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# A Scoping Review of Genetic Algorithms in Serious Games: Applications, Challenges, and Future Directions

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*Article*

# A Scoping Review of Genetic Algorithms in Serious Games: Applications, Challenges, and Future Directions

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**Abstract:** The integration of Genetic Algorithms (GAs) into Serious Games (SGs) has gained traction as a method to optimize game mechanics and personalize user experiences. While GAs are well-known for their effectiveness in solving complex optimization problems, their application in SGs remains relatively under-explored. This review aims to address this gap by systematically mapping the existing literature on the intersection of these two fields. The primary objective of this scoping review is to identify and synthesize the existing research on the application of GAs in SGs, with a focus on understanding the current state of the field, identifying common applications, challenges, and potential future directions. The review includes studies published in English that focus on the use of GAs within SGs. The search encompassed articles from academic journals and conference proceedings without restrictions on publication dates. Exclusion criteria included studies that did not specifically address the integration of GAs in SGs. A systematic search was conducted in databases such as ACM Digital Library, Web of Science, Scopus and Inspec in July 2024. The search terms used included "genetic algorithm," "evolutionary algorithm," "computational algorithm," and "serious games." Unpublished data and articles were not considered. Data were charted using a PRISMA flowchart developed by the author VV. Key categories for data extraction included study objectives, methods, outcomes, type of study and GA used and the specific applications of GAs in SGs. Data charting was conducted independently by two reviewers, with disagreements resolved through discussion and consensus. The search identified 154 studies, of which 23 met the inclusion criteria. The included studies highlight the diverse applications of GAs in SGs, ranging from optimizing game scenarios to personalizing learning experiences. Challenges identified include the computational complexity of GAs and difficulties in their integration into existing game frameworks. The findings of this review suggest that while the use of GAs in SGs is a promising area of research, it remains in its nascent stages. Future research should focus on addressing the technical challenges of integrating GAs into SGs and exploring their application across a wider range of game genres and educational contexts. Limitations of the review include the potential for publication bias and the exclusion of non-English language studies.

**Keywords:** mnemonics; genetic algorithms; serious games; evolutionary computation; game design; optimization; adaptive learning; personalized learning; evolutionary algorithms

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Highlights

- Genetic and evolutionary algorithms in serious games show predominantly positive outcomes, with 72.7% of studies reporting favorable results.
- The majority of studies (68.2%) on genetic and evolutionary algorithms in serious games lack comparison groups, indicating a need for more comparative research in this field.
- There's a balanced mix of objective and subjective evaluations in the reviewed studies, with 36.4% using objective type of assessments, suggesting a comprehensive approach to measuring the effectiveness of genetic and evolutionary algorithms in serious games.

## 1. Introduction

### *1.1. Rationale*

Serious Games (SGs) have gained significant traction in various fields such as education, healthcare, and professional training due to their ability to engage users in interactive and meaningful

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learning experiences [1]. These games are designed not just for entertainment, but with the primary purpose of education, skill development, or behavior change [2]. The efficacy of SGs in promoting learning outcomes has been well-documented across diverse domains, from medical education [3] to environmental awareness [4]. However, optimizing these games to cater to individual learning paths and preferences remains a significant challenge [5]. The heterogeneity of learners, with varying cognitive abilities, learning styles, and prior knowledge, necessitates adaptive game mechanisms that can provide personalized learning experiences [6]. This is where Genetic Algorithms (GAs) have emerged as a promising solution for enhancing SGs by providing adaptive and personalized content.

GAs are computational models inspired by natural selection, capable of solving optimization problems through iterative processes [7]. Their application in SGs can range from optimizing game mechanics to dynamically adjusting difficulty levels, thereby improving the overall user experience [8]. GAs have shown particular promise in areas such as: (1) Dynamic difficulty adjustment: Tailoring game challenges to match the player's skill level [9]; (2) Content generation: Creating diverse and personalized game scenarios [10]; and (3) Player modeling: Understanding and predicting player behavior to enhance engagement [11]. Despite the potential benefits, the integration of GAs in SGs is still an under-explored area, necessitating a comprehensive review to map the current state of research and identify gaps. The synergy between GAs and SGs offers a unique opportunity to address the long-standing challenge of creating truly adaptive learning environments [12].

### *1.2. Objectives*

The primary objective of this scoping review is to systematically map the existing literature on the use of GAs in SGs. This review follows the PRISMA extension for scoping reviews (PRISMA-ScR) guidelines to ensure a comprehensive and transparent reporting process [13]. Specifically, the review aims to: (1) Identify the various applications of GAs in SGs.; (2) Analyze the methodological approaches used in studies to explore GAs and SGs; (3) Highlight trends in the research, including geographical distribution, types of studies, and outcomes; and (4) Suggest potential directions for future research. We sought to answer the following research questions:

1. What are the primary applications of GAs in SGs, and how do they enhance game mechanics and learning experiences?
2. What are the common trends in the research on GAs and SGs, including geographical distribution, study types, and targeted domains?
3. What are the methodological approaches used in studies exploring GAs in SGs, and how do these approaches influence the findings and conclusions?
4. What are the future research directions for the application of GAs in SGs, and what potential advancements could further improve their effectiveness?

### *1.3. Background*

The integration of GAs into SGs represents a convergence of two powerful concepts in computer science and education. SGs have their roots in the broader field of game-based learning, which has shown significant potential in enhancing motivation and knowledge retention [14]. The term "serious games" was popularized by Clark Abt in 1970, but the field has evolved dramatically with the advent of digital technologies [15].

GAs, on the other hand, were first introduced by John Holland in the 1960s as a method for studying adaptive systems [16]. Since then, they have been applied to a wide range of optimization problems across various domains. The application of GAs to game design and development began in the 1990s, primarily focusing on commercial games [17]. However, their potential in SGs has only recently begun to be explored in depth.

The marriage of GAs and SGs offers several potential benefits including the following:

1. Adaptive Learning: GAs can help create SGs that adapt to the learner's progress and preferences, potentially leading to more effective and engaging learning experiences [18].

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2. Personalization: By using GAs to model player behavior and preferences, SGs can offer personalized content and challenges, increasing relevance and motivation [19].
3. Scalability: GAs can automate aspects of game design and content generation, potentially making it easier to create and maintain large-scale SGs [20].
4. Optimization: GAs can help optimize various aspects of SGs, from game mechanics to educational content delivery, potentially improving overall effectiveness [21].

Despite these potential benefits, the field faces several challenges, including the complexity of implementing GAs in educational contexts, the need for large datasets to train effective algorithms, and concerns about the interpretability of GA-driven decisions in educational settings. This scoping review aims to provide a comprehensive overview of how these challenges and opportunities are being addressed in the current literature, paving the way for more informed and effective integration of GAs into SGs in the future.

## 2. Methods

Here we discuss the methods we used in our scoping review, first by providing an overview of the order of our methods, then by describing each one in greater detail.

### *2.1. Overview*

To conduct the scoping review, we followed a 3-stage approach proposed by Tranfield et al. [22]. We first planned the review by including a preliminary scoping of the literature. This stage, done by the senior researcher (KO) and junior researcher cum student (VV), was aimed at identifying and refining the objectives of the review and developing a particular protocol which includes the search string for retrieving papers from the databases, the inclusion criteria for including papers in the review, and the method of conducting the analysis of the included papers. Next, we conducted the review by having 1 researcher (VV) systematically search 4 databases using our search string (see Appendix), screened the retrieved papers by their title and/or abstract, and further screened those that passed by conducting a full-paper review on each one. KO oversaw the full-paper review. Finally, we tabulated, analyzed and reported the characteristics of the papers that remained. Those papers that passed the inclusion criteria had their characteristics extracted and tabulated in a Google spreadsheet by VV under the guidance and supervision of KO. Afterwards, both VV and KO came together to write the review collaboratively using Overleaf.

### *2.2. Eligibility Criteria*

We used the eligibility criteria shown in Table 1 to determine the eligible papers during the screening process. For example, the scoping review only focused on papers written in English and papers which focused on the application of GAs within the context of SGs. Papers that were about GAs, but in some other contexts were excluded.

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**Table 1.** Eligibility criteria

| **Inclusion Criteria** | **Exclusion Criteria** |
|---|---|
| The article must be written in English | The article must not be written in English |
| The article must be a journal or conference paper | The article is a book chapter, literature review, etc. |
| The article must be about genetic algorithms and serious games. | The article is not about GAs and SGs together. |
| The article must focus on the application of GAs within the context of Serious Games. | The article is not focused on the application of GAs within the context of SGs. |

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### 2.3. Information Sources

To identify relevant papers for the scoping review, 4 databases (ACM Digital Library, Web of Science, Scopus, and Inspec) were searched between July 9, 2024, and July 11, 2024. We also searched IEEE Xplore but found no papers relevant to our review. We used the search strings provided in the Appendix. In constructing our search string, we were concerned with the synonyms for "genetic algorithms." As such, we included alternative or similar phrases related to GA such as "evolutionary algorithm*" and "computational biology*" in our search string so we could retrieve as many relevant papers as possible.

### 2.4. Search

The retrieved papers were based on titles, abstracts, and keywords. Using each database's export feature, we exported the papers to 4 .csv files (1 for each database). We then combined the data into one larger .csv file (which included duplicates) before transferring it into a Google Sheet. The initial search returned 154 studies including duplicates. We had the columns "Document Title", "Publication Year", "Abstract", "Authors", and "Paper Type". Next, for sets of rows that had the same document title, we marked the second and onward rows as duplicates. All rows not marked as duplicates had their featured papers screened. We found 50 duplicates, which left us to move forward with 104 papers for TAK (Title, Abstract, Keywords) screening.

### 2.5. Selection of Sources of Evidence

We used the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) flowchart [13] to screen the papers that we retrieved from the 4 databases. Two (2) researchers (VV and PM), guided and supervised by the senior researcher (KO), screened all unique papers independently. The papers were first screened based on their title and/or abstract, and those that passed the screening were subjected to a full text review. During title and/or abstract screening, papers that VV and PM disagreed on were moved forward for full-text review. During the full-text review phase of screening, there were no disagreements between VV and PM. KO oversaw both phases of the screening process.

Upon completion of the full-paper review, VV notified KO about which papers were rejected as well as why they were rejected. Both researchers then discussed the rationale for acceptance and rejection of each paper and came to a consensus.

### 2.6. Data Charting Process and Data Items

Data were extracted using a standardized form, which included variables such as study type, objectives, methods, outcomes, and relevance to the research questions. For the papers from the 4 databases that passed both phases of screening, we used a standardized form in extracting and tabulating the data shown in Table 2 in a Google spreadsheet. VV and KO discussed on what data needs to be extracted from each paper.

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**Table 2.** Data Items Extracted

| Characteristic | Description |
|---|---|
| Year | What year the paper was published |
| Author | Who wrote the paper |
| Title | Title of the paper |
| Country of Study | Which country the study featured in the paper took place in |
| Country of First Author | What is the country of the first author of the paper |
| Type of Study | Whether the study's data was qualitative, quantitative or mixed |
| Participants | Who participated in the study |
| Study Duration | How long study/experiment lasted |
| Type of GA and programming language | What type of GA was used in the study and in which programming language was it written |
| Evaluation Type and Metrics | What metrics were used in evaluation of the results and what type of evaluation it was (Subjective, Objective or Both) |
| Objective of the paper | What is the focus/purpose of the paper/study |
| Optimization (Objective) | What is the optimization objective of the paper/study |
| Domain | What is the domain of the study, e.g., Education, Health, etc. |
| Intervention Channel | On what device/channel, the study was conducted, e.g., mobile phone, desktop, etc. |
| Artifact (GA) | What is being optimized by GA |
| Study Outcome | Whether the outcome of study was positive, negative or indeterminate |
| Comparison | Whether an experimental group was compared against a control group, another experimental group, both, or there was no splitting of participants into groups |
| Summary of Findings | Summarize the findings of the study |
| Limitations | What limitations are stated by the authors |

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## 3. Results

In this section, we present the results of the scoping review, including the number of included papers and summary tables showing the main characteristics of the papers, which relate to the 4 main research questions.

### 3.1. Selection of Sources of Evidence

The review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart for the screening and inclusion of articles in the final analysis (Figure 1). A total of 154 papers were retrieved from the 4 databases that we searched. Removing around 32.47% (50/154) of them for being duplicates, we had 104 left. Next, we commenced the first proper phase of screening, which was based on title and/or abstract. There were 6 disagreements between 2 researchers (VV and PM), in which 4 were only accepted by the former and 2 by the latter. There were 98 agreements between them, in which 27 and 71 were accepted and rejected, respectively, by both researchers. This resulted in an agreement rate of around 94.23% (98/104) and Cohen's Kappa of around 0.86. We screened out around 68.27% (71/104) of them by title and abstract, which meant we had 33 remaining. Finally, we performed the second phase of screening, which was based on full-paper review. There were 0 disagreements between the 2 researchers (VV and PM). There were 33 agreements between them, with 23 of the associated papers accepted by both and 10 rejected by both. This resulted in an agreement rate of 100% (33/33) and a Cohen's Kappa of 1.00. We screened out 30.30% (10/33) of those based on a full-paper review, which would have resulted in us being left with 23 papers to report.

**Table 3.** Agreement between researchers during screening

| | Title/Abstract Screening | Full-Paper Screening |
|---|---|---|
| Both Accepted | 27 | 23 |
| Both Rejected | 71 | 10 |
| Only VV Accepted | 4 | 0 |
| Only PM Accepted | 2 | 0 |
| % Agreement | 94.23 | 100 |
| Cohen's Kappa Score | 0.86 | 1.00 |

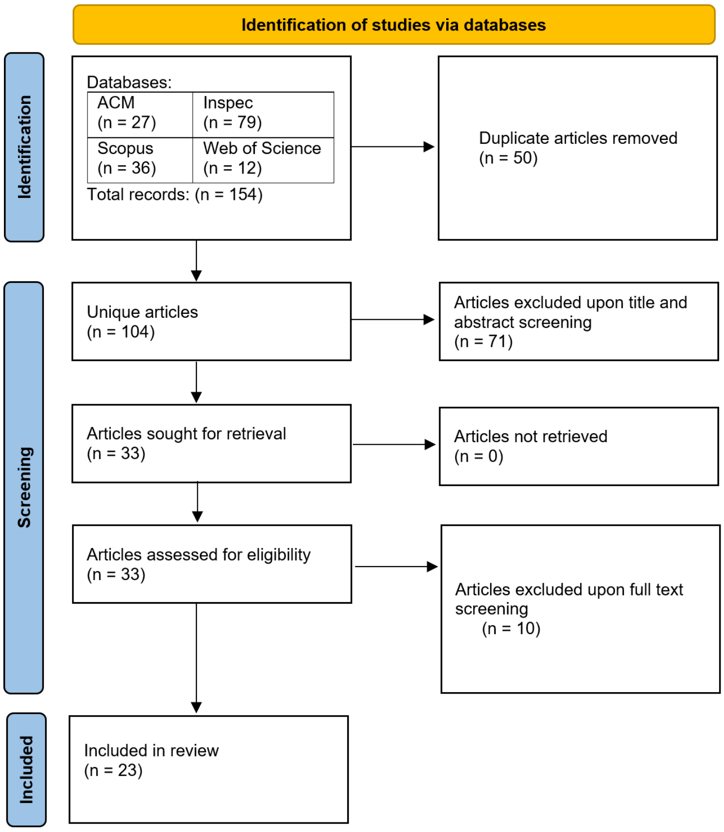


**Figure 1.** PRISMA flowchart for the screening and inclusion of articles in the scoping review.

### *3.2. Characteristics and Results of Individual Sources of Evidence*

The major characteristics for the papers like Year and Authors of the paper, Participants of the Experiment, Genetic Algorithm used in the paper, Main objective of the paper, Summary of the paper, etc, as described in Table 4, will be shown in charts, tables, and text.

**Table 4.** Summary of included articles and findings

| **Authors (Year of Publication)** | **Population Country (Participants)** | **Genetic Algorithm Type, Programming Language** | **Aim and Objective of Study** | **Summary of Findings** |
|---|---|---|---|---|
| Wiwatwattana N, Bunyakul N (2019) | Thailand (Not specified) | Not specified, Unity (using C#) | Implementation and Evaluation (The objective of the paper is to share the experience in developing two versions of the "Clinic Chemistry" game from the perspective of game designers/developers as part of an end-to-end educational game research.) | The study outcome is not explicitly stated, but the authors conclude that the rapid prototyping paradigm they adopted was key to their successful release of the game. |

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|---|---|---|---|---|
| Buditjahjanto, I.G.P.A. et al. (2024) | Indonesia (Not specified) | Non-Dominated Sorting Genetic Algorithm II (NSGA-II), Not specified | Implementation (The objectives of the paper are to build a Non-Player Character (NPC) as decision support for decision-making in a serious game, specifically for electric power production.) | The study used a simulation-based experiment to compare the performance of FCM and FLVQ clustering methods in reducing the number of optimal solutions generated by the NSGA2 algorithm. The study found that FLVQ outperforms FCM in terms of the number of iterations and error tolerance. The optimal number of clusters was determined to be 3, and the cluster centers were used as solutions for the NPC. |
| Ponticorvo, Michela et al. (2018) | Italy (Not specified) | Bio-inspired computational algorithms (genetic algorithms, artificial neural networks, agent-based models), Not specified | Implementation (The paper aims to introduce different approaches to embed bio-inspired computational algorithms in Serious and Educational Games.) | The paper discusses different approaches to embed bio-inspired computational algorithms in Serious and Educational Games at the shell level, core level, and evaluation/tutoring level. The authors provide examples of how these algorithms can be used to model game mechanics, game engine, and game narrative. |
| Caseau, Yves (2013) | France (Not specified) | Not specified (the paper discusses the use of game theory, machine learning, and Monte-Carlo sampling, but not specifically a genetic algorithm) | Implementation (The paper aims to present an approach for modeling a system of actors in complex enterprise problems using game theory and machine learning.) | The paper describes an approach for modeling complex systems using game theory and machine learning, and illustrates this approach with examples from the mobile telecommunication industry and smart grids. |
| Aslam, Hamna et al. (2017) | Russia (30 playtesters, bachelor's program students in information technology, average age 21) | Evolutionary Algorithm (EA), Not specified | Implementation and Evaluation (of a serious game for relief camp management) | The serious game and EA can be used for relief camp design and training, and EA can optimize resource placements. |

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| | | | | |
|---|---|---|---|---|
| Krouska, A. et al. (2020) | Greece (80 computer science students in a public university) | Not specified, Not specified | Implementation and Evaluation (of a genetic algorithm for recommending adequate competitors in mobile game-based learning environments) | The genetic algorithm-based system outperformed the system without intelligent recommendation in terms of student satisfaction and instructor evaluation. |
| Andrade, Kleber De O. et al. (2016) | Brazil (Not specified) | Evolutionary Algorithm (EA), Not specified | Implementation and Evaluation | The proposed EA adjusts game difficulty according to user ability in simulation; future work includes clinical tests with stroke subjects. |
| Vaassen, Frederik and Daelemans, Walter (2010) | Belgium (Not specified) | Standard Genetic Algorithm, Python | Implementation and Evaluation (of emotion classification for a serious game to train communication skills) | The best classification accuracy of 52.5% was achieved using a memory-based learner (TiMBL) with word unigrams, lemma trigrams and dependency structures as features. This significantly outperformed the baseline of 25.15%. |
| Volden, T. et al. (2023) | Denmark (Not specified) | Standard Genetic Algorithm, Python | Implementation and Evaluation (of procedurally generating rules to adapt difficulty for narrative puzzle games) | The genetic algorithm was able to approximate target solution sets with 99.9% accuracy on average within 22.3 generations. A large language model was successfully used to generate narrative contexts for the rules. |
| Monaco, A. et al. (2019) | Italy (Not specified, Patients affected by MCI of neurodegenerative and metabolic origin) | Standard Genetic Algorithm, Not specified | Implementation (of a serious game based on virtual reality for neurorehabilitation training, connected to a brain-computer interface based on electroencephalography (EEG) and to haptic devices) | The paper presents the tools developed within the PERSON project for cognitive rehabilitation using serious games based on virtual reality, connected to a brain-computer interface based on electroencephalography (EEG) and to haptic devices. |
| Koopmanschap, R. et al. (2015) | Netherlands (Not specified) | Genetic Algorithms, Not specified | Evaluation (of tailoring a cognitive model for situation awareness using machine learning) | The evolutionary algorithm outperformed the benchmark, and some extensions improved the results. |
| İnce, M. (2021) | Turkey (18 secondary school students, 10 male, 8 female) | Fuzzy AHP-GA hybrid, Not specified | Implementation and Evaluation (of a BiLSTM and dynamic fuzzy AHP-GA method for procedural game level generation) | The proposed BiLSTM-based FAHP-GA method performed better than other methods in generating procedural game levels adaptively based on player preferences. Generated levels were generally balanced, reachable, and rated highly for visual aesthetics and enjoyment by players. |

| | | | | |
|---|---|---|---|---|
| Mitsis, K. et al. (2020) | Greece (42 participants, 25 male, 17 female, mean age 27.90 ± 4.93 years) | Standard Genetic Algorithm, Not specified | Evaluation (of a procedural content generation technique based on a genetic algorithm in a serious game for obstructive sleep apnea) | Version B with smooth adaptive difficulty showed significantly higher competence and lower negative experience compared to non-adaptive version C. Version A with harsh difficulty scaling showed significantly lower competence and higher challenge/negative experience compared to version C. |
| Ramos, M.A. et al. (2015) | Mexico (Not specified) | Learning Classifier System (LCS), Not specified | To generate autonomous behavior to populate a virtual environment using serious games and learning classifier systems. | The paper proposes an approach using LCS and BDI architectures to create autonomous agents with social behaviors for serious games. Initial results show agents can navigate a virtual city environment with some basic behaviors. |
| Lach, Ewa (2018) | Poland (Not specified) | Modified Evolutionary Algorithm (EA), Not specified | Implementation and Evaluation (of new adaptations for reducing the number of training data for the evolutionary algorithms used to adjust the game challenge to the level of the human player abilities for a serious game.) | The paper presents new adaptations for reducing the number of training data for the evolutionary algorithms used to adjust the game challenge to the level of the human player abilities for a serious game, and the results show that the proposed adaptation causes substantial decrease in training data for different players. |
| Cai, Yundong et al. (2010) | Singapore (Not specified) | Interactive Evolutionary Computation (IEC), Not specified | The paper aims to implement and evaluate the E-FCM model for serious games. | The paper presents the E-FCM model as an effective cognitive computational model for modeling real-time variable states and dynamic, complex causally related context variables in serious games. The E-FCM model improves on existing serious game models by modeling both fuzzy and probabilistic causal relationships among the game's variables, allowing for asynchronous updates of the variables for a more engaging and immersive player experience. |
| Andrade, Kleber O. et al. (2018) | Brazil (Not specified) | Evolutionary Algorithms (EA1 and EA2), Not specified | Implementation and Evaluation | The study found that EA2 was able to identify a set of coefficients that can properly adjust the game difficulty for all different player profiles used. |

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| | | | | |
|---|---|---|---|---|
| Kalafatis, Eleftherios et al. (2023) | Greece (20 obese children aged 6-14) | Genetic Algorithm (GA), Not specified | Implementation and Evaluation (of a novel Procedural Content Generation (PCG) method in a serious game for health) | The PCG method was able to generate individualized content for users, and the study showed overall acceptance and usefulness of the method. |
| Kop R. et al. (2015) | Netherlands (Not specified) | Genetic Programming (GP), Not specified | The objective of the paper is to present a technique called Evolutionary Dynamic Scripting (EDS) for generating behavior for Non-Player Characters (NPCs) in serious games. | The study presents the EDS technique for generating behavior for NPCs in serious games and simulations. The technique was found to improve the rules in existing rule bases and lead to significant performance increases against four out of six enemy tactics in an air combat simulation. |
| Woo K.J. (2014) | South Korea (Not specified) | Genetic Algorithm (GA), Not specified | The paper aims to introduce a job shop scheduling game with GA-based evaluation. | The paper presents an enhanced version of a previous simple job shop scheduling game, where players can create their own JSP and have their schedules evaluated using a genetic algorithm. |
| Rasim et al. (2016) | Indonesia (Not specified) | Genetic Algorithm (GA), Not specified | Evaluation | The genetic algorithm (GA) has better composition than the random method in generating quiz questions in a 3D virtual environment. |
| Bellotti, F et al. (2009) | Italy (Not specified) | Hybrid Genetic Algorithm (HGA), Not specified | The objectives of the paper are to present the details of an approach for modeling an adaptive experience engine for serious games and to show the structure of the EE and discuss results obtained by testing an EE implementation based on genetic computation and reinforcement learning for two different operating modes. | The paper presents an implementation of the models of tasks, user, and delivery strategy that is based on studies and field experience. The models may be easily upgraded to account for different parameters. |

### 3.3. Synthesis of Results

The scoping review covers a diverse range of studies that have explored the use of GAs and other evolutionary algorithms in serious games across various domains, including education, healthcare, gaming, and enterprise simulation. Many of the reviewed studies focused on the implementation and evaluation of these algorithms for purposes such as content generation, difficulty adaptation, agent behavior modeling, and optimization of game elements. The studies employed a mix of qualitative, quantitative, and mixed methods approaches, with the majority (31.8%) using a quantitative methods

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approach. In terms of game outcomes, most studies (72.7%) reported positive results, with a smaller number reporting indeterminate (13.6%). About 31.8% of the studies involved user evaluation, while the other two-third did not. The reviewed studies originated from various countries 3, including Thailand, Indonesia, Italy, France, Russia, Greece, Brazil, Denmark, and Mexico, suggesting a global interest in this research area. The reviewed studies were distributed over 16 years period from 2009 to 2024 2. Overall, the scoping review highlights the potential of genetic algorithms and other evolutionary algorithms to enhance the design, adaptation, and optimization of serious games across a wide range of application domains.

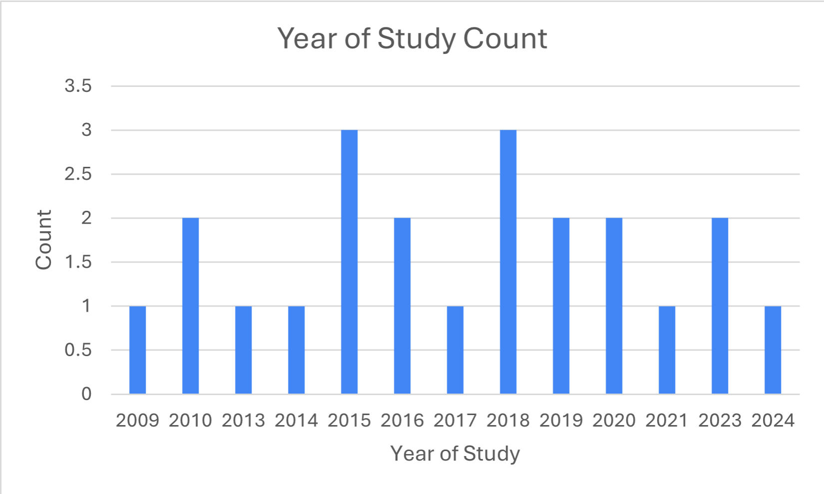


**Figure 2.** Distribution of the reviewed papers over a 16-year period

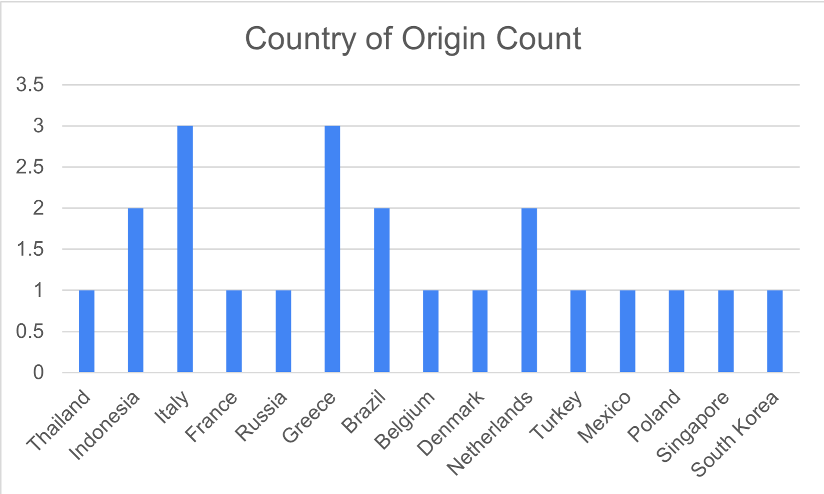


**Figure 3.** Count of the countries of origin of reviewed papers

**Table 5.** Characteristics of the reviewed studies

| Characteristic | Value | Papers | Count (%) |
|---|---|---|---|
| Type of Evaluation | Objective | [23–30] | 8 (34.8%) |
| | Subjective | [31] | 1 (4.3%) |
| | Both | [32–36] | 5 (21.7%) |
| | Not specified | [37–43] | 7 (30.4%) |
| Type of Study | Qualitative | [32,34,41] | 3 (13.0%) |
| | Quantitative | [25,26,29,31,35,40,43] | 7 (30.4%) |
| | Mixed | [23,27,33,36,42] | 5 (21.7%) |
| | Not Specified | [24,28,30,37–39,44] | 7 (30.4%) |
| Game Outcome | Positive | [23–29,31,33–36,39,41–43] | 16 (69.6%) |
| | Negative | - | 0 (0%) |
| | Indeterminate | [30,40,44] | 3 (13.0%) |
| | Not Specified | [32,37,38] | 3 (13.0%) |
| Comparison | vs. control group | [33] | 1 (4.3%) |
| | vs. other experimental | [25–27,31,34,35] | 6 (26.1%) |
| | both | - | 0 (0%) |
| | no comparison | [23,24,28–30,32,36–44] | 15 (65.2%) |
| User Evaluation | Yes | [29,31,33–35,39,41] | 7 (30.4%) |
| | No | [23–28,30,32,36–38,40,42–44] | 15 (65.2%) |

## 4. Discussion

### *4.1. Summary of Evidence*

Based on the presented results, we discuss the key findings of the scoping review considering the 4 main research questions.

#### 4.1.1. Applications Areas and Domains

The primary applications of GAs and other EGs in SGs, as revealed by the scoping review, include content generation, difficulty adjustment, agent behavior modeling, optimization of game elements, and player modeling and adaptation.

*Content Generation:* GAs are widely used for procedural content generation (PCG), which refers to the automatic creation of game content such as levels, maps, and challenges. This is particularly beneficial in serious games, where diverse and dynamic environments can be tailored to suit varying learning goals. Studies by Volden et al. [26] and İnce [35] showcase the application of GAs to create adaptive and non-repetitive game levels, promoting increased replayability. By leveraging GAs, game developers can generate personalized content that adapts to player performance and preferences, thereby enriching the educational experience and keeping learners engaged over time. This adaptability in content creation supports various skill levels and learning paths, making serious games more effective in catering to diverse audiences.

*Difficulty Adjustment:* Dynamic difficulty adjustment (DDA) is a key area where GAs are employed, as seen in the work of Andrade et al. [24] and Lach [28]. GAs allow games to continuously calibrate the difficulty of tasks based on the player's performance, ensuring a balanced and engaging experience. In the context of serious games, DDA ensures that the challenge level aligns with the player's current capabilities, preventing frustration or boredom. This adaptive difficulty mechanism is crucial in educational games, where maintaining an optimal level of challenge is necessary to sustain motivation and foster effective learning. GAs provide an efficient way to adjust difficulty in real-time, optimizing the player's learning curve by tailoring the game's challenge to individual skill levels.

*Agent Behavior Modeling:* In many serious games, Non-Player Characters (NPCs) play a critical role in creating realistic and engaging learning scenarios. GAs have been utilized to evolve NPC behaviors, as shown in studies by Buditjahjanto [23] and Ramos et al. [40]. These algorithms enable NPCs to learn and adapt over time, providing players with more immersive and challenging interactions. By evolving NPC strategies and decision-making processes, GAs contribute to a more dynamic and

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varied game environment. This application is particularly beneficial in educational games, where NPC behavior can simulate real-world interactions or problem-solving scenarios, offering players unique learning experiences each time they engage with the game.

*Optimization of Game Elements:* GAs are also used to optimize various game elements such as resource allocation, level design, and task sequencing. For example, the work of [33] explores how GAs can be applied to efficiently allocate resources within a game, ensuring that gameplay remains balanced while fulfilling educational objectives. Similarly, task sequencing, as investigated by [44], can be optimized using GAs to present challenges in a pedagogically effective order, facilitating smoother learning progression. This optimization not only improves the design and flow of the game but also enhances the player's learning experience by structuring content in a way that maximizes retention and skill acquisition.

*Player Modeling and Adaptation:* Personalized learning is a critical goal in serious games, and GAs play a pivotal role in player modeling and adaptation. Studies like Krouska et al. [34] demonstrate the use of GAs to recommend appropriate competitors or collaborators in multiplayer learning environments. By analyzing player data and evolving optimal configurations, GAs can create tailored experiences that match players with suitable opponents or teammates, enhancing both engagement and learning outcomes. This personalization ensures that players are constantly challenged at an appropriate level, which is essential for maintaining motivation and ensuring the educational efficacy of the game.

These applications enhance game mechanics by introducing adaptivity, personalization, and optimization. They improve learning experiences by ensuring appropriate challenge levels, creating diverse and engaging content, and tailoring the game to individual learner needs.

#### 4.1.2. Research Trend and Study Distributions

Geographical Distribution: The reviewed studies originate from various countries, including Thailand, Indonesia, Italy, France, Russia, Greece, Brazil, Denmark, Mexico, Belgium, Netherlands, Singapore, South Korea, and Poland. This diverse geographical distribution suggests a global interest in applying GAs to Serious Games.

Study Types: The review revealed a mix of study types:

The review revealed a diverse mix of study types within the literature on GA-enhanced serious games, each contributing unique insights to the field. Qualitative studies comprised 13.6% of the total, focusing on in-depth exploration of user experiences, perceptions, and the contextual factors influencing the effectiveness of GA-based interventions. These studies often employ interviews, focus groups, or case studies, providing rich, descriptive data that help to uncover the nuances of how GAs impact serious games. Although these studies are valuable for understanding the subjective experiences of users, they are often limited in their generalizability due to smaller sample sizes and context-specific findings.

Quantitative studies represented a larger proportion, accounting for 31.8% of the reviewed research. These studies typically utilize statistical methods to analyze the effectiveness of GA-enhanced serious games, often through controlled experiments or large-scale surveys. The quantitative approach allows for the measurement of specific outcomes, such as learning gains, engagement levels, or adaptability, providing more objective evidence of the benefits or limitations of GAs in serious games. The use of larger sample sizes and rigorous data analysis methods in these studies helps to enhance the generalizability of the findings, making them a cornerstone of evidence-based practice in this area.

Mixed methods studies, which combine both qualitative and quantitative approaches, made up 22.7% of the studies in the review. These studies leverage the strengths of both methodologies, offering a more comprehensive understanding of GA-enhanced serious games by integrating numerical data with detailed contextual insights. Mixed methods research is particularly valuable in this field as it provides a holistic view, capturing both the measurable outcomes and the underlying reasons behind

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those outcomes. This approach can bridge the gap between subjective user experiences and objective performance metrics, leading to more robust and actionable conclusions.

Interestingly, 31.8% of the studies did not specify their methodological approach. This lack of clarity may be due to various factors, such as the interdisciplinary nature of the research, where different fields may have different conventions for reporting methods, or it might reflect a trend towards exploratory or formative research that does not fit neatly into traditional methodological categories. While these studies can still offer valuable insights, the absence of a clearly defined methodology can make it challenging to assess the reliability and validity of their findings. Moving forward, it would be beneficial for researchers to more explicitly articulate their methodological choices to enhance the transparency and reproducibility of their work.

This distribution indicates a trend towards comprehensive research approaches that combine both qualitative insights and quantitative measurements.

Targeted Domains: The studies cover a wide range of domains, including:

The application of GAs in SGs spans various domains, each addressing unique challenges and contributing to the advancement of the field. In education, several studies have leveraged GAs to enhance learning experiences in subjects such as mathematics [28] and clinical laboratory education [32]. These educational applications typically focus on personalizing the learning process, optimizing the content delivery to match individual student needs, and improving engagement through adaptive gameplay. The ability of GAs to tailor educational experiences to diverse learner profiles has shown promising results, particularly in improving comprehension and retention in complex subjects.

In the healthcare domain, GAs have been applied to address a range of health-related issues through serious games. For instance, studies by Monaco et al. [39] and Kalafatis et al. [41] have utilized GAs to develop games that target cognitive impairment and childhood obesity, respectively. These health-focused games benefit from the adaptability of GAs, which allow for the customization of interventions to meet the specific needs of individual patients or user groups. The success of these applications underscores the potential of GAs to contribute to personalized healthcare solutions, offering tailored interventions that can adapt in real-time to the user's progress or condition.

The field of gaming and simulation has also seen significant contributions from GA-enhanced SGs. Many studies have focused on using GAs to improve general gaming experiences and simulations, as noted in works like [36,42]. In these contexts, GAs are often employed to optimize game mechanics, create dynamic content, and enhance the overall user experience. By introducing adaptive elements into the gameplay, GAs help to maintain player engagement and challenge, which are critical for both entertainment and educational outcomes in serious games.

Rehabilitation is another area where GAs have made a substantial impact, particularly in the development of robotics games for rehabilitation purposes. Studies like those by Andrade et al. [29] have explored the use of GAs in designing games that aid in the rehabilitation process, providing adaptive challenges that can adjust to the patient's progress. These applications are crucial in creating effective and motivating rehabilitation tools that can be personalized to the specific needs and abilities of patients, thereby enhancing the recovery process.

Lastly, enterprise and industrial applications of GAs in serious games have explored domains such as job shop scheduling [30] and enterprise problem-solving [38]. In these areas, GAs are used to simulate and optimize complex processes, providing solutions that can improve efficiency and decision-making in industrial settings. The use of serious games in these contexts allows for interactive and engaging ways to train employees, test scenarios, and solve problems, with GAs providing the adaptive algorithms needed to handle the complexity and variability inherent in these tasks.

#### 4.1.3. Current Methodological Approaches

The methodological approaches used in the reviewed studies include:

The research on the application of GAs in SGs has yielded several key insights. They include: (1) Implementation and evaluation studies often reported positive outcomes, demonstrating the potential

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of GAs in serious games; (2) Comparative studies provided more concrete evidence of the benefits of GAs compared to alternative approaches; (3) User evaluation studies offered insights into the practical impact of GA-enhanced games on user experience and learning outcomes; (4) Simulation-based studies allowed for extensive testing but may have limited ecological validity; and (5) Long-term studies provided valuable insights into the sustained effects of GA-enhanced serious games.

The implementation and evaluation of GA-based systems have been a focal point in numerous studies, highlighting their effectiveness in enhancing serious games. Many researchers have undertaken the task of integrating Genetic Algorithms into various game mechanics and subsequently evaluating their performance. The results have often been positive, demonstrating that GAs can significantly improve the adaptability and personalization of serious games. This has been particularly evident in educational and training contexts, where GA-enhanced games have shown potential in tailoring learning experiences to individual needs and optimizing content delivery.

Comparative studies have further strengthened the case for GAs in serious games. By comparing GA-based approaches with other methods or control groups, these studies provide more robust evidence of the benefits GAs bring to serious games. The findings consistently indicate that GA-enhanced games outperform traditional methods in terms of player engagement, learning outcomes, and adaptability. This comparative approach allows for a clearer understanding of the unique advantages GAs offer, making it easier to advocate for their adoption in game development.

User evaluation plays a critical role in assessing the real-world applicability of GA-enhanced serious games. Approximately 31.8% of the studies in this area incorporated user evaluations, offering valuable insights into how users perceive and interact with these games. These evaluations have revealed that users generally find GA-enhanced games to be more engaging and effective compared to non-GA games. The feedback from these studies is crucial, as it helps developers understand the user experience and make necessary adjustments to improve the effectiveness and appeal of the games.

Simulation-based studies have also been prominent in the literature, particularly for testing GA implementations in controlled environments. While simulations allow for rigorous experimentation and the fine-tuning of algorithms, they may limit the real-world applicability of the findings. Nonetheless, these studies provide a foundational understanding of how GAs can be utilized in serious games, offering a controlled environment to experiment with different configurations and parameters before real-world deployment.

Lastly, long-term studies, though less common, have provided valuable insights into the sustained effects of GA-enhanced serious games. For example, Kalafatis et al. [41] conducted a longer-term evaluation that offered a deeper understanding of how GA-based interventions impact users over extended periods. These studies are critical for assessing the long-term viability and impact of serious games, particularly in fields like education and healthcare, where lasting behavior change and learning outcomes are of paramount importance.

These methodological approaches influenced the findings and conclusions in several ways:

The implementation and evaluation of Genetic Algorithms (GAs) in serious games have frequently been met with positive outcomes, underscoring the significant potential these algorithms hold. Many studies have demonstrated that the inclusion of GAs can greatly enhance the adaptability and effectiveness of serious games, particularly in domains such as education and training. These studies typically report improvements in personalized learning experiences, where GAs are used to tailor content to individual users, thereby enhancing engagement and learning outcomes.

In addition to implementation studies, comparative research has provided more concrete evidence regarding the benefits of GAs when compared to alternative approaches. By directly comparing GA-enhanced games with those using traditional methods, these studies have shown that GAs consistently outperform other techniques in terms of player engagement, learning efficacy, and adaptability. The findings from these comparative analyses reinforce the argument that GAs offer a superior approach to serious game design, particularly in environments that require adaptive learning paths.

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User evaluation studies further contribute to our understanding of the practical impact of GA-enhanced serious games. These studies, which focus on how users interact with and perceive the effectiveness of these games, reveal that players generally have a more positive experience with GA-based games. The feedback gathered from users highlights the importance of considering user experience in the design and implementation of serious games, as this directly influences the game's educational effectiveness and overall appeal.

Simulation-based studies have also played a key role in advancing our understanding of GAs in serious games. These studies allow researchers to conduct extensive testing of GA algorithms in controlled environments, which is invaluable for refining the algorithms and testing various configurations. However, the reliance on simulations may sometimes limit the ecological validity of the findings, as simulated environments cannot fully replicate the complexities of real-world settings. Nonetheless, these studies are crucial for the initial stages of GA development and provide a foundation for more applied research.

Lastly, long-term studies have provided valuable insights into the sustained effects of GA-enhanced serious games. These studies, though relatively few in number, are particularly important for understanding how the benefits of GA-based games persist over time. For instance, long-term evaluations can reveal whether the improvements in learning outcomes and user engagement observed in short-term studies are maintained in the long run, which is especially critical in fields like education and healthcare where enduring impacts are desired.

#### 4.1.4. Future Research Directions

Based on the reviewed studies, several future research directions and potential advancements emerge:

*Integration with Other AI Techniques:* The integration of Genetic Algorithms (GAs) with other AI techniques, such as machine learning and neural networks, presents a promising avenue for future research in serious games. GAs have been widely used for optimization problems in game design, but their combination with machine learning models could lead to more adaptive and intelligent game systems. For instance, neural networks can be trained to predict player behavior or preferences, and GAs can optimize game parameters in real-time based on these predictions [45]. This synergy could lead to games that not only adapt to individual players' needs but also evolve in complexity as the player's skills improve, creating a dynamic learning environment. Future work could explore hybrid approaches where GAs optimize the architecture or parameters of machine learning models, leading to more sophisticated gameplay mechanics and educational outcomes [46].

*Real-World Implementation and Evaluation:* Implementing and evaluating GA-enhanced serious games in real-world settings, especially in education and healthcare, is crucial for understanding their practical impact. While many studies have demonstrated the potential of GAs in controlled environments, there is a need for more field studies that assess their effectiveness in real-world applications [47]. For example, serious games in healthcare that use GAs to personalize rehabilitation exercises could be tested in clinical settings to evaluate their efficacy in improving patient outcomes. Similarly, educational games that adapt content using GAs could be implemented in classrooms to assess their impact on student learning and engagement. Real-world evaluations will provide valuable insights into the challenges and benefits of GA-enhanced serious games, informing future design and development practices.

*Long-term Impact Studies* While short-term studies have shown promising results for GA-enhanced serious games, there is a significant gap in the literature regarding their long-term effects on learning outcomes and behavior change. Longitudinal studies are needed to determine whether the benefits of using GAs in serious games are sustained over time [48]. For instance, in educational contexts, it would be valuable to assess whether games that adapt to individual learning styles using GAs continue to engage students and improve their academic performance over several months or years. In healthcare, long-term studies could examine whether GA-optimized rehabilitation games lead to lasting improvements in patient mobility and health. Such research would provide a deeper understanding of the enduring impact of serious games and guide future developments in this field.

*Standardization of Evaluation Metrics:* The lack of standardized metrics for evaluating the effectiveness of GA-enhanced serious games is a major challenge in the field. Different studies often use varied criteria for assessing outcomes, making it difficult to compare results and draw general conclusions [49]. Developing standardized evaluation metrics would facilitate more consistent and reliable assessments of serious games across different domains and applications. These metrics could include measures of engagement, learning outcomes, behavioral changes, and user satisfaction, among others. By adopting common evaluation frameworks, researchers and developers could better understand the strengths and weaknesses of different GA approaches, leading to more refined and effective game designs.

*Personalization and Adaptive Learning:* Personalization and adaptive learning are critical components of effective serious games, and GAs offer powerful tools for enhancing these aspects. GAs can be used to tailor learning paths and content to individual players, optimizing the game's difficulty and pacing based on the player's progress [50]. This personalized approach can increase engagement and improve learning outcomes by ensuring that each player receives a unique and challenging experience. Future research should explore advanced GA techniques for adaptive learning, such as multi-objective optimization, which could balance competing goals like maximizing learning while maintaining high levels of engagement [51]. Additionally, the use of GAs for generating adaptive game content, such as levels or challenges, could lead to more diverse and personalized gameplay experiences.

*Ethical Considerations:* As GAs become more sophisticated, the ethical implications of their use in serious games must be carefully considered. In sensitive domains like healthcare and education, where games can have significant impacts on users' well-being and development, it is essential to ensure that GA-driven adaptations do not inadvertently cause harm or bias [52]. For example, a GA that personalizes educational content must be designed to avoid reinforcing existing biases or stereotypes, which could negatively affect certain groups of students. Similarly, in healthcare, GAs must be carefully monitored to ensure that they provide safe and effective recommendations for patient treatment. Ethical research in this area should focus on developing guidelines and best practices for the responsible use of GAs in serious games, ensuring that these technologies are used to benefit all users equitably.

*Cross-Domain Applications:* Exploring the application of successful GA approaches from one domain, such as education, to others, like healthcare, could lead to novel and effective serious game designs. For example, GAs used to optimize learning paths in educational games could be adapted to create personalized rehabilitation programs in healthcare games [53]. Cross-domain research could uncover new ways to apply GAs, leading to innovative solutions that address the unique challenges of different fields. This approach could also foster collaboration between researchers and practitioners from various disciplines, leading to more comprehensive and impactful serious games.

*User Experience Focus:* While much of the research on GAs in serious games has focused on technical aspects, more attention should be paid to how these enhancements affect user experience. GAs that optimize game mechanics or content generation must also consider the impact on user engagement, motivation, and overall enjoyment [54]. Studies should examine how players perceive and interact with GA-driven features, and whether these features improve or detract from the gaming experience. Understanding the user experience is essential for creating serious games that are not only effective but also enjoyable and engaging for players.

*Scalability and Efficiency:* Scalability and computational efficiency are critical considerations for the widespread adoption of GAs in serious games. As games become more complex and require real-time adaptivity, the computational demands of GAs can become a bottleneck [55]. Future research should explore methods to improve the scalability of GAs, such as parallel processing or cloud-based solutions, allowing them to be used in larger and more dynamic game environments. Additionally, optimizing the efficiency of GA algorithms could reduce the computational load, enabling real-time

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adaptations without compromising performance. These advancements would make GA-enhanced serious games more accessible and practical for a broader range of applications.

These future directions and potential advancements could significantly improve the effectiveness of GAs in serious games by addressing current limitations, expanding their application domains, and enhancing their ability to create personalized, engaging, and optimized learning experiences.

### *4.2. Limitations*

The scoping review identified several limitations across the included studies:

**Methodological Limitations:** The literature review revealed several methodological limitations across the studied works. Many studies were constrained by small sample sizes or narrow participant demographics, potentially limiting the broader applicability of their results. Some research relied heavily on theoretical models or simulations without incorporating real-world user testing, which may affect the practical relevance of their findings. A notable issue was the lack of comprehensive details regarding the specific genetic or evolutionary algorithm techniques employed in some studies, hindering the ability to fully evaluate and reproduce the methods. Additionally, the absence of formal comparison or control groups in certain studies made it challenging to attribute observed outcomes exclusively to the proposed evolutionary algorithms. These limitations collectively underscore the need for more rigorous, well-documented, and practically-oriented research in this field to enhance the reliability and generalizability of findings.

**Reporting Limitations:** The review also uncovered several reporting limitations across the analyzed studies. Some researchers failed to clearly articulate their specific objectives, evaluation metrics, or study outcomes, which hampered efforts to synthesize findings across the body of literature. Additionally, a number of studies lacked comprehensive details about the limitations acknowledged by the authors themselves, potentially depriving readers of crucial context for interpreting the results. The review also noted that some studies were published in formats such as conference papers or book chapters, which typically offer less space for in-depth reporting compared to journal articles. This brevity may have resulted in less detailed presentations of methodologies, results, or discussions, further complicating efforts to fully assess and integrate these studies' contributions to the field.

**Domain-Specific Limitations:** The review highlighted certain domain-specific limitations in the existing research. Many studies concentrated on particular application areas like education, healthcare, or rehabilitation robotics, potentially constraining the applicability of their findings to other serious game contexts. This narrow focus, while valuable for those specific domains, may not fully represent the diverse landscape of serious games. Additionally, several researchers acknowledged the necessity for further validation or testing in authentic, real-world environments, as many evaluations were conducted primarily in simulated or laboratory settings. This limitation underscores the importance of bridging the gap between controlled research environments and practical, real-world applications to ensure the robustness and effectiveness of evolutionary algorithms in diverse serious game scenarios.

**Potential Biases:** The review also identified potential sources of bias in the existing research. A notable concern was that several studies originated from research teams within the same institution or country, which could introduce inherent biases or contextual limitations to the findings. This geographical or institutional concentration may inadvertently narrow the perspective and applicability of the research. Additionally, the review acknowledges the possibility of publication bias affecting the overall body of literature. This bias stems from the tendency for studies with positive or significant results to be published more readily than those with negative or inconclusive outcomes. Consequently, the available literature may present an overly optimistic or skewed representation of the effectiveness of evolutionary algorithms in serious games, potentially overlooking valuable insights from less favorable or ambiguous results.

Despite these limitations, the scoping review provides a comprehensive overview of the current state of research on the use of genetic algorithms and evolutionary algorithms in serious games. The identified limitations highlight areas for future research to address, such as expanding the diversity

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of study populations, incorporating more rigorous comparative evaluations, and ensuring thorough reporting of methodological details and limitations.

## 5. Conclusion

The scoping review on the use of GAs and EAs in SGs reveals a growing body of research exploring the potential of these techniques in enhancing the design, adaptation, and optimization of SGs across a variety of application domains. The reviewed studies demonstrate the versatility of GAs and EAs in addressing various challenges in serious game development, such as content generation, difficulty adjustment, agent behavior modeling, and optimization of game elements. The predominance of positive outcomes reported in the studies suggests that these algorithms can effectively support the creation of engaging and adaptive serious games. The mix of qualitative, quantitative, and mixed methods approaches employed in the reviewed studies provides a nuanced understanding of the potential and limitations of these algorithms. The incorporation of both objective and subjective evaluations, including user feedback, underscores the importance of considering both performance metrics and user experience in the development and assessment of SGs. While the scoping review identified several methodological and reporting limitations, the overall findings indicate that GAs and EAs hold significant promise for enhancing the effectiveness and adaptability of serious games. The identified limitations and future research directions provide a roadmap for addressing the current gaps and advancing the field. The scoping review's findings have implications for serious game developers, researchers, and practitioners across various domains. By leveraging GAs and EAs, developers can create more engaging, adaptive, and effective SGs that cater to diverse user needs and preferences. Researchers can explore new applications and domains, investigate the underlying mechanisms, and develop more sophisticated algorithms to further improve the performance and impact of SGs. The review's results also highlight the importance of interdisciplinary collaboration between computer scientists, game developers, domain experts, and end-users to ensure that the developed serious games are both theoretically grounded and practically relevant. In conclusion, the scoping review provides a comprehensive overview of the current state of research on the use of GAs and EAs in SGs. The findings demonstrate the potential of these techniques to enhance the design, adaptation, and optimization of SGs, and identify areas for future research to address the current limitations and gaps.

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## Appendix A My Appendix

**Table A1.** Search strings for each database

| Database | Search Strings |
|---|---|
| ACM Digital Library | Title:(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*")) OR<br>Abstract:(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*")) OR<br>Keyword:(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*")) |

Continued on next page

**Table A1 – continued from previous page**

| Database | Search Strings |
|---|---|
| Inspec | ((("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*")) WN KY) |
| Scopus | TITLE-ABS-KEY ( ( "genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology" ) AND ( "serious game*" ) ) |
| Web of Science | ((TI=(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*"))) OR AB=(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*"))) OR AK=(("genetic algorithm*" OR "evolutionary algorithm*" OR "computational algorithm*" OR "computational evolution*" OR "computational biology") AND ("serious game*")) |

*Appendix A.1 Abbreviations*

- **GA**: Genetic Algorithm
- **GAs**: Genetic Algorithms
- **KO**: Kiemute Oyibo
- **PM**: Philip Michalowski
- **PRISMA-ScR**: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
- **SG**: Serious Game
- **SGs**: Serious Games
- **VV**: Vrushank Vaghani

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