# Game Learning Analytics in Serious Games: A Systematic Review Study and Perspectives for Integration with Generative Artificial Intelligence

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***Abstract. Introduction:*** *Game Learning Analytics (GLA) has increasingly been used in serious games to monitor learning processes and analyze player behavior, while advances in Generative Artificial Intelligence (GenAI) create new opportunities for adaptive systems.* ***Objective:*** *This study systematically maps the use of GLA in serious games and investigates the presence of Artificial Intelligence (AI) techniques, focusing on opportunities for integration with GenAI.* ***Methodology:*** *A systematic review was conducted across major scientific databases, resulting in a set of primary studies analyzed according to predefined research questions.* ***Results:*** *GLA is mainly applied to performance analysis, behavior tracking, and learning assessment, often using Machine Learning (ML) and data mining. However, AI usage is largely limited to analytical tasks, with little evidence of generative approaches for dynamic adaptation.* ***Conclusion:*** *The results reveal a gap between data-driven analysis and adaptive content generation, highlighting the potential for integrating GLA with GenAI to enable real-time personalization in serious games.*
***Keywords*** *Serious Games, Game Learning Analytics, Generative Artificial Intelligence, Systematic Review.*

## 1. Introduction

Contemporary education has undergone significant transformations, especially after the pandemic period, which led to an increased use of digital technologies and highlighted the need for more interactive, personalized, and student-centered approaches [Lara et al. 2023]. Serious games, although not a recent development, have gained renewed attention in this context as educational tools capable of promoting engagement, active learning, and the development of complex cognitive skills [Zeng et al. 2020, Yu et al. 2021]. By integrating playful elements with pedagogical content, these systems enable knowledge construction through experience, fostering reasoning, decision-making, and autonomous learning [Savi and Ulbricht 2008].

Despite these advances, personalization in serious games remains a significant challenge. Many systems still provide uniform experiences for all users, disregarding individual differences such as learning pace, prior knowledge, and cognitive styles. This limitation reduces the potential of games as adaptive educational tools, particularly in contexts that require interdisciplinarity and meaningful knowledge construction [Rhee et al. 2020].

In this scenario, Game Learning Analytics (GLA) has emerged as a promising approach for collecting and analyzing data from player interactions, enabling the identification of behavioral patterns, progress, and difficulties throughout the experience [Alonso-Fernández et al. 2022]. Several studies demonstrate that GLA can be used to assess learning, support game design, and inform pedagogical decision-making based on data such as response time, number of attempts, errors, and navigation paths [Alonso-Fernández et al. 2022, Avila-Pesantez et al. 2021a, Cano et al. 2016, Honda et al. 2023, Silva et al. 2022]. However, most GLA applications focus on retrospective data analysis, with limited exploration of its use as an active mechanism for real-time adaptation during gameplay. In parallel, recent advances in Generative Artificial Intelligence (GenAI) have enabled the creation of dynamic content, such as adaptive narratives and scenarios, opening new possibilities for real-time personalization.

Despite the potential of these approaches, it remains unclear how GLA and GenAI have been integrated within the context of serious games. The literature presents significant advances in both areas independently but lacks a systematic analysis of their intersection, particularly in identifying technological and scientific gaps. In light of this, this work presents a systematic review study aimed at analyzing how GLA has been applied in serious games, identifying the Artificial Intelligence (AI) techniques employed, and investigating the presence (or absence) of approaches related to GenAI. Based on this analysis, we seek to identify gaps and opportunities for the development of more adaptive educational systems capable of integrating data-driven analysis with real-time dynamic content generation.

This work contributes by (i) systematically reviewing GLA applications in serious games, (ii) identifying the lack of integration with GenAI approaches, and (iii) outlining research directions for real-time adaptive systems. This paper is organized as follows: Section 2 presents the theoretical background supporting the topics addressed in this review; Section 3 describes the systematic review methodology, including the research questions and selection criteria; Section 4 presents the obtained results; Section 5 discusses the main findings and identified gaps; and finally, Section 6 outlines the conclusions and future perspectives.

## 2. Theoretical Foundations

This section presents the conceptual foundations that support the analysis of the use of GLA and AI in serious games, with a focus on learning personalization and the adaptation of interactive educational experiences.

Serious games are recognized as educational tools capable of promoting engagement, active learning, and the development of cognitive and socio-emotional skills. Unlike games designed exclusively for entertainment, serious games are developed with educational objectives, aiming to integrate pedagogical content with interactive mechanics that encourage student participation [Abt 1970, Laamarti et al. 2014]. Studies indicate that these systems can enhance the understanding of complex concepts, critical thinking, and interdisciplinary learning, especially when structured to allow exploration, decision-making, and problem-solving [Savi and Ulbricht 2008, Zeng et al. 2020, Yu et al. 2021].

In this context, GLA emerges as an approach focused on the collection, analysis, and interpretation of data generated during player interaction with the educational environment. Unlike traditional assessment methods, which are based on pre- and post-tests, GLA enables continuous monitoring of the learning process, considering variables such as response time, number of attempts, errors, progression, and behavioral patterns [Calderón and Ruiz 2015, Freire et al. 2016]. Based on these data, it is possible not only to evaluate student performance but also to understand their learning trajectory and identify specific difficulties throughout the interaction. Furthermore, GLA has been used to support the design of serious games, enabling data-driven adjustments and contributing to improvements in both user experience and learning outcomes. However, its implementation presents challenges, such as defining relevant pedagogical indicators and the need for integration among specialists from different fields, including education, game design, and data science [Silva et al. 2022].

In parallel, AI has been incorporated into educational systems with the aim of automating analysis, identifying patterns, and supporting the personalization of learning. Techniques such as Machine Learning (ML) [Rawassizadeh 2025], including clustering, and predictive models are often used in conjunction with GLA for data analysis and inference of student behavior. However, these approaches are predominantly focused on analytical tasks, emphasizing data interpretation after collection. More recently, GenAI has gained prominence due to its ability to produce dynamic content, such as text, images, and narratives, based on patterns learned from large volumes of data [Goodfellow et al. 2016, Banh and Strobel 2023]. In the educational context, this technology has been explored for automated feedback generation, creation of personalized materials, and development of adaptive interactive experiences [Baggen 2024]. In serious games, GenAI presents potential for generating dynamic scenarios and multiple narrative paths adjusted to the player's profile and decisions [Moon et al. 2025].

Thus, the literature points to the need to investigate how these technologies can be combined to enable more adaptive systems, capable of using interaction data to generate personalized experiences in real time. This gap underpins the need for a systematic review study to analyze the current state of GLA and AI applications in serious games, identifying limitations and opportunities for integration with generative approaches.

## 3. Methodology

This study was conducted as a Systematic Literature Review, aiming to identify, classify, and analyze how GLA has been applied in serious games, as well as to investigate the use of AI techniques in this context. This type of study is appropriate for providing a comprehensive overview of a research field, enabling the identification of trends, gaps, and opportunities for future investigations.

The methodological process was structured based on established guidelines from the PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [Tugwell and Tovey 2021], particularly with regard to the processes of search, selection, and filtering of studies.

### 3.1. Research Questions

To guide the review, the following research questions were defined:

- **RQ1:** What applications of Game Learning Analytics have been developed in serious games?
- **RQ2:** What GLA models have been proposed in the literature?
- **RQ3:** How do GLA models contribute to the assessment and personalization of learning?
- **RQ4:** What types of data are collected in GLA-based systems and how are these variables defined?
- **RQ5:** What AI techniques have been used combined with GLA?

### 3.2. Search Strategy

Initially, an exploratory search was conducted to understand the distribution of studies, followed by structured searches using Boolean operators. The search strings were defined by combining terms related to GLA, serious games, and AI (Table 1), as presented below:

> (*"game learning analytics"* OR *"learning analytics in games"* OR *"educational data mining in games"*) AND (*"serious games"* OR *"serious games"* OR *"game-based learning"*)

**Table 1. Search Terms and Synonyms Strategy**

| Terms | Synonyms (Portuguese and English) |
|---|---|
| **"Game Learning Analytics"** | "learning analytics in games" |
| **"Education"** | "education", "school" |
| **"Student"** | "student", "user" |

The search was conducted in well-established scientific databases, including Web of Science, Scopus, IEEE Xplore, and the International Journal of Serious Games.

### 3.3. Inclusion and Exclusion Criteria

Selection criteria were defined to ensure relevance and scientific quality. The inclusion criteria considered: (i) studies published from 2010 to 2025; (ii) studies with citations; (iii) studies with full text available; (iv) primary studies; and (v) research explicitly addressing the use of GLA in serious games.

The exclusion criteria included: (i) studies available only as abstracts; (ii) articles without access to full text; and (iii) studies that do not directly address GLA in the educational context.

### 3.4. Data Extraction and Analysis

Data were extracted in a structured manner, considering information such as: GLA applications, models used, types of collected data, AI techniques employed, and contributions to learning assessment and personalization.

The analysis was conducted qualitatively and categorized according to the research questions, enabling the identification of gaps in the literature and opportunities for integration with emerging approaches, such as Generative Artificial Intelligence.

### 3.5. Study Selection Process

The selection process followed multiple stages inspired by the PRISMA method [Tugwell and Tovey 2021], including duplicate removal, title and abstract screening, and full-text reading of selected studies. Additional criteria were applied, such as the presence of citations and alignment with the research questions. This stage was carried out with the support of the EndNote software, which enabled the identification and removal of duplicates, as well as the management of the screening process.

## 4. Results

This section presents the results of the systematic review, including the search overview, the study selection process, and the analysis of the selected works based on the defined research questions.

### 4.1. Search Overview

A total of 411 studies were initially retrieved, distributed across the different databases analyzed (Table 2). The distribution of studies highlights the interdisciplinary nature of the field, encompassing research in education, computer science, and educational technologies.

**Table 2. Number of articles retrieved per database**

| Database | Number of retrieved articles |
|---|---|
| Scopus | 359 |
| IEEE Xplore | 16 |
| Web of Science | 36 |
| **Total** | **411** |

The volume of identified studies indicates a growing interest in the application of GLA in serious games, particularly in contexts related to learning monitoring and player behavior analysis.

### 4.2. Selection Process Outcome

The initial search resulted in 411 studies. After duplicate removal and application of the inclusion and exclusion criteria, 60 studies remained for title screening. Abstract reading further refined the selection to 16 studies, of which 10 (Table 3) were analyzed in full (Figure 1). This table presents the identifiers A1-A10 to facilitate references to the studies throughout the results and discussion sections and do not represent a quality ranking. The Technique column summarizes the main analytical or technological approach adopted in each study. GLA refers to Game Learning Analytics approaches focused on collecting and analyzing player interaction data; RPA denotes Robotic Process Automation, used to automate data-processing tasks; and GLAID refers to a specific GLA model designed to analyze the learning processes of users with intellectual disabilities. The table also identifies complementary methods, such as eye-tracking for recording visual attention, data mining for extracting patterns from interaction data, clustering for grouping players according to similar characteristics, and predictive analytics for estimating future performance or behavior.

**Identified studies**
n = 411
↓
**After duplicate removal and initial criteria**
n = 60
↓
**After title and abstract screening**
n = 16
↓
**Final studies**
n = 10

**Figure 1. Study selection flow based on PRISMA [Tugwell and Tovey 2021]**

**Table 3. Selected studies**

| ID | Reference | Article | Technique | Citations |
|---|---|---|---|---|
| A1 | [Perez-Colado et al. 2021] | A Tool Supported Approach for Teaching Serious Game Learning Analytics | GLA | 6 |
| A2 | [Qasrawi et al. 2020] | Automatic Analytics Model for Learning Skills Analysis Using Game Player Data and Robotic Process Automation in a Serious Game for Education | GLA + RPA | 13 |
| A3 | [Morata et al. 2019] | Game Learning Analytics for Educators | GLA | 8 |
| A4 | [Cloude et al. 2021] | Game-based learning analytics for supporting adolescents' reflection | GLA | 35 |
| A5 | [Cano et al. 2016] | GLAID: Designing a Game Learning Analytics Model to Analyze the Learning Process in Users with Intellectual Disabilities | GLAID (Descriptive + Clustering + Predictive Analytics) | 20 |
| A6 | [Calvo-Morata et al. 2025] | Learning Analytics to Guide Serious Game Development: A Case Study Using Articoding | GLA | 15 |
| A7 | [Antonio Calvo-Morata et al. 2019] | Improving teacher game learning analytics dashboards through ad-hoc development | GLA | 19 |
| A8 | [Barrera Yañez et al. 2025] | Video Games That Educate: Breaking Gender Stereotypes and Promoting Gender Equality with a Serious Video Game | GLA | 8 |
| A9 | [Avila-Pesantez et al. 2021b] | Improving the Serious Game design using Game Learning Analytics and Eye-tracking: A pilot study | GLA + Eye-tracking | 5 |
| A10 | [Alonso-Fernández et al. 2022] | Game Learning Analytics: Blending Visual and Data Mining Techniques to Improve Serious Games and to Better Understand Player Learning | GLA + Data Mining + Predictive Analytics | 39 |

#### 4.2.1. Study Characterization

The selected studies present a diversity of approaches and applications of Game Learning Analytics in serious games. As illustrated in Figure 2, there is a predominance of studies adopting core GLA approaches across different years, alongside the emergence of more advanced methodologies, such as ML and automation.

There is also a concentration of works focused on teaching areas such as mathematics, programming, and science, with emphasis on learning assessment and game design improvement.

From a methodological perspective, most studies correspond to validation or evaluation research conducted in controlled experimental settings. These studies typically involve small groups of participants, predefined tasks, short interaction sessions, and close researcher supervision, often under idealized conditions. Consequently, they do

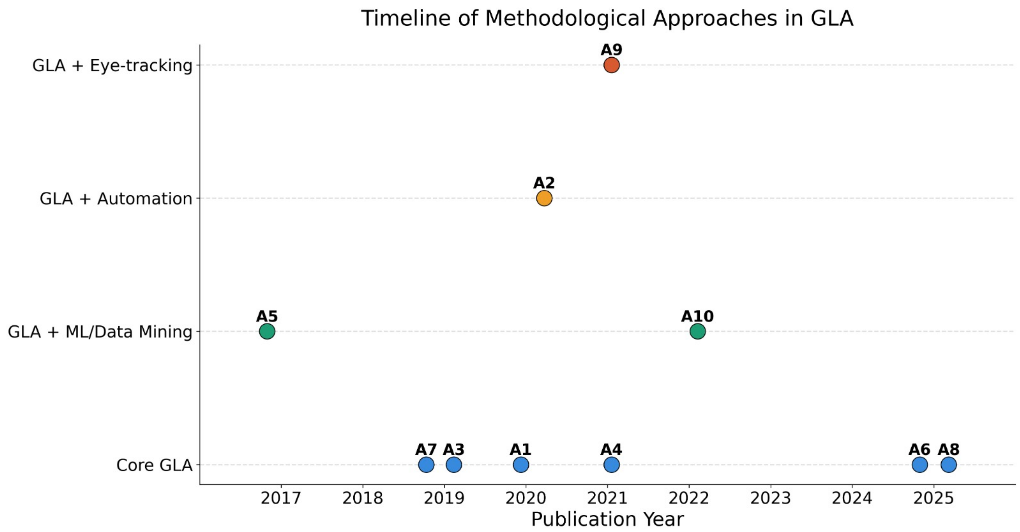


**Figure 2. Timeline of publications showing the distribution of methodological approaches in GLA over the years. Each point represents a study, positioned by publication year and categorized by the approach used.**

not fully reflect the complexity of real-world educational environments or large-scale data scenarios. There are fewer studies reporting large-scale applications in authentic educational contexts, where systems are integrated into regular classroom activities over extended periods. Additionally, modular systems are commonly observed, incorporating automatic data collection and report generation, often integrated with frameworks such as xAPI and educational dashboards.

### 4.3. Results Synthesis by Research Question

This subsection synthesizes the findings of the selected studies according to the five research questions that guided the systematic review. The analysis progresses from the main applications and models of GLA in serious games to their contributions to learning assessment and personalization, the types of interaction data collected, and the AI techniques employed.

**RQ1 - GLA Applications:** The analyzed studies indicate that GLA has been primarily applied for monitoring player performance, analyzing engagement, and supporting the design of serious games. In some cases, GLA is used to adapt game elements, such as difficulty and feedback; however, such adaptive approaches are still incipient, being explored in a limited number of studies and typically restricted to simple or predefined adaptation mechanisms. Despite this, the results suggest a promising potential for more advanced and widespread adaptive applications.

**RQ2 - GLA Models:** Various models were identified, including approaches based on xAPI, specific models such as GLAID (Game Learning Analytics for Intellectual Disabilities), and customized systems for data collection and analysis. These models vary in complexity and scope but generally follow modular structures for capturing and analyzing interactions.

**RQ3 - Contributions to assessment and personalization:** The results indicate that GLA significantly contributes to learning assessment, enabling more detailed analyses of player behavior compared to traditional methods. However, personalization remains limited, often being applied at a global rather than individual level.

**RQ4 - Types of collected data:** The main types of collected data include response time, number of attempts, errors, scores, progression, and interactions with game elements. In some studies, more advanced data, such as eye-tracking, are also used to analyze player behavior.

**RQ5 - AI techniques:** The identified AI techniques include ML, clustering, particularly clustering and predictive modeling approaches, which are used for data analysis and inference of learning patterns. These techniques are predominantly applied for retrospective analysis, with limited use for dynamic adaptation of the experience.

Overall, the results show that, although GLA is widely used for data analysis in serious games, there are still limitations in leveraging these data for real-time personalization and dynamic content adaptation.

## 5. Discussion

To interpret our findings, this section organizes the discussion into analytical dimensions that reflect the main patterns identified in the literature and directly address the research questions. The results reveal three main patterns: (i) predominance of retrospective analysis, (ii) limited personalization, and (iii) lack of integration with generative approaches.

Overall, the analyzed studies indicate that GLA has been widely used as a tool for analyzing the learning process in serious games, with a focus on the collection and interpretation of interaction data.

### 5.1. Applications of GLA in serious games

The analyzed studies indicate that GLA has been primarily applied for monitoring player performance, analyzing engagement, and supporting the design of serious games. Studies such as [Avila-Pesantez et al. 2021b] and [Alonso-Fernández et al. 2022] demonstrate the use of GLA to analyze interactions and identify behavioral patterns, enabling adjustments to the interface and pedagogical elements of the game.

In particular, the combination of GLA with technologies such as eye-tracking [Avila-Pesantez et al. 2021b] makes it possible to identify areas of greater visual attention, contributing to design optimization and improvements in user experience. Overall, these applications highlight the potential of GLA as a tool to support the iterative development of serious games.

However, it is observed that most adaptations occur at an aggregated level, considering groups of users rather than individual trajectories, which limits the potential for personalization.

### 5.2. GLA Models and Data Types

The approaches identified in the literature encompass different levels of abstraction, including conceptual models, data collection standards, and system-oriented architectures.

Conceptual models, such as GLAID [Cano et al. 2016], define structured frameworks for analyzing learning processes in serious games. GLAID proposes a multi-layered approach that integrates data collection, processing, and analysis, organizing the interpretation of player interactions into different levels, including descriptive (what the player did), diagnostic (why the behavior occurred), and predictive (what is likely to happen next). This structure enables a more comprehensive understanding of the learning process and supports the identification of patterns, difficulties, and potential learning outcomes. Additionally, GLAID has been applied to specific contexts, such as users with intellectual disabilities, demonstrating the adaptability of GLA models to different educational needs.

At the implementation level, standards such as the eXperience API (xAPI) are widely adopted for capturing interaction events, enabling the recording of detailed player actions in a structured and interoperable format. These standards are often integrated into modular system architectures that support data collection, storage, processing, and visualization.

The collected data include metrics such as response time, number of attempts, errors, progression, and interactions with game elements. In some cases, additional data sources, such as eye-tracking and detailed navigation logs, are incorporated, enabling deeper analyses of player behavior.

Despite the availability of rich interaction data, the studies point to challenges related to the standardization, visualization, and interpretation of this information, particularly in scenarios involving large numbers of users.

### 5.3. AI implementation in GLA

The analysis of the studies reveals a consistent use of AI techniques along with GLA, mainly for data analysis and inference of learning patterns. Methods such as ML, clustering, and predictive models are widely used, as observed in studies [Cloude et al. 2021], [Cano et al. 2016] and [Alonso-Fernández et al. 2022].

These techniques enable the identification of player profiles, prediction of performance, and understanding of learning trajectories. However, their application remains predominantly focused on retrospective analysis, with limited use for dynamic adaptation during player interaction, as most approaches rely on post-hoc data processing rather than real-time decision-making within the game.

Furthermore, most implemented systems operate as decision-support tools for teachers and designers, rather than as autonomous systems capable of real-time adaptation. However, challenges such as reliability, bias, and pedagogical alignment remain open issues.

### 5.4. Gap in Integration with GenAI

Recent empirical studies [Moon et al. 2025, Honda et al. 2023, Honda et al. 2025b, Filho et al. 2025, Bastos et al. 2025a], begin to address this gap by demonstrating that GenAI can act as a transversal support ecosystem across the GLA lifecycle, from design to data interpretation. In the design phase, studies investigate the use of Large Language Models (LLMs) as "specialist agents" (e*GLA Specialist*) to support the definition of data collection variables (*path_player*). These works show that, through prompting techniques, GenAI can suggest a significant number of pedagogical metrics for developers [Honda et al. 2025a], presenting high qualitative acceptance and practical usefulness when critically evaluated by learning designers [Honda et al. 2025a].

At later stages, integration also advances toward retrospective analysis, where LLMs demonstrate the ability to assist GLA specialists in interpreting educational data collected from games [Bastos et al. 2025b]. However, this emerging literature converges in emphasizing that GenAI primarily acts as a co-creation tool. It does not replace the analytical role and autonomy of specialists, designers, and educators, who must guide the AI iteratively to avoid the omission of essential variables, interpretative biases, or pedagogical inconsistencies [Honda et al. 2025a, Bastos et al. 2025b].

Thus, the results indicate that the development of truly adaptive educational systems begins with human–AI orchestration, in which GenAI is used both to structure the data foundation that the game must capture and to accelerate subsequent analytical interpretation.

## 6. Conclusion

The results obtained from this systematic review provide a comprehensive overview of the use of GLA in serious games, highlighting its established role as a tool for analyzing the learning process and understanding player behavior. The analyzed literature demonstrates that GLA has been widely used for performance monitoring, engagement analysis, and support for pedagogical design, contributing to the development of more data-driven educational systems.

However, the findings indicate that these approaches are still predominantly focused on retrospective analysis of interactions, with limited exploration of mechanisms for dynamic adaptation of the experience during system use. Although AI techniques are frequently employed, their use remains centered on analysis and prediction, and has not yet been fully explored for real-time personalization. In this regard, this study advances beyond previous work by systematically identifying the lack of integration between GLA and GenAI approaches in the context of serious games. This gap highlights a significant opportunity for the development of more adaptive educational systems capable of using interaction data to guide the dynamic generation of content.

The integration of GLA and GenAI has the potential to transform serious games into adaptive systems, promoting personalized, continuous, and student-centered experiences. However, this transition depends on overcoming challenges related to student modeling, control of generated content, and the integration between data analysis and generation mechanisms. As future work, the need for investigating architectures that integrate GLA and GenAI is emphasized, as well as conducting empirical studies to evaluate the impact of these approaches on learning outcomes. Additionally, there is room to explore integration patterns between different AI techniques and adaptive design strategies, aiming to expand the potential of serious games as innovative educational tools.

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