Detection of behavior in electronic games - a systematic mapping

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Abstract. Introduction: *Behavior detection in electronic games enables adaptive experiences, yet lacks comprehensive analysis of techniques for constructivist serious games.*
Objective: *To systematically map behavior detection technologies, analyzing their purposes, efficiency, and adaptability for educational contexts.*
Methodology: *Systematic mapping using Parsifal, evaluating technologies, implementation challenges, and effectiveness metrics across 39 selected studies.*
Results: *Machine learning, statistical methods, and ensemble approaches dominate, applied for dynamic difficulty and emotion detection. Key challenges include data requirements and visualization tool limitations.*
Keywords *Behavior detection, Player modeling, Serious games, Constructivist learning, Systematic mapping, Educational Technologies.*

1. Introdution

Games are increasingly recognized as effective tools for education, training, and behavior analysis. Serious games, in particular, stand out for merging entertainment with pedagogical goals, enhancing engagement and learning beyond traditional methods [Loh et al. 2016].

However, detecting and modeling player behavior—such as in gamified platforms like Duolingo [Zhao et al. 2023]—remains a challenge with no established standard. Accurate modeling could enable tailored experiences that boost both enjoyment and learning outcomes [Harrison e Roberts 2012, Chrysafiadi e Virvou 2013, Croissant et al. 2023].

This study presents a systematic mapping of behavior detection techniques in digital games, with emphasis on serious games due to their prevalence. We examine modeling techniques, reported benefits, and application strategies to provide a comprehensive overview and uncover research opportunities.

Following established software engineering guidelines [Petersen et al. 2015, Kitchenham e Charters 2007, Scannavino et al. 2017], we searched five major databases using predefined strings and applied inclusion/exclusion criteria via the *Parsifal* tool.

From over 500 initial results, 38 studies were selected. Most targeted serious games (15), followed by general-purpose modeling (8). Use-test cases were most common (27), along with ensemble approaches (22), analytical methods (21), and AI/ML techniques (21). Common strategies included clustering and heuristics (8 each), outlier detection, pattern recognition, and explicit feedback (7 each). Accuracy (12), real-time response (8), and generalization/interpretability (7 each) were the most cited advantages.

Our contributions include a comprehensive synthesis of behavior detection methods, their objectives, and reported advantages, along with practical recommendations to guide future research toward adaptive, effective, and engaging serious games.

2. Background

The rising complexity of electronic games and the demand for personalized learning have intensified interest in behavior detection techniques. These enable games to adapt dynamically to players' actions, preferences, and learning needs, fostering more immersive and effective educational experiences [Zook e Riedl 2012]. Adaptive difficulty and emotion detection, for instance, can enhance engagement and learning outcomes [Shaker et al. 2015].

Despite their potential, applying such techniques in serious games faces key challenges: high data demands, integration of heterogeneous sources, and limited cross-context generalizability [Bahrololloomi et al. 2023]. Overcoming these barriers is essential for successful deployment in educational environments.

2.1. Technologies for Behavior Detection

The effectiveness of behavior detection in games heavily depends on the underlying technologies. Recent advances have expanded the available toolkit for capturing and interpreting player behavior, ranging from classical algorithms to state-of-the-art machine learning approaches [Hooshyar et al. 2016].

Behavior detection systems rely on heterogeneous data sources [Vaz de Carvalho 2016]: in-game metrics (e.g., actions, navigation, and interactions with objects); interface metrics (e.g., menu interactions and configuration changes); and physiological data, such as gameplay data streams that indicate player states in real time. These may also include interaction patterns (action sequences [Kleinman et al. 2020]), physiological signals (affective computing data [Shaker et al. 2015]), or performance metrics (accuracy, response times [Moon et al. 2022])[Shaker et al. 2015].

These technologies present several technical barriers that demand attention, real-time processing faces latency constraints in educational game environments [Streicher et al. 2021], data fusion struggles with integrating heterogeneous logs and physiological signals [Khoshkangini et al. 2018]; and there is an ongoing need for interpretability in explainable AI for learning contexts [Ingram et al. 2023]. This systematic mapping will evaluate technologies through the lens of these challenges, aligning with the core research objectives.

2.2. Player Modeling and Behavior Detection

Player modeling has emerged as a critical field in game-based learning, allowing systems to infer player states and adapt experiences dynamically [Yannakakis e Togelius 2018].

As defined by [Liao et al. 2017], it involves *"the computational modeling of players' cognitive, behavioral, and affective states based on data or theories"*.

This capability is especially relevant in serious games, where adaptation can enhance educational outcomes [Said et al. 2019].

Three core paradigms dominate player modeling research:

- **Behavioral Analysis**: Techniques like action sequence mining [Kleinman et al. 2020] and outlier detection [Kang e Kim 2022] identify patterns in gameplay logs. For example, [Min et al. 2016] encodes player actions using four properties: action type, location, narrative state, and previously achieved goals.
- **Knowledge Tracing**: Models such as [Kantharaju et al. 2018] estimate learners' concept mastery, while [Hooshyar et al. 2022] uses deep learning for real-time assessment in educational games.
- **Affective Computing**: Emotion-aware systems (e.g., [Shaker et al. 2015]) leverage physiological or in-game data to adjust difficulty and mitigate disengagement.

Despite progress, critical gaps remain:

- **Data Sparsity**: Few labeled datasets are available for educational contexts [Hooshyar et al. 2016].
- **Generalization**: Models trained on entertainment games often fail to transfer effectively to serious game contexts [Zhu e Ontañón 2020].
- **Ethics**: Transparent player modeling is essential to prevent manipulative design [Machado et al. 2011].

This systematic mapping will synthesize solutions to these challenges, highlighting the most common techniques, their applications, and their main benefits.

2.3. Related works

Previous systematic studies on behavior detection have explored broad applications, such as data science integration [Alonso-Fernández et al. 2019] or adaptive systems [Aydin et al. 2023], while others focused on specific domains like player modeling [Hare e Tang 2022b]; the latter two addressed only serious games.

Our review diverges by systematically mapping behavior detection technologies through the lens of **deployability** and **efficiency**, targeting the early stages of technology adoption. We identify **Core techniques** most frequently employed across domains (e.g., sensors, ML models), **Critical needs** to guide project scoping and application targets, and **Opportunities** for real-world applicability, such as the advantages of each technique. Furthermore, we consider both entertainment and educational serious games, expanding the scope beyond those of [Aydin et al. 2023] and [Hare e Tang 2022b].

3. Review Planning

The mapping conducted in this study was based on the guidelines proposed by [Petersen et al. 2015, Kitchenham e Charters 2007, Scannavino et al. 2017]. For this document, the mapping is structured into three phases: planning, execution, and analysis. The first phase highlights the objectives, research questions, and search strategy, as presented below.

3.1. Objectives of the Systematic Mapping

This systematic mapping aims to (1) identify and classify behavior detection technologies in games, (2) analyze their purposes, efficiency, and implementation challenges, and (3) evaluate the technical requirements and effectiveness of proposed solutions.

3.2. Research Questions

Our research questions aim to clarify the topics so that better strategies can be adopted in the context of player modeling focused on content adaptation. In this context, the research questions guiding this mapping are as follows:

Q1 - What are the most used technologies in behavior detection in electronic games?
Q2 - How do they align with the needs of serious games?
Q3 - For what specific purposes (e.g., dynamic difficulty adjustment, procedural content generation, etc.) are these technologies applied?
Q4 - What is the efficiency of these technologies in terms of accuracy, notification speed, and computational cost?
Q5 - What data and tools are necessary to apply behavior detection techniques ?

3.3. Research Sources

The study used *ACM Digital Library*, *El Compendex*, *IEEE Xplore*, *Scopus*, and *ScienceDirect* as primary sources—authoritative databases in Computer Science that offer comprehensive coverage. Only English-language publications from 2002 to 2024 were considered (see Figure 1).

3.4. Choice of Keywords

The keywords were selected based on the mapping objectives, including terms such as *electronic games*, *player modeling*, and their semantic variations.

- ***Electronic games:*** *digital games, computer games, serious games*;
- ***Player modeling:*** *user modeling, behavior detection, affective computing*.

3.5. Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were established to ensure the relevance of the selected studies.

1. **Inclusion criteria:**
   - Generic methodologies adaptable to games;
   - Non-digital game techniques applicable to digital platforms.
2. **Exclusion criteria:**
   - Non-English materials;
   - Specific strategies not adaptable to other contexts;
   - Non-educational serious games.

To mitigate bias in applying the criteria, we adopted clear definitions and documented all decisions. We focused on educational serious games and entertainment digital games to narrow the scope and focus on our stated goals.

4. Metodology

The search was conducted in the listed databases using customized search strings based on the keywords from Section 3.4. Results were organized using the *Parsifal* tool and evaluated according to the criteria in Section 3.5.

4.1. Search Strings

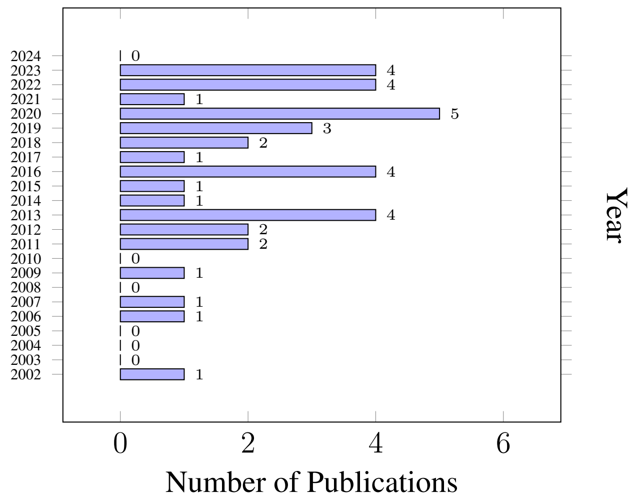
The search strings were built using boolean logic with *AND/OR* operators to combine terms. The final string applied across databases was:

("Electronic games" OR "Digital games" OR "Computer games" OR "Serious games") AND ("Player modeling" OR "User modeling" OR "Behavior detection" OR "Affective computing")

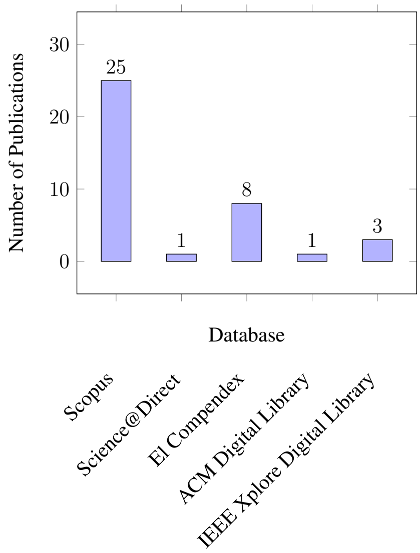
4.2. Study Selection

After duplicate removal, we applied inclusion/exclusion criteria through three phases: title screening → abstract analysis → full-text review. The final selection comprised 38 relevant studies (see Figure 1).

Figure 1. Number of scientific publications per year (a), categorized by database source (b).



(a)



(b)

Source: The author.

5. Analysis

5.1. The use of player modeling

In [Loh et al. 2016], the authors outline various uses of player modeling: UX studies [Tychsen e Canossa 2008], gameplay balancing [Desurvire e El-Nasr 2013], navigation analysis [Chittaro et al. 2006], movement prediction [Gambs et al. 2012], player profiles [Moura et al. 2011], and Dynamic Difficulty Adjustment (DDA) [Charles et al. 2005].

These applications are consistently supported across the selected studies. In Figure 2 is illustrated the analysis of publications.

Adaptation of Non-Playable Character (NPC)s (5 publications): [Conroy et al. 2011, Huang 2002, Carneiro et al. 2014, Yoon et al. 2007, Hare e Tang 2022b].

DDA (3 publications): [Zook e Riedl 2012, Missura e Gärtner 2009, Moon et al. 2022].

Behavior tracking (3 publications): [Kleinman et al. 2020, Hooshyar et al. 2023, Vallim et al. 2013].

Labeling gameplay data (2 publications): [Liao et al. 2017, Hooshyar et al. 2016].

Emotion detection (4 publications): [Hare e Tang 2022b, Hooshyar et al. 2016, Shaker et al. 2015, Kang e Kim 2022] .

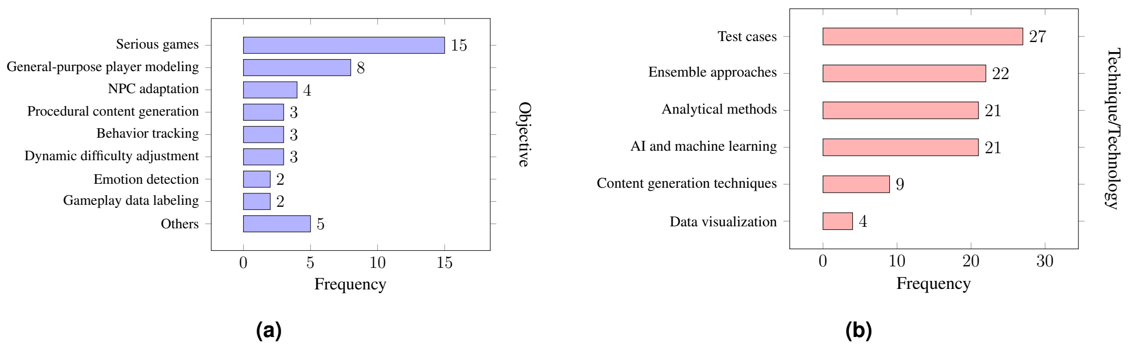
Procedural Content Generation (PCG) (3 publications): [Catarino e Martinho 2019, Zook et al. 2012, Kantharaju et al. 2018].

Serious games (15 publications): [Said et al. 2019, Hooshyar et al. 2020, Hooshyar et al. 2022, Hare e Tang 2022a, Kantharaju et al. 2018, Min et al. 2016, Streicher et al. 2021, Khoshkangini et al. 2018, Harpstead et al. 2013, Sun et al. 2016, Hooshyar et al. 2016, Hare e Tang 2022b, Hooshyar et al. 2023, Butler 2013, Vaz de Carvalho 2016] .

Player modeling for general purpose (8 publications): [Gray et al. 2020, Bindewald et al. 2017, Liao et al. 2017, Ingram et al. 2023, Thue e Bulitko 2006, Machado et al. 2011, Zhu e Ontañón 2020, Cowley 2020]

Other objectives (5 publications): [Bahrololloomi et al. 2023, Snodgrass et al. 2019, Min et al. 2016, Said et al. 2019, Liao et al. 2017].

Figure 2. Analysis of player modeling approaches in the literature: (a) primary objectives and (b) techniques employed.



Source: The author.

5.2. Techniques and technologies used in player modeling

Analytical and statistical methods (22 publications) .

Key approaches included: [Huang 2002]'s Dynamic Probabilistic Network (DPNs) for gameplay styles and [Kleinman et al. 2020]'s trajectory analysis (*TraMineR*, Selective Analysis (SA)), extended in Teamwork Agent Personality (TAP)/Decision Making System (DMS) systems [Carneiro et al. 2014]. Pattern detection via Outlier Behavior Different from the Intention (OBDI)/Outlier Behavior Different from the Intention (OBDA) [Kang e Kim 2022, Cowley 2020] contrasted with [Bahrololloomi et al. 2023]'s *E-Sports* regression models (Extreme Gradient Boosting (XGBoost)). Player taxonomy work spanned [Said et al. 2019]'s *BranHex* models to [Khoshkangini et al. 2018]'s adaptive archetypes. Diverse validation methods emerged, from [Vallim et al. 2013]'s *DBScan*+Adaptive Windowing (ADWIN) to [Liao et al. 2017]'s *Wilcoxon* tests and SHapley Additive exPlanations (SHAP) analysis [Hooshyar et al. 2023]. Each group will be presented with some examples.

Artificial intelligence and machine learning: The use of technology from artificial intelligence was observed in 21 studies , with neural networks dominating (11 cases). Key examples include [Hare e Tang 2022a]'s *Boltzmann exploration*, [Min et al. 2016]'s feedforward networks, and [Hooshyar et al. 2022]'s CNN/LSTM approach.

Machine learning appeared in 10 publications , featuring random forests, SVMs, and Monte-Carlo search. Genetic algorithms in [Zook et al. 2012] and [Shaker et al. 2015], plus heuristic logic in 5 studies , completed the landscape with [Hare e Tang 2022b]'s fuzzy logic.

Content generation techniques (12 publications): Key methodologies included matrix factorization ([Zook e Riedl 2012]), branching strategies ([Gray et al. 2020]) and DDA adaptation, with [Butler 2013] focusing on performance prediction and [Vaz de Carvalho 2016] on serious game modeling.

Ensemble and interaction approaches (23 publications): [Hare e Tang 2022b] employed *Markov* chains for emotional modeling, while [Hooshyar et al. 2016] used sentiment analysis via feedback. [Conroy et al. 2011, Kang e Kim 2022] synchronized multimodal data (video/speech, cameras/keyboards).

Test cases with games and players (29 publications): To evaluate the applicability of the techniques and strategies adopted in their works.

Optimizers, result validation, and efficiency checking (9 publications): [Bahrololloomi et al. 2023] focused on resource/feature reduction, while [Butler 2013] implemented domain retention, burnout prevention, and controlled evaluations. In [Hare e Tang 2022a] the authors introduced *grading functions* and *experience replay* within a *Hierarchical* Markov Decision Process (MDP) framework, contrasting with [Liu et al. 2013]'s random action smoothing and state collapse in *Markov* models. [Thue e Bulitko 2006] reduced state complexity via similarity measures. Three studies validated results through cross-validation [Hooshyar et al. 2022, Hooshyar et al. 2023, Shaker et al. 2015].

Data visualization (6 publications): [Hooshyar et al. 2016] used graphs/heatmaps, while [Kang e Kim 2022] visualized input patterns with emotional tension graphs. [Cowley 2020] simulated behavior patterns, contrasting with [Harpstead et al. 2013]'s replay system and [Liu et al. 2013]'s readable hybrid model.

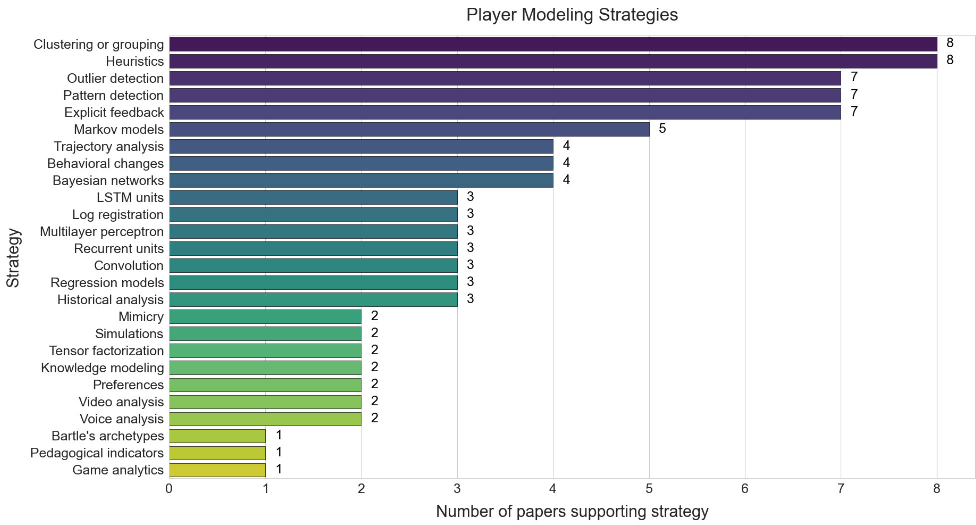


Figure 3. Sum of references using each player modeling strategy found in our mapping.

This scarcity suggests an unexplored gap for tutor-focused behavior analysis tools.

Figure 3 shows how many references used each player modeling strategy found in our review. The most common were clustering and heuristic-based approaches, followed by outlier and pattern detection and explicit feedback alternatives. Then, we had the use of Markov models. The fourth most used methods were trajectory analysis, behavioral changes and Bayesian networks. Many other strategies exist, but are not commonly used, as the Figure shows.

Then, Figure 4 shows how many references advocated a said advantage of their player modeling strategy found in our review. We can observe that the most proclaimed advantage was the accuracy, while having a real-time method was the second most common advantage. Then, a generalized or interpretable method was the third most common. Other advantages are relatively common, such as having validation, behavior detection, automation, personalization, and others. Few of them showed as advantages a high engagement, early detection, visualization or requiring low resources.

5.3. Efficiency, notification, and detection speed

All works demonstrated validated benefits: [Kleinman et al. 2020]'s Interactive Behavior Analytics (IBA) enabled interpretable trajectory analysis, while [Zook e Riedl 2012]'s temporal approach improved Role-Playing Game (RPG) difficulty adjustment (validated via Kruskal-Wallis/Dunnett tests). [Carneiro et al. 2014] used certifiable DMS, and [Bindewald et al. 2017] achieved real-time mimicry in *Space Navigator* .

Model accuracies varied: [Liao et al. 2017] reached near game-specific performance, [Bahrololloomi et al. 2023] *GradB* predicted *League* outcomes, and [Khoshkangini et al. 2018] matched expert classifications. [Hooshyar et al. 2023] *GameDKT* predicted 4 steps ahead, while [Vallim et al. 2013] *eM-DBScanNB* outperformed others in F1 scores.

Adaptive systems showed promise: [Streicher et al. 2021]'s Adaptive Control of Thought - Rational (ACT-R) modeled memory activation, [Cowley 2020]'s *behavlets*

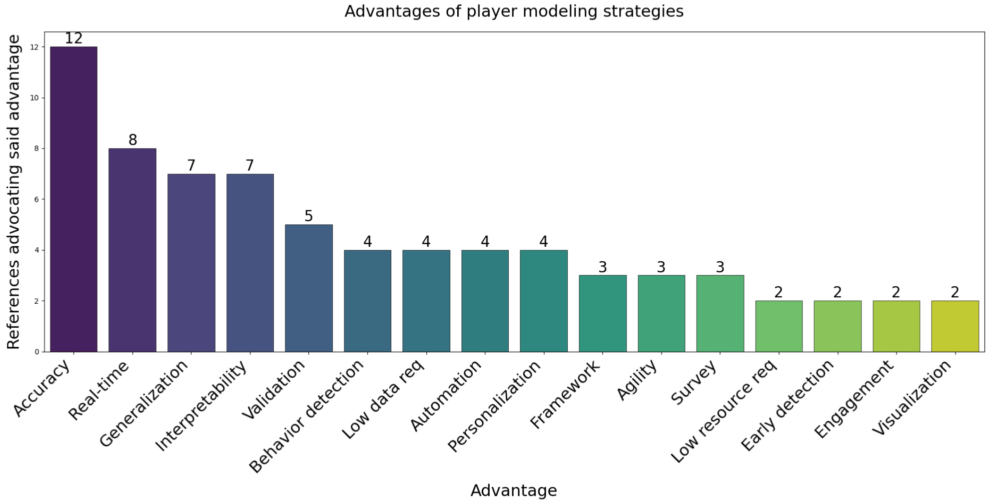


Figure 4. Sum of references advocating each advantage for their player modeling strategy found in our mapping.

generalized real-time behavior, and [Hare e Tang 2022a]'s Petri nets reduced training time. 6 works [Kleinman et al. 2020, Bindewald et al. 2017, Kantharaju et al. 2018, Min et al. 2016, Carneiro et al. 2014, Cowley 2020] enabled continuous real-time adaptation.

5.4. Needs and adaptability for content adaptability

Our mapping shows strategy's efficiencies vary by scope, with adaptability and tooling requirements being key considerations and varying widely. Many approaches rely on intensive data collection (e.g., [Bahrololloomi et al. 2023] 29,010-player *League* dataset) or non-scalable methods like manual questionnaires, this is unfeasible for indie games or serious games, that usually have a smaller player database or no previous data to train said models. Reusable tools like [Harpstead et al. 2013] log analyzer and [Carneiro et al. 2014] lightweight architecture are an interesting approach for a wider use. The Player, Environment, Agent, System (PEAS) framework [Snodgrass et al. 2019] also helps to guide developers to a robust and generalized player model. Nonetheless, an accurate, generalizable, interpretable, automated and personalizable player model that requires a small amount of data and resources to train, or can transfer its learning from different games is still unreached, even subsets of these characteristics are still unreachable by recent works.

6. Final considerations

As evidenced in Figure 1, scholarly interest in player modeling has grown consistently over the studied period. The analysis identified three equally prevalent technological approaches (Figure 2) : ensemble methods, statistical techniques, and AI/ML. While most studies relied on game-specific testing, the scarcity of visualization tools—those requiring fewer resources, modeling engagement, or enabling early detection of player models—remains a key gap (addressing Q1 and Q2).

Player modeling demonstrated versatile applications, from NPC adaptation to DDA and PCG (5.1, 2a), with particularly strong adoption in serious game contexts (addressing Q3).

Efficiency assessments (addressing Q4) confirmed benefits such as real-time adaptation and cognitive load measurement, though significant challenges persist, including data-intensive requirements and peripheral dependencies.

Some studies proposed adaptive solutions through log reinterpretation and rule-based systems, yet novel methods are needed to model more complex players and support developers working with smaller datasets (addressing Q5).

This systematic mapping identified three dominant technological paradigms for player modeling: ensemble/interaction approaches, analytical/statistical methods, and AI/ML techniques.

While these and other methods showed robust applications—from NPC adaptation to DDA—with positive outcomes especially in accuracy, real-time response, generalization, and interpretability, several barriers emerged: extensive data/resource requirements, lack of visualization tools (useful for educational practitioners), delays in player model detection, lack of generalizable development frameworks, limited automation and personalization, scarce modeling of engagement, and relatively few ML techniques addressing these gaps, such as simulating player behaviors through testing.

The results presented in Figures 3 and 4 suggest that clustering and heuristic-based approaches should be considered. We recommend that future applications evaluate their solutions primarily in terms of accuracy, generalization, and interpretability. This findings reinforce the teaching potential of accurate and rapid player modeling to enable personalized instruction. By identifying learners' difficulties and recommending targeted content, serious games can maintain engagement while introducing new material.

6.1. Limitations of the Study

Four limitations warrant consideration: (1) English-language publication bias (2) the absence of additional serious games in the mapping (3) difficulty in separating the interface from the educational aspect of modeling and (4) the omission of related keywords such as "behavioral analytics", "player profiling", "adaptive gaming", and "adaptive interface".

6.2. Future Work

Future research should prioritize five key directions: (1) tutor-focused behavior visualization interfaces, (2) lightweight data collection frameworks, (3) learning integration methodologies, (4) validation studies in game environments and (5) didactic applications of player modeling in constructivist learning environments, including content recommendation and adaptive feedback.

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