (green) −5, if s′ is a setback state (red) +1, if s′ is a neutral state and a secondary task was completed 0, otherwise}.

*[Knowledge Representation and Evaluation]* The student's knowledge is represented by a knowledge vector $\vec{K} = [k_1, k_2, \ldots, k_n]$, where each $k_i$ corresponds to the mastery level of a specific concept (e.g., use_coa, irrigation_technique, corn_cycle). Each state $s \in S$ has an associated target knowledge vector $\vec{K}_{obj}(s)$. The tutor's role is to guide the student so that their vector $\vec{K}$ approaches the target vector. The final evaluation, *E*, is performed using an adaptive questionnaire that updates $\vec{K}$. The feedback is formalized as an update:

$$\vec{K}_{new} = \vec{K}_{previous} + \eta \cdot (\vec{K}_{correct\_answer} - \vec{K}_{previous}) \qquad (2)$$

where $\eta$ is the learning rate, and $\vec{K}_{correct\_answer}$ is the knowledge vector associated with the correct answer.

## III. Development

### A. *Description of the Developed Virtual Environment*

The virtual environment, built on a digital model of the Teotihuacan Valley (Figure 3), materializes the defined states. The user can perform the actions in set *A* using VR headsets and haptic controllers.

Figure 3. 3D model of the great city of Teotihuacan.

Each phase of the system corresponds to a subset of states in the *MDP*.

- Phase 1 (Preparation): $S_{f1} = \{s_{start}, s_{cleaning}, s_{tools}\}$. The goal is for the student to learn to use the tools and update $k_{uso\_coa}$. The action $a = clearing\_the\_ground$ correctly leads to $s_{ready}$ with $R = +10$.

Figure 4 shows the initial conditions of the crop land that the student can see in the virtual model; this shows the possible conditions of the land and the work that must be done.

Figure 4. Initial conditions of the land in the Teotihuacan environment.

- Phase 2 (Sowing): $S_{f2} = \{s_{planting}\}$. $K_{nowing}$ is reinforced.

If the objectives were achieved in phase 1 and the tools were used, one can move on to the next phase, which is planting, as shown in the figure 5.

 

Figure 5. Maize Planting

Phase 3 is a critical stage for the student in the care of their crop; the tutor's intervention is important to prevent uncontrolled situations.

- Phase 3 (Growing Conditions): $S_{f3} = \{s_{heavy\_rain}, s_{light\_rain}, s_{irrigation}\}$. Here, the system's randomness is modeled by $P(s'|s, a)$. If the previous state was $s_{ready}$, the probability of entering each of these three states is 1/3, unless the tutor intervenes. Secondary tasks in $s_{light\_rain}$ are actions $a$ that increase $K_{community}$ and modify future rewards.

Figure 6. Climatic conditions with heavy rain that affect the crop.

- Phase 4 (Consequences): $S_{f4} = \{s_{disaster}, s_{careful\_cultivation}, s_{neglected\_cultivation}\}$. The state achieved is a deterministic function of previous actions and the reward history.

Figure 7 illustrates one possible consequence of failing to take action to care for the crop. In this case, the figure shows how the corn plants die from excess water, which can be due to the weather or a lack of irrigation. Here, the tutor can advise the student on the precautions to take to achieve successful harvests.

Figure 7. Corn dies due to a lack of care.

- Phase 5 (Results and Evaluation): $S_{f5} = \{s_{dry\_harvest}, s_{scarce\_harvest}, s_{satisfactory\_harvest}\} \cup \{s_{questionnaire}\}$. The transition to these final states depends on the accumulated reward sum, $\Sigma R$. Then, in the $s_{questionnaire}$, $\vec{K}$ is evaluated.

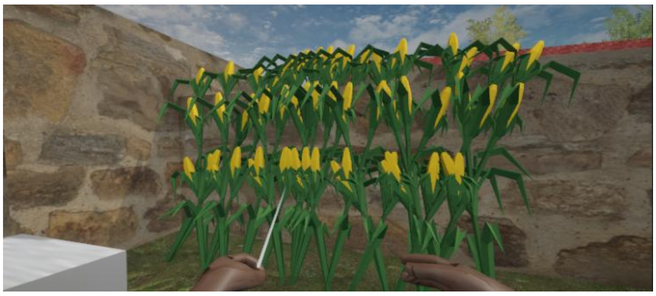

Figure 8. It ends with a good corn harvest.

Figure 8 shows the results after the student has completed all the stages, allowing them to observe their performance and enabling the tutor to recommend new activities to reinforce what they have learned.

### B. *AI Tutor Implementation*

The "Chief Farmer" is an intelligent agent that implements a policy $\pi : S \rightarrow A_t$. It observes the student's state $s$ and the elapsed time, and selects a tutoring action. For example:

- If the student spends a long time in $s_{cleaning}$, $\pi(s_{cleaning})$ could be "explain_instructions."
- If the student is in $s_{scarce\_harvest}$, $\pi(s_{scarce\_harvest})$ could be provide_feedback_on_irrigation.


Figure 9. Corn dies due to a lack of care.

Figure 9 shows the tutor interacting with the student via a text interface, suggesting new activities and offering advice to help the student learn and recognize how corn was cultivated in the Teotihuacan culture.

## IV. RESULTS

The resulting system transcends the traditional method of learning history through rote memorization by placing the student in a decision-making context with visible consequences. The AI tutor ensures that, regardless of the path taken (even in "bad endings"), the student receives corrective feedback, thus reinforcing learning through experience and reflection. This directly addresses the problem of a lack of interest in history by transforming it into an interactive and personal experience.

The mathematical formalism presented, which allows:

1. Systematic Design: The creation of the virtual environment ceases to be an ad-hoc process and becomes the implementation of a well-defined model.

2. Quantitative Evaluation: The use of rewards (R) and the evolution of the knowledge vector ($\vec{K}$) allow for the objective measurement of student progress.

3. Enhanced Adaptability: The MDP model provides a framework for the AI tutor to make optimal decisions (e.g., using reinforcement learning algorithms) to maximize long-term rewards, which equates to maximizing student learning.

4. Reproducibility: Other researchers can implement similar systems following the same formalism.

Figures 4 to 8 show the different scenarios corresponding to the states $s \in S$: from land preparation with virtual tools, through climatic phenomena, to the final harvest. The "Farmer Manager" and the "Farmer" are the visual agents that execute the tutoring actions $A_t$, guiding the user through the state space.

## V. Conclusions and Future Work

An immersive educational system integrating VR and AI has been developed to teach the agricultural history of Teotihuacan. The core innovation lies in the mathematical formalization of the gamified learning process using a Mathematical Development Model (MDM), providing a solid foundation for the system's design, implementation, and evaluation. Qualitative results suggest that this approach has the potential to motivate students and facilitate a deeper and more lasting understanding by enabling them to "learn by doing" in a historically inspired virtual environment. Future work will focus on:

- Validating the model quantitatively with a sample of students, analyzing the correlation between rewards accumulated in the MDM and standardized knowledge test results.

- Extending the formalism to include dynamic difficulty personalization, where the AI tutor adjusts $P$ in real time based on student performance.

- Incorporating more crops and agricultural techniques, as well as social and religious elements, to enrich the knowledge model $\vec{K}$.

- Integrating a large language model (LLM) such as ChatGPT to allow natural language queries within the environment, creating a virtually infinite state space S for knowledge exploration, formalizing this interaction as a special action question whose result updates $\vec{K}$ in a non-deterministic way.

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