A Conceptual Proposal for an Architecture of an Adaptive Gamebook with GLA and GenAI for Interdisciplinary Learning

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Abstract

Serious games have been widely explored to promote engagement and active learning. However, most systems lack mechanisms to dynamically adapt educational content based on learner interactions during gameplay. This work proposes a conceptual architecture for an adaptive educational gamebook that integrates Game Learning Analytics (GLA) and Generative Artificial Intelligence (GenAI) for real-time personalization of the learning experience. Based on Intelligent Tutoring Systems, the architecture defines a continuous cycle in which GLA analyzes player interactions to update a Student Model, whose state guides GenAI-based scenario and narrative generation. A functional Unity prototype was developed to instantiate selected architectural components and demonstrate the technical feasibility of connecting player choices with GenAI-generated content. The pilot evaluation provided preliminary feedback on usability, narrative clarity, visual design, and perceived educational potential, but did not assess learning outcomes or validate the proposed adaptation mechanisms. The complete closed loop involving GLA-based Student Model updates and Domain Model-conditioned generation remains to be implemented and empirically validated. The proposed architecture provides a conceptual and technical foundation for personalized, adaptive, and interdisciplinary learning environments.

Keywords

Serious Games, Game Learning Analytics, Generative Artificial Intelligence.

1 Introduction

Education, especially after the COVID-19 pandemic, has undergone significant transformations, highlighting the need to reconsider traditional forms of curriculum and pedagogy [34]. Complementary teaching tools, such as serious games, have stood out as effective instruments in the learning process [7, 31]. Traditional teaching approaches may provide limited opportunities for active student participation, while student-centered and active-learning strategies can support deeper and more authentic learning experiences [11, 34]. In this context, serious games [1, 33] emerge as an educational tool capable of transforming the learning process into an interactive and motivating experience [24]. By integrating game elements with complex concepts, serious games can promote a more solid understanding of the topics addressed, while also stimulating reasoning, problem-solving, and autonomous learning [24]. Several studies demonstrate the effectiveness of applying serious games in education [5, 16, 28, 32, 33], providing a rich environment for interdisciplinarity by proposing problems and challenges [23].

One of the strategies that has proven promising for creating a connection with the student is the use of Role-Playing Games (RPG), a tool that aims to provide an interactive and immersive experience, allowing the player to have multiple options and control over their trajectory within the virtual environment [2, 30], in addition to offering a structured narrative environment that can support problem-solving and knowledge construction [8].

Thus, in the first part of the present work, the incorporation of self-regulated learning into RPG games was studied. Astrobiology was selected as the major field due to its interdisciplinarity, enabling the integration of knowledge from different disciplines and the practical application of concepts from exact, natural, and social sciences [17, 23]. Accordingly, this work proposes a conceptual architecture for an adaptive digital gamebook that addresses Astrobiology through RPG concepts, self-regulated learning, serious games, GLA, and GenAI, enabling personalization, dynamic generation of fictional scenarios, and multiple endings based on player choices. As evidence of feasibility, the architecture is instantiated through the *Destino Cósmico* prototype, presented in Section 4.6. The primary target audience comprises lower secondary education students (Fundamental II), typically aged 11 to 14 years, with Astrobiology serving as a motivational framework to connect and contextualize core concepts across subjects.

2 Theoretical Foundations

Serious games combine game elements with educational objectives and serve as supporting educational tools by promoting active learning, engagement, and the contextualization of complex concepts [2, 7, 31]. Unlike traditional approaches, they place students in an active role, allowing them to interact with scenarios and make decisions that influence learning [21].

In this context, there is a need for mechanisms capable of continuously understanding and adapting the player's experience. Game Learning Analytics (GLA) has been used to collect and analyze data from player interactions, supporting the identification of behavioral patterns, learning progress, and specific difficulties [3, 25]. Unlike traditional assessment models based on pre- and post-tests, GLA allows the observation of the learning process in real time, providing support for more precise interventions. Despite this potential, several GLA applications emphasize retrospective analysis, visualization, or performance prediction, while their use as an active mechanism for generating and adapting content during interaction remains comparatively underexplored [3, 6, 22]. This limitation raises the possibility of integrating techniques that not only analyze player behavior but are also capable of dynamically modifying the learning experience.

As a complementary approach, Generative Artificial Intelligence (GenAI) emerges as a promising solution by enabling the generation of dynamic content, such as narratives, scenarios, and adaptive challenges [15, 18]. GenAI makes it possible to create new elements in real time, adjusted to the context and user interactions, enhancing game personalization. The integration between GLA and GenAI allows the establishment of a continuous adaptation cycle, in which data collected from player behavior are used to guide the generation of new content, promoting a personalized and dynamic experience. However, this integration is still underexplored in a structured way within educational game architectures.

Within this context, Intelligent Tutoring Systems (ITS) provide a well-established framework for delivering personalized learning experiences. ITS aim to provide personalized instruction by modeling the learner, monitoring their progress, and adapting educational content according to individual needs. Traditional ITS architectures commonly include components representing domain knowledge, the learner's state, pedagogical decisions, and the learner-facing interface [12]. Learning analytics and artificial intelligence techniques have increasingly been investigated as mechanisms for supporting data-driven learner modeling and educational adaptation [3, 12, 15, 18]. In this context, the integration of GLA and GenAI can be viewed as an evolution of ITS, where player interaction data continuously update the student model and guide the generation of personalized educational experiences.

To enable this integration, mechanisms for data collection and organization become essential. Tools such as GLBoard allow the standardized capture of information during gameplay, including interactions, progress, and player performance, serving as a basis for further analysis and system adaptation.

Furthermore, the proposal of this work is situated within an interdisciplinary context, using astrobiology as the application domain and guiding theme. This field, due to its integrative nature, enables the connection of concepts from different disciplines, supporting the construction of knowledge in a contextualized manner. Such an approach aligns with principles of meaningful learning, in which new knowledge is built upon the student's pre-existing cognitive structures. Taken together, prior research on serious games, ITS, GLA, GenAI, and student modeling provides the conceptual basis for investigating continuously adaptive educational systems [3, 12, 15, 18, 25]. However, as discussed in Section 3, these elements are generally addressed separately, and their integration into a closed adaptation loop remains underexplored. This gap motivates the architecture proposed in this work.

3 Related Work

The use of serious games in the educational context has been widely explored as a strategy to promote engagement and active learning, especially in STEM (Science, Technology, Engineering, and Mathematics) areas and interdisciplinary contexts. Several studies demonstrate that these systems can support the development of cognitive skills, decision-making, and the understanding of complex concepts through interactive experiences [10, 19, 26]. In the domain of commercial games that touch on themes of evolution and astrobiology, examples include Spore [9], which allows players to guide the evolution of a creature through different stages, from the cellular level to space exploration; The Universim [27], No Man's Sky [14], and Stellaris [20], which explore civilization management, space exploration, and interstellar strategy. However, the high complexity of the first is not ideal for younger audiences, while none of the others focus primarily on astrobiology or evolution, reinforcing the gap that the present proposal aims to address.

Furthermore, adapting the learning experience in these games still represents a challenge. In this regard, GLA has been studied as a means to collect and analyze player interaction data, enabling the identification of behavioral patterns, performance evaluation, and the inference of learning trajectories. Works such as Alonso-Fernández et al. (2022) and Honda et al. (2023) explore the use of data mining techniques and predictive models to extract pedagogical insights from these interactions [3]. The study by Silva et al. (2020) presents a parameterized system proposal to support data capture and GLA analysis, introducing GLBoard based on a generic data model for educational games, which automatically organizes common information such as timestamps, attempts, level transitions, and user interactions (Fig. 1). The package can be directly integrated into the Unity engine [27], which facilitates its implementation.

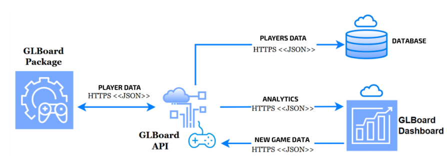

Figure 1: The architecture of the GLBoard system for data capture and analytics. Scheme adapted from [25].

In addition, approaches such as the GLAID model [6] demonstrate the possibility of adapting analyses for specific audiences, while other studies combine GLA with technologies such as eye-tracking and data visualization to deepen the understanding of player behavior [4]. The work of Qasrawi et al. (2020) proposes a model as an alternative to traditional assessment methods, in which, using Robotic Process Automation (RPA), the system collects and processes data such as response time and errors made, eliminating the need for manual intervention and enabling continuous, real-time feedback on student performance. Alonso-Fernández et al. (2022) explored the combination of data visualization and predictive models, such as neural networks and SVR (Support Vector Regression), to select the most relevant variables (such as player progress and interactions with specific components) and infer which behaviors positively or negatively impact learning in a first aid game. However, despite these advances, most GLA applications focus on retrospective data analysis, with limited exploration of its use for dynamic adaptation of the experience during interaction.

In parallel, GenAI has emerged as a promising technology in the development of adaptive educational games. Recent studies indicate its potential in generating dynamic content, such as narratives, scenarios, and personalized challenges, adjusted to the player's profile and actions [15, 18]. These works show that GenAI can act both as a personalization tool and as support for creating more complex interactive experiences.

However, these approaches are often explored in isolation: GLA focuses on player behavior analysis, while GenAI focuses on content generation. This work addresses this gap by proposing an architecture that integrates both in a continuous cycle, using interaction data to guide dynamic content generation and support a personalized, adaptive learning experience.

Table 1 summarizes this comparison. Unlike GLA-focused approaches [3, 6, 22], which analyze interaction data without feeding it back into content generation, and unlike GenAI-focused approaches [15, 18], which generate content without a persistent, continuously updated learner model, the architecture proposed in this work closes this loop structurally: the Student Model, maintained as an ITS-style hybrid overlay/perturbation representation, is the explicit interface between the GLA analysis stage and the GenAI generation stage, so that every adaptation decision is conditioned on an explicit, auditable state of the learner's knowledge rather than on raw interaction data or an unconditioned prompt.

More specifically, the contribution of this work is threefold: (i) a conceptual architecture that connects real-time GLA, an explicit Student Model, and GenAI-based content generation in a closed adaptation loop; (ii) a domain-modeling strategy that organizes interdisciplinary concepts through prerequisite relationships; and (iii) an executable gamebook prototype that instantiates selected components of the architecture in the context of astrobiology education.

4 Proposed Architecture

The architecture proposed in this work is organized in a modular and dynamic way, integrating the three main models of ITS[12]: the Domain Model, the Student Model, and the Intelligence Model. These components communicate dynamically to enable a personalized and meaningful learning experience.

4.1 Architecture Overview

The architecture follows the ITS paradigm, in which different models represent knowledge, the student's state, and the adaptation mechanism. The Domain Model defines the concepts to be learned and their pedagogical organization. The Student Model represents the player's knowledge state and is continuously updated based on their interactions. The Intelligence Model acts as the central component, being responsible for interpreting the collected data and dynamically adapting the experience. The way these three models interact as a continuous adaptive cycle is described in Section 4.2.

4.2 Adaptive System Cycle

The system operates as a continuous cycle, illustrated in Fig. 2, in which the Domain Model, Student Model, and Intelligence Model continuously exchange information: the Domain Model provides the conceptual foundation that guides the game phases, the Student Model represents the learner's evolving knowledge state, and the Intelligence Model integrates GLA-based analysis with GenAI-driven content generation. The cycle comprises four main stages:

(1) **Initialization**: the learner completes a diagnostic questionnaire, initializing the Student Model with an estimate of prior knowledge; the collected responses are forwarded to the GLA component of the Intelligence Model, which analyzes the learner's profile and determines how the concepts defined in the Domain Model will be presented throughout the game.
(2) **Interaction**: the learner interacts directly with the gamebook interface, making narrative choices, responding to challenges, and navigating different paths within each phase.
(3) **Analysis**: the GLA component continuously records and analyzes these interactions, including response time and navigation paths, dynamically updating the Student Model based on the collected evidence.
(4) **Adaptation**: at the end of each phase, the GenAI component is invoked to generate new fictional scenarios and adaptive choices, combining (i) the concepts defined in the Domain Model, which specifies what should be introduced or reinforced, with (ii) the updated Student Model, representing the learner's current knowledge state.

These four stages repeat throughout gameplay, establishing a continuous personalization mechanism in which the learning experience is dynamically adjusted based on the learner's performance. At the end of the gameplay, the final interaction data are sent to GLBoard, where pedagogical reports and dashboards are generated to support the analysis of the learner's progression, and the Student Model receives its final update and is compared with the Domain Model to estimate the learner's knowledge acquisition. The expected outcome is that, by the end of the game, the Student Model closely approximates the Domain Model.

4.3 Domain Model

The Domain Model defines the pedagogical structure of the intelligent gamebook by organizing the scientific concepts that should be learned throughout the gameplay. In this work, the model is organized into sequential phases, where each phase introduces prerequisite concepts that support the understanding of subsequent topics. This organization ensures that the learner progresses through the content in a structured manner while providing the conceptual foundation used by the adaptive mechanisms of the proposed architecture.

Table 1: Positioning relative to closest related systems.

System	Learner model	GLA use	Generation mechanism	Closed loop
GLBoard [25]	–	Retrospective	–	No
GLAID [6]	–	Audience-adapted	–	No
Alonso-Fernández et al. [3]	–	Predictive (SVR)	–	No
Qasrawi et al. [22]	–	Real-time (RPA)	–	No
GenAI game design [15, 18]	Implicit / none	–	LLM content	No
This work	**Explicit (overlay+perturbation)**	**Real-time**	**LLM content**	**Yes**

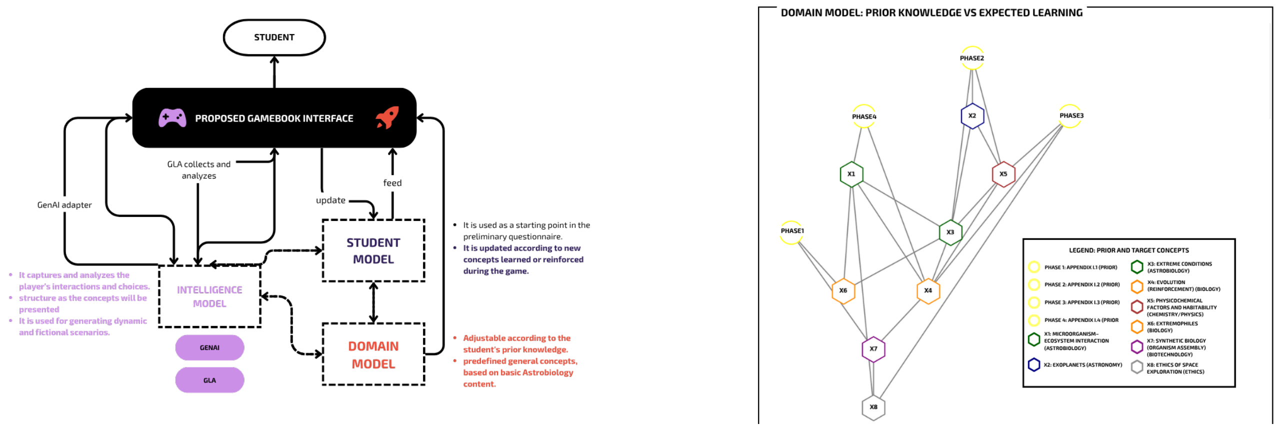

Figure 2: Overview of the proposed system architecture and Domain Model. The system architecture (left) integrates the Student, Domain, and Intelligence Models, while the Domain Model (right) organizes the knowledge domains into sequential learning phases connected by prerequisite relationships.

Figure 2 illustrates how the knowledge domains are organized into sequential learning phases connected by prerequisite relationships. Each phase builds upon concepts introduced in previous phases, supporting a progressive and structured learning process throughout the game.

In this model, Astrobiology is considered the central interdisciplinary axis. Based on Knowledge Space Theory, the designed phases represent the prerequisite concepts, which connect with the knowledge domains that the system aims to teach the student. The expected foundation consists of concepts from Natural Sciences, Earth Sciences, and Social Sciences defined in the middle school curriculum, according to the Brazilian National Common Curricular Base (BNCC), and with each new phase, new concepts are consolidated based on the mapped prerequisite foundations.

4.3.1 Application of the Agnostic Diagnostic Questionnaire. To assess the learner's prior knowledge, the proposed system includes an agnostic diagnostic questionnaire inspired by the approach adopted by the ALEKS (Assessment and Learning in Knowledge Spaces) platform [13]. The questionnaire design draws conceptually on Knowledge Space Theory (KST), according to which responses can be interpreted in relation to prerequisite relationships among concepts rather than as isolated items. Within the proposed architecture, this information is intended to support the estimation of the learner's knowledge state even when only a subset of questions is answered. However, the current prototype does not implement a formal KST inference algorithm. At this stage, KST is used as a conceptual basis for organizing the prerequisite relationships represented in the Domain Model, while the formal knowledge-state inference and update procedure remains part of the planned implementation.

Within the proposed architecture, the diagnostic questionnaire is administered at the beginning of the interaction to establish the learner's initial knowledge profile. The collected responses are processed by the Intelligence Model, which initializes the Student Model with the learner's prior knowledge related to Natural Sciences, Earth Sciences, and Social Sciences. This initial profile is subsequently used to adapt the presentation of the concepts defined in the Domain Model by adjusting both the progression of the game phases and the complexity of the proposed challenges according to the learner's estimated knowledge state.

4.4 Student Model

The Student Model is responsible for representing the player's cognitive state. For this purpose, a hybrid approach is adopted, combining characteristics of the overlay model, which represents the student's knowledge as a subset of the domain, with the perturbation model, which considers the presence of misconceptions. The evidence used to update the model is derived directly from player interactions during the narrative, including decisions, errors, and behavioral patterns.

4.5 Intelligence Model

Based on the analysis of the learner's profile described in the subsection 4.2 the Intelligence Model will act as the central component of the architecture, integrating analysis and adaptation mechanisms. Based on the data collected via GLA, the system identifies learning patterns and adjusts the presentation of content. The integration with GenAI enables the generation of dynamic and personalized scenarios, in which domain content is contextualized within adaptive narratives. This process allows different learning trajectories to be explored while maintaining pedagogical coherence and alignment with educational objectives.

4.5.1 Integration with GLA and GenAI. GLA is responsible for collecting and analyzing interaction data, including response time, narrative choices, and player trajectory. These data feed the Student Model and guide the adaptation process.

GenAI is used to generate dynamic content, such as scenario descriptions, events, and consequences of player decisions. The inputs for generation include the current state of the student and the concepts defined in the Domain Model, enabling the creation of personalized experiences.

4.5.2 Implementation. To simulate the game's central concept: life adapting to extraterrestrial environments, GenAI was integrated. In "*Destino Cósmico*", the AI generates unique planetary scenarios and narrative outcomes based on the player's decisions. This allows the chosen organism to evolve in response to various environmental pressures selected during the game. The game then presents custom-tailored environments and adaptive paths based on these inputs.

The prototype uses GPT-4o mini through the OpenAI API, integrated directly into Unity using C#. Dedicated classes handle prompt construction, API communication, response processing, and synchronization with the game interface, enabling real-time integration of generated content into gameplay.

Prompt Template

```
For a <cellType> of <cellSize> with a <membrane>
membrane,
<metabolism> metabolism, <nutrition> nutrition,
and
<reproduction> reproduction strategy, what would
be the
optimal survival conditions on fictional celestial
bodies?
Structure your answer as follows:

Gas Planet:
- Pressure:
- Temperature:
- Atmospheric Composition:

Rocky Planet:
...

Dwarf Planet:
...

Moon:
...
```

Figure 3: Prompt template used to instruct the Large Language Model (LLM) to generate the environmental survival conditions for microorganisms on different fictional celestial bodies.

Figure 4: Screens from the initial screening phase. Top left: introductory screen presenting the mission context. Top right: introduction to the screening questionnaire. Bottom left: example of a screening question with multiple-choice answers. Bottom right: confirmation screen indicating that the screening has been completed and the simulation has been personalized.

The prompts (Fig. 3) were developed through iterative testing to establish standardized templates capable of producing consistent outputs while reducing fluctuations (different responses to equivalent inputs) and hallucinations (factually incorrect or pedagogically inappropriate content). Each prompt combines fixed instructional text with dynamic variables extracted from the current game state, including the organism type, cell size, membrane, metabolism, nutrition strategy, reproduction strategy, and selected environmental conditions. An excerpt of the prompt template used when the player assembles a custom lifeform is shown below:

4.6 Prototype

The game was initially designed as a navigable interface mockup in Figma and subsequently implemented as a functional prototype using the Unity [27] game engine. The game follows an interactive gamebook format, allowing multiple narrative paths in which the player's decisions directly influence the development of the story.

The integration with GenAI was implemented through APIs, enabling the dynamic generation of scenarios. The prototype provides preliminary evidence of the technical feasibility of connecting player choices to API-based scenario generation. It does not, however, validate the effectiveness of the complete adaptation cycle proposed by the architecture.

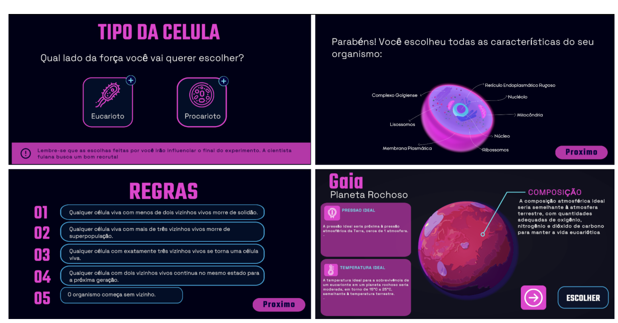

Figure 5: Top row, left: cell type selection screen; right: illustrative view of the assembled cell. Bottom row, left: rules configuration screen for the cellular automaton step; right: descriptive screen of the rocky planet Gaia.

4.6.1 Dynamic play. The creation of fictional interactive scenarios is made possible through API calls, which gather the variables selected by the player and determine the next choices to be displayed on the game screen. These simulations occur at two points during the game: (i) the generation of celestial bodies after the player chooses/assembles a living organism; and (ii) the presentation, at the end of the game, of the possible evolution of the chosen life form over time, according to the variables selected by the user throughout gameplay.

In the second part of the game, for example, players engage in a cellular automata–based "Game of Life" where they select variables to test the survival and evolution of their organism, affecting the life or death of neighboring cells. The rules governing this section are presented to the players before the decision screens. The available choices include whether or not to introduce random events on the selected celestial body, such as volcanic activity or environmental contamination, as well as whether to allow the organism to evolve.

If the user chooses to evolve the organism, the generative AI simulates the evolution of the microorganism population over time, taking into account environmental factors and genetic mutations. This is achieved by providing the AI with specific natural language instructions (known as prompts), which include, among other elements, the desired style of the response, the overall context of the game, the characteristics of the organism selected by the player, and the environment in which the organism was placed.

Before gameplay, the user answers initial questions to initialize the learner model with prior knowledge. In the complete architecture, this model would be continuously updated from pedagogically mapped interaction evidence, a mechanism not yet fully implemented in the current prototype.

A navigable interface mockup was first designed in Figma to model the player's interaction flow with the gamebook. It includes the initial screens of *Destino Cósmico*, covering: (i) the narrative introduction; (ii) an example of the initial questionnaire (agnostic diagnostic assessment); (iii) an overview of the game stages and adaptive challenges; and (iv) a dynamic feedback panel designed to respond to the player's performance. The Figma mockup was used as a design and interaction reference during the subsequent implementation of the game in Unity. The mockup is publicly available through the link provided in the Artifact Availability section.

4.6.2 Scoring system. The scoring system in "*Destino Cósmico*" was designed not to reward or punish players conventionally but to support inquiry-based learning and hypothesis testing. During Part I of the game, which involves assembling or selecting a microorganism and defining its target environment, no numerical score is assigned. This design choice encourages players to adopt an investigative mindset, allowing them to hypothesize and test which choices might be most suitable based on the characteristics of their selected life form. Upon entering Part II, players must reflect on their previous choices and consider how new decisions will impact the survival of their organism. Each beneficial decision that enhances the organism's survival results in the birth of a new entity. However, players must be cautious about potential overpopulation, which could lead to mass deaths due to resource depletion. To maintain engagement and stimulate curiosity, the scoring mechanics in Part II never result in a strictly negative outcome. Instead, the game adapts based on player choices, either leading to the organism's continuation or its evolutionary progression, according to the previous selected variables. This approach demonstrates the versatility of life, emphasizing its high mutation rates and adaptability to different environments, allowing it to evolve into diverse forms.

4.7 Evaluation Methodology

The pilot evaluation addressed three research questions: (RQ1) perceived usability and visual design; (RQ2) which game sections participants considered most relevant to learning; and (RQ3) how adult participants perceived the prototype's potential suitability for different age groups. Data were collected via a structured post-session questionnaire combining closed-ended items (single-choice and 5-point Likert scales on satisfaction, usability, and audience suitability) with open-ended questions on strengths and points for improvement. Closed-ended responses were analyzed descriptively; open-ended responses were thematically grouped by two authors and consolidated by discussion. Participation was voluntary and anonymous, with no personally identifiable information collected.

4.8 Pilot Evaluation

During classroom development, the prototype was tested by students in the "Artificial Life in Computing" course, receiving an average score above 9/10 and feedback on gameplay, immersion, clarity, and narrative. Recurring suggestions included the desire for more distinct positive endings, clearer trajectory feedback, greater visibility/control over the organism being created, and a more fictional, less technical tone. These insights guided refinements to narrative clarity, ending diversity, science-fiction balance, and player agency.

The final version was evaluated with 14 participants (educators, undergraduates, IT professionals, and biotechnologists), who played the game in a computer lab and completed a post-session form covering age classification, acquired knowledge, satisfaction, section relevance, and open-ended feedback. Percentages are reported against the full sample (n=14) unless stated otherwise.

(i) **Engagement and design**: the Organism Selection stage was the most valued (78.6% "very relevant"), followed by Celestial Body Selection (57.1%), both praised for creative agency and integration of biological/environmental concepts. Visual design received the highest satisfaction rating from 64.3% of participants, consistent with prior findings on the role of aesthetics in educational-game engagement [29].

(ii) **Perceived educational value**: Regarding perceived educational value, 78.6% of participants agreed that they had gained useful knowledge at 4+ (5-point scale). Qualitative feedback linked the branching structure and scientific logic to critical thinking, with synthetic biology and extremophile adaptation cited as particularly novel topics.

(iii) **Target audience**: 57.1% considered the game suited to a general audience interested in the topic, 21.4% recommended it for teenagers, and 21.4% for children aged 10–14, suggesting flexibility across formal and informal educational contexts. These responses reflect adult participants' perceptions of the potential audience and should not be interpreted as evidence of age suitability for students aged 11-14 years.

(iv) **Criticism and suggestions**: excessive on-screen text was the main complaint (35.7%), with suggestions to replace part of it with interactive/audiovisual elements, add audio narration for accessibility, improve the survival mini-game's interactivity, include tooltips for scientific terms, and add "back" navigation.

These results suggest that visual appeal and narrative freedom drive engagement [29], while textual density highlights the need for dynamic formats such as audio narration, tutorials, and interactive infographics. The audience results suggest flexibility, with appeal among science enthusiasts. However, as participants were not from the primary target group, no conclusions can yet be drawn about accessibility or suitability for formal use with students aged 11-14.

This pilot evaluation was conducted as an exploratory and formative stage of the project. Since ethical approval for conducting research with minors had not yet been obtained, the study did not involve the primary target audience of students aged 11-14 years. Instead, the prototype was evaluated by adult participants affiliated with or connected to the research group, with backgrounds in education, computing, biotechnology, and related fields. The purpose of this preliminary evaluation was to assess the perceived feasibility of the proposal, identify usability and design issues, and collect feedback to guide the refinement of the prototype before a future study with the intended users. Therefore, the results concern participants' perceptions of usability, narrative clarity, visual design, and educational potential, and should not be interpreted as evidence of learning effectiveness, age suitability, or validated adaptive behavior for lower-secondary students.

5 Discussion

The proposed architecture presents as its main contribution the integration of GLA and GenAI in a continuous cycle of learning experience adaptation. Unlike traditional approaches, which use interaction data primarily for posterior evaluation, the proposed architecture defines a feedback loop in which player interactions are intended to update the Student Model and guide subsequent content generation. This integration enables the generation of adaptive scenarios and narratives aligned with the student's profile and progression, supporting personalized learning trajectories within the same environment. However, its effects on engagement and learning remain to be empirically evaluated.

Compared with existing works, which predominantly focus either on data analysis through GLA or on content generation through GenAI, this work integrates both perspectives, allowing collected interaction data to directly influence subsequent content generation.

As evidence of technical feasibility, a functional gamebook prototype was developed in Unity, demonstrating the integration between player choices, interactive narrative, and GenAI-based scenario generation. However, the prototype instantiates only selected components of the architecture and does not validate the complete adaptive cycle involving GLA-based Student Model updates and Domain Model-conditioned generation.

6 Limitations

Some limitations should be acknowledged. First, the architecture was only partially instantiated through a prototype of the *Destino Cósmico* gamebook. Although the pilot examined perceptions of the prototype, it did not validate the complete architecture or its adaptation mechanisms. Moreover, its applicability to other educational games and domains remains untested. Future work should evaluate the architecture across different genres and educational contexts to assess its generalizability.

Second, although Table 1 provides a structured comparison with closely related approaches, no empirical head-to-head evaluation was conducted. Future studies should compare alternative implementations in terms of learning outcomes, engagement, scalability, latency, and implementation complexity.

Additionally, GenAI introduces challenges related to content consistency, controllability, and generation variability. The work also does not report operational metrics relevant to real-world deployment, such as generation latency, estimated API cost, or offline fallback behavior. These aspects should be investigated in future evaluations.

Finally, given the target context of Brazilian public schools and the involvement of minors, future work must address compliance with Brazil's General Data Protection Law (LGPD), including data transmission, processing, retention, and consent from legal guardians.

7 Conclusion and Future Work

This work proposed an architecture integrating serious games, GenAI, and GLA to support personalized and adaptive learning. The three central models—Student, Domain, and Intelligence—interact to guide learning adaptation. A Unity prototype demonstrates the integration of interactive narrative, player choices, and GenAI-based scenario generation, although scalability and the complete adaptive cycle remain to be evaluated.

Future work will validate the architecture with students aged 11–14 years, subject to ethics approval and consent procedures. The evaluation will investigate its effects on engagement, comprehension, and learning outcomes, as well as student modeling, GenAI consistency, and applicability across educational contexts.

Artifact Availability

The artifacts associated with this study are publicly available. A navigable Figma mockup illustrating the proposed adaptive interaction flow, including the diagnostic questionnaire, is available on *Figma*. The source code for the Unity prototype, including the implemented GLA and GenAI integration components, is available in the `VACPlay GitHub repository`. The artifacts are publicly accessible for inspection; no explicit reuse license is currently provided.

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