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Improved Non-Player Character (NPC) behavior using evolutionary algorithm—A systematic review

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ABSTRACT

Games, once solely intended for entertainment, have emerged as a significant research focus in recent years, with the primary goal of enhancing the gaming experience. Research in the gaming domain has expanded to encompass a wide range of topics, spanning from game theory to artificial intelligence. Within the realm of artificial intelligence itself, Non-Player Characters (NPCs) play a crucial role in shaping the overall gaming experience. The quality of NPC behavior directly influences player satisfaction. Evolutionary algorithms stand out as a key algorithm for optimizing NPC behavior and interactions. This review paper extensively explores the intricate relationship between evolutionary algorithms and NPC behavior, proposing six categories (planning, user interaction, position modification, parameter modification, character state modification, and target assignment strategy), each delineating a distinct role for evolutionary algorithms. Ultimately, the paper draws three main conclusions: the pervasive use of evolutionary algorithms in gaming research, the diversity in game selection for research trials, and the varying strategies employed by researchers in selecting testing techniques. This comprehensive review aims to serve as a valuable reference for future research, particularly in the domain of evolutionary algorithms applied to NPC behavior.

Contents

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1. Introduction

Games have evolved beyond mere sources of entertainment and now serve various purposes, including promotion [1], physiology [2], and even education [3]. This widespread utilization of games has sparked significant interest in the research community, making them a captivating subject for scholarly exploration. Several studies have been carried out so far, including in the fields of artificial intelligence [4,5], recommendation systems [6], virtual tours [7], outreach [8], game concepts [9–11], game mechanics [12], business [13], forecasting the player's gaming experience [14], and other fields. Despite the broad range of research conducted on games, the utilization of evolutionary algorithms remains relatively scarce. This holds for both general game research [15] and more specific investigations, such as studying the behavior of NPCs. The underutilization of evolutionary algorithms in these areas highlights an opportunity for further exploration and experimentation to unlock their potential for advancing game-related research. The primary objective of this paper is to conduct a comprehensive systematic review specifically focusing on NPC behavior in games using evolutionary algorithms. Generally, the term NPC can have various meanings, but in this article, we focus on NPCs as AI-driven agents that interact with players, not with the environment or other objects in the game. These agents can either be allies who play alongside the player on the same team or opponents who act as the player's enemies. By undertaking this systematic review, the intention is to increase awareness and understanding of evolutionary algorithms within the realm of game studies. Moreover, it aims to shed light on the potential applications and benefits of utilizing evolutionary algorithms in future research about game-related NPC behavior. This paper encompasses discussions about research concerning evolutionary algorithms applied to NPCs in a broad sense, as well as a deeper exploration into research focused on the behavior of NPCs using evolutionary algorithms. Additionally, it includes an analysis of the key findings presented in this literature review, like how evolutionary algorithms are used, which games are chosen for testing, and the methods for validating trials.

2. Method

The purpose of this review paper is to provide an overview of current research developments in the field of NPCs, both in general and specifically in the scope of NPC behavior utilizing evolutionary algorithms. Ultimately, the paper analyzes a combination of various research papers from international databases, leading to interesting conclusions for further developments. As the focus of this paper is a Systematic Literature Review (SLR), both quantitative and qualitative approaches will be employed to achieve the expected results.

2.1. Data source

We conducted a literature review using various international databases such as Scopus, Web of Science, ScienceDirect, IEEE Xplore, Springer Link, and Google Scholar. These databases were chosen for their global recognition and ability to facilitate easy searches while offering high-quality articles. Our search was limited to the period from 2008 to 2024. The year 2008 was selected as the starting point because it marks the period when evolutionary algorithms began to see significant development and use in various research areas.

2.2. Search keyword

We conducted a literature search using various search strings that combine the main keywords of this SLR, including:

1. (Non-player character OR Non-playing character OR NPC) AND (Evolutionary Algorithms OR Meta-heuristic Algorithms)
2. (Non-player character OR Non-playing character OR NPC) AND Behavior AND (Evolutionary Algorithms OR Meta-heuristic Algorithms)
3. (Non-player character OR Non-playing character OR NPC) AND (Decision OR Strategy) AND (Evolutionary Algorithms OR Meta-heuristic Algorithms)

In addition to the literature found through our database search, we also considered additional articles cited by the articles we used. This approach is important because it helps us identify valuable references that may not appear in database search results.

2.3. Inclusion and exclusion

Not all of the literature we found was used in our review. After a thorough examination of each piece, we had to eliminate several studies. Here are the exclusion criteria we applied:

1. Articles not related to the scope of NPC or evolutionary algorithms.
2. Non-peer-reviewed articles or those from less reputable sources.
3. Article had different titles but covered the same research.
4. An article with more recent similar research was available.

3. Evolutionary algorithm in NPC

The research topic of NPCs encompasses a wide range of subtopics, each with its unique challenges and considerations. However, not all these subtopics have been thoroughly explored in the context of evolutionary algorithms. In this subchapter, we will briefly discuss several subtopics within NPC research that have incorporated evolutionary algorithms. It is important to note that the discussion will not delve into extensive details, as the focus of this paper review lies in subchapter 3, specifically on NPC behavior. There are 4 subtopics in this discussion, including NPC Behavior, Dynamic Difficulty Adjustment (DDA), Generate Map/Character, and Hybrid Evolutionary Algorithm.

NPC behavior is a specific subtopic within the broader field of non-player character research, and it serves as the main focal point of discussion in this review paper. The primary objective of this research is to utilize evolutionary algorithms to enhance NPC behavior, making it more dynamic and avoiding repetitive patterns. For a comprehensive understanding of the evolutionary research conducted on NPC behavior, readers are encouraged to refer to subchapter 3, where detailed information and findings regarding this topic will be presented.

In the context of game research, DDA is a subtopic that focuses on dynamically adjusting the difficulty level of NPCs in a game. In this discussion, we will specifically focus on the application of evolutionary algorithms as the primary algorithm for determining the difficulty level of NPCs. Some research studies that concentrate on DDA comprise: DDA in Digital Games [16–18], DDA in Real-time Strategy Games [19,20], DDA in Shooter Games [21], and DDA in Platform Game [22].

The generation of maps and characters is an important subtopic within evolutionary algorithm research in games. Although it may not

Table 1
Position modification research group.

No	Research	Evolutionary algorithm	Game	Experiment
1	Optimization of Real-Time Strategy [27]	NSGA-II	FastEcslent (StarCraft II Game Mode)	NPC Vs NPC
2	Communication Strategies and Emergent Behavior of Multi-Agents in Pursuit Domains [28]	GA	Metal Gear Solid (MGS)	NPC vs. NPC Prey
3	Ant Colonies for Video Games [29]	ACO	Ms. Pacman	Scenario-Based Environment and NPC vs. NPC
4	Behavioral Design of Non-Player Characters in a FPS Video Game [30]	PSO	First-Person Shooter (FPS) Game	CPU and Time Calculation
5	Movement Algorithms for Artificially Intelligent NPC [31]	PSO Vs Firefly Algorithm	Tag-o-rithms	Player Vs NPC
6	Swarm Intelligence for Pathfinding and Action Planning of Non-player Characters [32]	PSO	Isolated	CPU Time Calculation
7	Multi-modal Behavior in NPCs [33]	Combine of NSGA-II and TWEANNs	Fight or Flight	NPC Vs NPC
8	GA with dynamic infectability for pathfinding in a tower defense game [34]	GA	3D Environment Only	GA Parameter Combination
9	Strategy Based on Grey Wolf Optimization [35]	Grey Wolf Optimizer (GWO)	None	None

Research 1 to 3 used popular games that were widely known to the public, Research 4 to 7 used self-made games (The game was independently developed by the researchers solely for the purpose of substantiating their research findings), Research 8 did not apply games but only the environment (The research objective revolved around achieving proficient NPC mobility within this environment) and Research 9 did not conduct trials in its study. Specifically, Research 2 used NPC Prey. The NPC Prey employs two distinct algorithms for its movement: Linear Movement and Random Movement. The primary objective of this NPC variant is to evade the pursuit of the advanced NPC.

solely focus on NPCs, the design and arrangement of maps can significantly impact NPC behavior, as well as the behavior of player characters. Some research studies that concentrate on Generate Map/Character comprise: Procedural Generation for Endless Platform Game [23], Procedural Video Game Scene Generation [24], Map Generation [25], and Procedural Content Generation in Game Design [26].

The subtopic of utilizing evolutionary algorithms in combination with other algorithms in game research is a significant area of study. It recognizes that not all problems within game development can be effectively addressed solely using evolutionary algorithms. In certain cases, the integration of other algorithms becomes necessary to achieve optimal results. Some research studies that concentrate on Hybrid Evolutionary Algorithm comprise: Evolving a Neural Network [36–44], Evolving a Behavior Trees [45,46], Evolving a layered influence map [47], and Evolving a group of co-ordinated AI [48].

4. Evolutionary algorithm in NPCs behaviors

The study of NPC behavior is significant in game research, directly impacting the player's gaming experience. This aspect encompasses various processes such as movement, decision-making, group strategies, actions, interactions with the environment, and adjustments to game dynamics. In Section 3 of this review, we categorize and briefly discuss NPC behavior research utilizing evolutionary algorithms. We propose six categories-planning, user interaction, parameter modification, position modification, character state modification, and target assignment strategy-based on a thorough analysis of existing research. Fig. 1 provides a schematic representation of the review paper's position within the broader landscape of artificial intelligence for games research. This figure illustrates that each research category has its distinct focus. For instance, planning and target assignment categories concentrate on game strategy, character state modification centers on decision-making, and position modification emphasizes the player's movement area. Additionally, two supporting research categories, user interaction, and parameter modification, play crucial roles in enhancing NPC behavior despite their auxiliary nature. This section aims to offer insights for researchers and game developers into the current state of NPC behavior research employing evolutionary algorithms.

4.1. Position modification

An alternative avenue for shaping NPC behavior involves the manipulation of their movement positions. While perhaps seemingly subtle, an NPC's position can confer noteworthy advantages. In scenarios where multiple NPCs share comparable attributes, skills, and gameplay tactics, strategic positioning can decisively sway the outcome of an NPC's encounter with other NPCs or even human players [52,53]. As such, the position assumes a pivotal role in determining the success of an NPC within a game. Table 1 serves as a compilation of studies that have harnessed evolutionary algorithms to manipulate the movement positions of NPCs. These studies collectively illustrate that positioning can wield a tangible impact on gameplay dynamics. By exploring how the placement of NPCs influences their interactions and outcomes, researchers shed light on the significance of strategic positioning in enhancing game experiences.

Table 1 offers a comprehensive glimpse into the expansive spectrum of research conducted on this subject. The diversity observed encompasses a wide array of factors, ranging from the choice of evolutionary algorithm, and selection of games for experimentation, to the methodologies employed to validate the research outcomes. This diversity underscores the adaptable nature of evolutionary algorithms in addressing NPC movement challenges. Notably, while various evolutionary algorithms have been utilized, it is worth noting that no entirely novel algorithm has emerged in the last five years.

A noteworthy trend is evident in the games used during experimentation: half of the studies relied on custom-designed games to substantiate their findings. Some are made with Unreal Engine 4 by adopting the Counter-Strike game concept, some use the tag-based

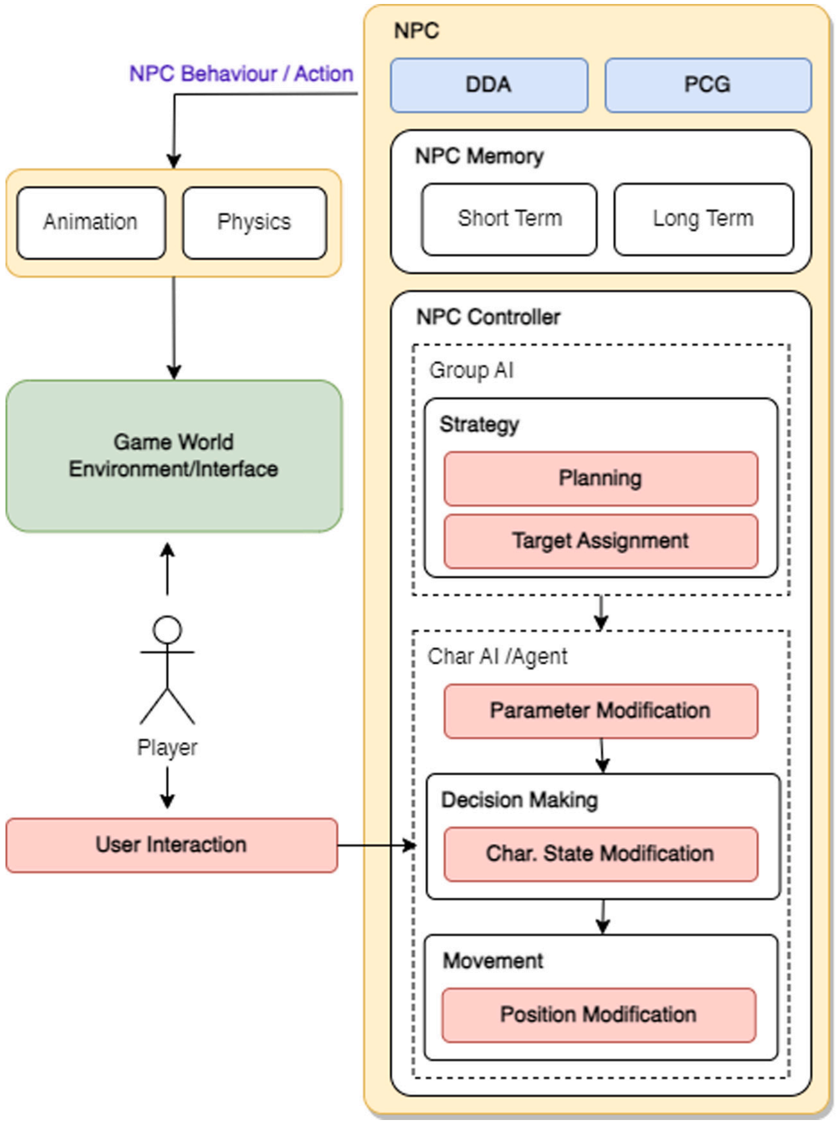

Fig. 1. Review Paper Position in Artificial Intelligence for Games Research. A limited subset of this image has been adopted from [49–51].

concept and feature four different levels of difficulty, and others implement two types of scenarios: scenarios for fighting and scenarios for escaping from NPCs. Although these games were internally created, the viability of their outcomes remains substantiated, primarily focused on evaluating the efficacy of the evolutionary algorithm itself rather than directly measuring the NPC's movement success. Contrarily, other studies employed widely recognized and popular games to verify the effectiveness of their NPC behaviors. These evaluations typically involved comparisons with other NPCs, whether self-generated or drawn from case study games, to establish the achievements of the evolutionary algorithm.

4.2. Planning

The spectrum of gameplay is not confined solely to battle scenarios; several games encompass concepts like production, resource gathering, and price planning. Such games necessitate the development of specialized strategy for NPCs to function optimally within their designated roles. Although the gameplay differs, the applicability of evolutionary algorithms in NPC development remains evident. Table 2 catalogs studies that leverage evolutionary algorithms to fine-tune NPC behavior within contexts related to production, resource gathering, and price planning. These studies illuminate the versatility of evolutionary algorithms in enhancing NPC actions beyond traditional battle scenarios.

The entries in Table 2 underscore a notable trend: research success in the realm of production, resources, and pricing is not solely reliant on NPC vs. NPC comparisons. Given the intricate nature of these aspects, direct comparison proves challenging. As a result, 2 out of 6 studies of the research endeavors employ simulation methods. These simulations can take various forms, including text-based or visual representations. While the popularity of NPC vs. NPC validation might not dominate this field, it remains relevant, accounting for 50% of the studies. In these cases, the efficacy of NPCs is gauged through speed, which directly influences the attainment of profits. This blend of validation approaches mirrors the diversity of factors at play in the production, resource, and pricing domains, enabling researchers to derive meaningful insights across varied contexts.

4.3. Parameter modification

Parameter Modification was done to address the wide range of parameters that have been explored in research. The modification of these parameters is primarily aimed at aiding NPCs in decision-making, ensuring that the decisions obtained are more precise and contextually

Table 2
Planning research group.

No	Research	Evolutionary algorithm	Game	Experiment
1	Address Planning in a RTS Game [54]	Multi-Objective Ant Colony Optimization (MOACO) Vs NSGA-II	Text Simulation[a]	Planning Calculation
2	Resource Gathering Behaviors in Real-time Strategy Games [55]	Memetic Ant Colony System (MACS)	Visual Simulation[b]	Planning Calculation
3	Build Order Optimization in StarCraft II [56]	NSGA-II	StarCraft II	Time Vs Production[c]
4	Evolutionary Algorithm Approach for A Real Time Strategy Game [57]	GA	Bos Wars	NPC Vs NPC
5	Intelligent Agent for NPC Behavior Decision [58]	NSGA-II	Reog Ponorogo[d]	NPC Vs NPC
6	Automatic StarCraft Strategy Generation [59]	Genetic Programming (GP)	StarCraft	NPC Vs NPC

[a] The research under consideration abstains from using games as a demonstration of its research findings. Instead, it relies on analytical methods that pertain to the outcomes of the devised planning strategies.
[b] In this study, games are not utilized to substantiate the research; rather, the emphasis lies in providing planning through graph modeling. The graph in question incorporates the travel paths of NPCs along with the established supply locations.
[c] The study conducted trials by juxtaposing the time taken with the production speed or construction of buildings within the game. The primary objective was to expedite and optimize the construction of buildings, striving for maximum efficiency.
[d] This game was specifically designed for the purpose of research validation. Within the game, two distinct roles are present: buyers and sellers. Buyers' behaviors are governed by finite-state machines, while the evolutionary algorithm developed in this study assumes the role of sellers.

Table 3
NPC weight parameter research group.

No	Research	Evolutionary algorithm	Game	Number of parameters	Experiment
1	Real-Time Strategy Games Player Behavior Optimization [63]	GA	Planet Wars	7	Parameter Optimization and Noisy Fitness Study
2	Player behavior in a real-time strategy game [64]	GA	Planet Wars	7	Parameter Optimization and NPC vs. NPC
3	Optimizing Hearthstone agents [65]	Evolution Strategy (ES)	Hearth-stone	21	Analysis of ES Solution and NPC vs. NPC (Hearthstone AI Competition)
4	Effective Micro Behaviors in RTS Game [66]	GA	StarCraft	14	NPC vs. NPC with Varian Scenario

appropriate [53]. This research category can be further divided into two groups based on the parameters involved: Parameters from NPC Weight and Parameters from the NPC Profile. By categorizing research into these two groups, the discussion becomes more organized and allows for a deeper exploration of the specific modifications made within each category. This approach helps to highlight the different aspects of NPC behavior and provides valuable insights into the impact of parameter adjustments on NPC performance and gameplay [60].

4.3.1. NPC weight parameter

The NPC weight parameter group focuses on utilizing an evolutionary algorithm to modify the weights that influence NPC behavior. These weights are used to determine the importance or significance of certain properties exhibited by the NPCs [61,62]. For instance, weight may affect the percentage of NPCs that engage in attacks, the weight assigned to reducing the health of the NPC, or the weight assigned to the influence of a unit within a specific range. By adjusting these weights, researchers aim to steer the behavior of NPCs in the desired direction. Table 3 provides a collection of studies within the weight parameter group, accompanied by corresponding discussions for each study. The table serves as a reference for understanding the diverse research conducted in this area. Each study listed in the table explores different aspects of weight modification and its impact on NPC behavior.

The studies presented in Table 3 employ a range of weight[1] parameters to shape and guide NPC behavior. These weights hold no predetermined or fixed rules, which renders the application of evolutionary algorithms highly suitable for these investigations. The absence of strict guidelines for weight setting allows the evolutionary algorithm to dynamically adjust these parameters based on the game's context and objectives [61,67]. Consequently, this approach leads to a diverse array of weights, ultimately yielding a wide spectrum of NPC behaviors that are intricate and present varying levels of challenge. During the evaluation phase of each study, most tests involve NPC vs. NPC scenarios. In these scenarios, one NPC serves as the opponent and is chosen from a pool of previously developed NPCs. These NPCs have either been created by game developers or have emerged from prior research endeavors. This setup facilitates controlled testing, enabling researchers to systematically analyze how modifications to weight parameters impact NPC behavior when pitted against other intelligent opponents.

[1] Examples of weights: planet growth weight (research 1 and 2), percentage when sent from the home planet (research 1 and 2), HP Hero reduction weight (research 3), mana reduction weight (research 3), terrain weight (research 4), the weight of the distance between the unit and the target (research 4).

Table 4
NPC profile parameter research group.

No	Research	Evolutionary algorithm	Game	Number of parameters	Experiment
1	Controlling bots in a First Person Shooter game [68]	NSGA-II	Unreal Tournament 2004	7 Profile and 35 Threshold	NPC Behavior Validation and NPC vs NPC
2	Learning to win in a first-person shooter game [69]	Particle Swarm Optimization (PSO)	Quake III Arena	9	Battle Royal between NPC
3	AECT in gaming [70]	Fusion of GA and Ant Colony Optimization (ACO)	Zombie Redemption (ZR)	12 Intrinsic Features and 5 Extrinsic Features	Human Vs NPC

4.3.2. NPC profile parameter

In contrast to the utilization of weights as parameters within the evolutionary algorithm, which aims to fine-tune the values of NPC behavior to accommodate diverse encountered conditions, the utilization of the NPC Profile focuses on establishing the distinct attributes of an NPC. These attributes encompass traits such as attack accuracy, responsiveness when under attack, and the level of aggression exhibited by the NPC. These defining characteristics play a pivotal role in shaping the NPC's movement and actions. Much like humans, each NPC possesses unique attributes. Some may be swift, robust, assertive, or possess other distinct traits. Table 4 provides an overview of diverse studies that have implemented the NPC Profile in conjunction with an evolutionary algorithm. These studies delve into the nuanced characteristics that collectively shape an NPC's behavior. By leveraging evolutionary algorithms, researchers aim to generate NPCs with multifaceted and tailored profiles, thereby enriching the gaming experience.

Despite employing distinct evolutionary algorithms, all three studies detailed in Table 4 effectively manipulated the NPC Profile[2] to yield appropriate behavior. The successful outcomes of these studies underscore the versatility of evolutionary algorithms in tailoring NPC behavior to desired specifications. Notably, the manipulation of NPC profiles varied across the case studies due to differences in the game type and difficulty level employed in each study [71,72]. Furthermore, aside from variations in case studies, the three research efforts also adopted different experimental methodologies. The first study observed and analyzed patterns of NPC behavior, subjecting proficient NPCs to confrontations with other pre-developed NPCs. In the second study, a battle royale scenario was simulated, where NPCs generated by the PSO algorithm competed amongst themselves, enabling researchers to scrutinize their behavioral tendencies. The third study, however, opted for a human-against-NPC approach. While the methodologies diverged, a common thread in the validation process across these studies was the use of consistent statistical measures extracted from match outcomes. Key parameters encompassed the number of victories, the frequency of attacks launched, the intensity of attacks sustained, and the duration of each match. By unifying the validation criteria, researchers ensured robust and comparable evaluation across the diverse experimental approaches.

4.4. Character state modification

In addition to character profiles, each NPC is characterized by a distinct behavioral state. This state encapsulates the NPC's position or stance while executing specific actions [73]. Unlike profiles that predominantly influence NPC attributes, states dictate the actual behaviors and actions undertaken by the NPC. In Table 5, a compilation of studies is presented where evolutionary algorithms are harnessed to manipulate the behavioral states of NPCs. These studies collectively shed light on the role of evolutionary algorithms in shaping NPC actions and responses within diverse gaming contexts.

Table 5 provides insight into the limited number of studies focused on the modification of character states. Notably, the studies primarily rely on GA, indicating a prevailing preference for this approach. Despite the potential of newer and potentially faster evolutionary algorithms, their application has not been explored extensively within this specific context.

Of the three studies featured in the table, two adopt the NPC vs. NPC framework to validate their research outcomes. This approach underscores the significance of NPC interactions in gauging the efficacy of state modifications. Conversely, the third study embraces time and memory calculations as the basis for validation. This decision is largely attributed to the chosen game, Super Mario Bros., which is designed as a single-player experience rather than a team-based competitive game. The utilization of varying validation approaches further accentuates the adaptability of evolutionary algorithms in tackling diverse research scenarios.

4.5. User interaction

Player interaction stands as a critical focal point in contemporary game research. Despite its significance, there is a scarcity of studies specifically addressing NPC behavior with a dedicated focus on player interaction. In this approach, the evolutionary algorithm not only relies on fitness evaluations but also incorporates direct input from the user to guide its evolutionary process. Among the studies conducted in the last five years, a notable research paper [77] was identified. The objective of this research was to create NPCs that could adapt their behaviors based on the decisions and actions of players. The primary aim was to prevent NPCs from exhibiting repetitive and predictable patterns of behavior, which could lead to a less immersive and engaging gameplay experience. This approach holds promise for improving the quality and immersion of NPC behaviors in games, as it allows for more personalized and player-driven experiences.

Fig. 2 depicts the proposed model in this research, showcasing the evolutionary process of NPCs based on player behavior from the previous stage. This model suggests that NPCs will undergo continuous evolution, adapting and changing according to the actions and decisions of the players. However, it is worth noting that this research is currently at the initial idea stage and has not been further developed. Although the model offers potential benefits and contributions to the field, the research itself has not been continued beyond its conceptual phase. By exploring and refining this model, future studies could potentially make significant contributions to the field of game AI and enhance the gameplay experiences for a wide range of players.

4.6. Target assignment strategy

In games, particularly those involving matches like first-person shooters (FPS) or multiplayer online battle arenas (MOBA), a crucial strategy for achieving victory is identifying the optimal target for effective and strategic attacks. Evolutionary algorithms are employed to enhance the efficiency and effectiveness of NPC attacks. Employing these algorithms aims to optimize the selection of attack targets for

[2] Examples of NPC Profiles: accuracy in shooting, aggressiveness, jumpiness, vengefulness, velocity, health bar, patrolling area, etc.

Table 5
Character state modification research group.

No	Research	Evolutionary algorithm	Game	Number of action[a]	Experiment
1	Cooperative Predation Strategies [74]	GA	Flat Plane Environment[b]	5	Scenario Based NPC Vs NPC Prey
2	Creating autonomous agents for playing Super Mario Bros game [75]	GA	Super Mario Bros	5	Time and Memory Calculation
3	Evolving a team in a first-person shooter game [76]	GA	Quake III Arena	6	NPC Vs NPC

[a] Every action undertaken by an NPC triggers a transition to a new state within their behavioral repertoire. These actions encompass a range of behaviors, including attacking, defending, patrolling, and more.
[b] In this study, games were not employed as the case study; instead, the research centered on an environment characterized by a flat plane devoid of obstacles or constraints.

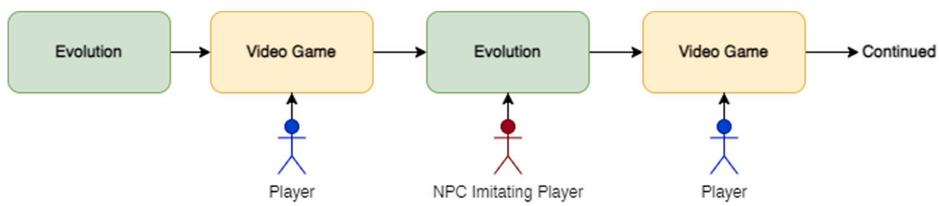

Fig. 2. Research Model for NPC Behavior Based on User Interaction.
Source: Adopted from [77].

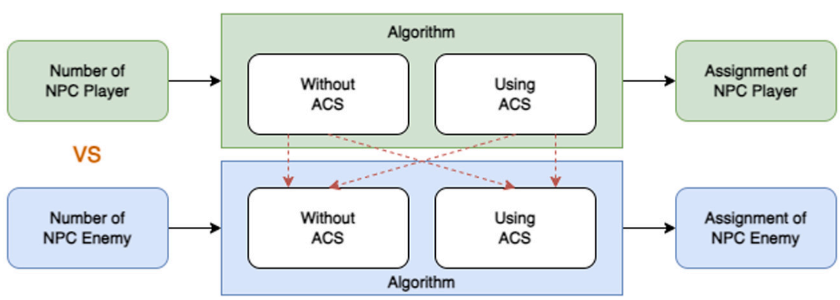

Fig. 3. Trial Model for NPC Behavior Based on Target Assignment Strategy.
Source: Adopted from [78].

NPCs, leading to improved attack strategies. It is worth noting that research in this particular category is relatively scarce, with the most recent study found dating back to 2014 [78]. Since then, no further research has focused on determining attack targets using evolutionary algorithms.

In this study,[3] the ant colony system (ACS) is employed as the evolutionary algorithm of choice. The ACS algorithm is utilized to determine the sequential order of targets for NPCs based on the distances between them. Throughout the game, the ACS algorithm continuously determines the order of targets for NPCs, ensuring that their movements remain dynamic and avoid repetitive patterns. By leveraging the capabilities of the ACS algorithm, the study seeks to optimize the decision-making process for NPCs in selecting their targets. This approach can potentially lead to more efficient and effective NPC attacks, contributing to a more engaging and immersive gaming experience for players.

Fig. 3 presents the trial concept proposed in the study. The experiment involved 30 NPCs, comprising both NPC Players and NPC Enemies, all utilizing the same algorithm. The objective of the trial was to compare the number of NPC movements when applying ACS algorithm versus when it was not used. Through the trials, it was observed that the application of the ACS algorithm led to efficient target selection among the NPCs, resulting in a reduced total movement distance. This was particularly evident when both NPC camps utilized the ACS algorithm for target determination. By utilizing the ACS algorithm, NPCs were able to intelligently assess and select their targets based on distance considerations. This resulted in optimized movements, as NPCs minimized unnecessary travel distances while efficiently engaging with their designated targets.

5. Literature review findings analysis

The comprehensive exploration of the discussed literature offers several valuable insights. The analysis is structured into three main categories: the application of evolutionary algorithms, the game selection for testing, and the strategies employed by researchers during validation trials. This assessment aims to furnish prospective researchers with valuable input for future endeavors in similar domains.

1. Utilization of Evolutionary Algorithms: The studies showcased a diverse employment of evolutionary algorithms, demonstrating their adaptability across a broad spectrum of NPC behaviors. These algorithms, ranging from GA to particle swarm optimization, were instrumental in influencing NPC behaviors. However, it is noteworthy that a tendency towards conventional algorithms (GA, GP, NSGA-II, PSO, GWO, ACO, FIREFLY, MOACO,

[3] Optimization of NPC Assignment for Attack Strategy in the Game Using Ant Colony System [78].

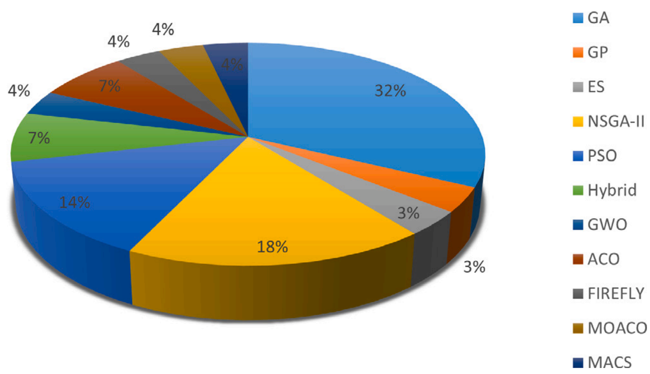

Fig. 4. Utilization of Evolutionary Algorithms.

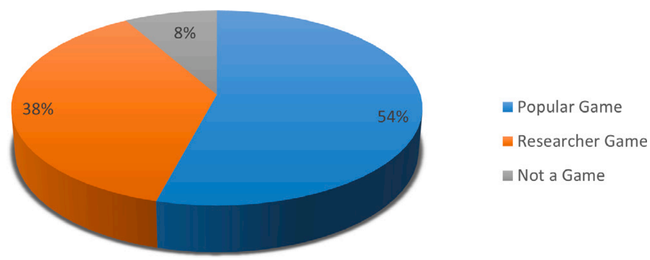

Fig. 5. Game choice as Testing Ground.

MACS) was observed, indicating potential room for the incorporation of more contemporary approaches. This suggests that novel algorithmic approaches (Queen Honey Bee Colony [79], Artificial Salmon [80], ORCA [81], etc.) could potentially offer improved NPC behavior outcomes, enhancing the versatility of these AI systems. While these new algorithms have shown success in solving problems outside of gaming, there is a belief that if these algorithms are applied to the gaming field, they can also perform effectively. Fig. 4 illustrates the distribution of the utilization of each evolutionary algorithm in the discussed context.

2. Game Choice as a Testing Ground: The selection of game environments for research trials was intriguing. Notably, researchers often designed their games exclusively for research purposes [31–33] (Researcher Game), harnessing various engines such as Unreal 4 or Unity. Such a choice is strategic as it provides full control over the testing conditions. In contrast, some studies opted to use established games (Popular Games) [65,66,68], leveraging their familiarity and complexity. This dual approach reflects a practical blend, enabling researchers to either scrutinize their controlled environments or gauge the AI's effectiveness in established game dynamics. Fig. 5 illustrates the distribution of the game choice in the discussed context.
3. Strategies for Validation Trials: The methodologies employed during validation trials showcased a spectrum of strategies. The NPC vs. NPC approach [27,28,64,68] was frequently used, allowing for the assessment of NPC behaviors under competition. This approach delivered insightful data, especially when considering behavior modifications. In addition to NPC vs. NPC validation, another common method used to validate NPC behavior is Player vs. NPC interaction [31,70]. Researchers also frequently assess resource utilization, including CPU, memory, and time, to evaluate the performance of their NPC behavior models [30,32]. However, simulation-based methods emerged as a significant alternative, especially when the focus veered towards production, resources, and pricing. By relying on simulations, researchers effectively navigated the complexities of these aspects, revealing a distinctive research dimension. Fig. 6 illustrates the distribution of the strategies for validation trials in the discussed context.

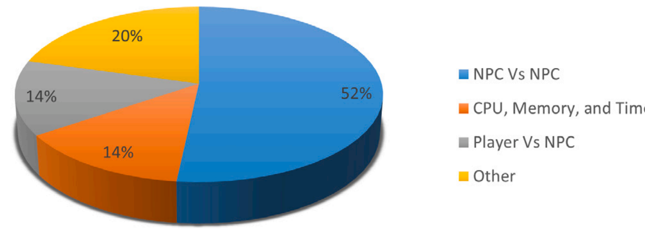

Fig. 6. Strategies for Validation Trials.

Collectively, these findings underscore the adaptability and potential of evolutionary algorithms in NPC behavior manipulation. Researchers can capitalize on the diverse insights from different game environments and validation strategies. Future studies may explore uncharted algorithmic territory, consider hybrid approaches, and embrace newer methodologies to further refine NPC behaviors in dynamic gaming scenarios.

6. Conclusion

This systematic literature review highlights the significant progress and ongoing potential in NPC behavior research, particularly through evolutionary algorithms. The study identifies six main categories where these algorithms play a crucial role: planning, user interaction, position modification, parameter modification, character state modification, and target assignment strategy. Despite advancements, further exploration of new evolutionary algorithms and their integration with other techniques is needed to address the growing complexity of modern games. Continuously evolving NPC behaviors to be more human-like is crucial for enhancing player engagement and game realism.

NPC design can be improved by incorporating educational and instructional elements. By integrating educational theories and adaptive learning algorithms [82–84], NPCs can provide hints, feedback, or challenges that adjust to the player's learning curve. This makes NPCs effective as tutors or guides, offering a more interactive and engaging learning experience. Pedagogical strategies within NPC behavior can create a more immersive and effective educational environment.

Several areas in NPC design remain underexplored. Emotional intelligence [85–87] in NPCs needs further study to understand its impact on player engagement. Additionally, the social dynamics of NPC interactions, such as forming alliances, exhibiting social hierarchies, and responding to social cues, are areas ripe for deeper investigation. Incorporating insights from psychology, sociology, and cognitive science into NPC design can lead to more nuanced and realistic behaviors, enhancing the gaming experience.

Current large language models (LLMs) and advanced agent technologies have a significant impact on NPCs and game development. LLMs [88,89], such as GPT-4, can enhance NPCs' conversational abilities, making their interactions more natural and contextually relevant, leading to richer storytelling and immersive experiences. Advanced agent-based models improve NPC decision-making, allowing for more adaptive and intelligent behaviors. These technologies enable NPCs to learn from player interactions and environmental changes, leading to more dynamic and responsive gameplay.

Moreover, advancements in LLMs and agent technologies influence related creative industries, such as interactive storytelling, virtual reality experiences, and simulation-based training. Realistic and adaptive NPCs can significantly enhance user engagement and training efficacy in these areas. By addressing these areas and leveraging current technological advancements, future research and development in NPC design can lead to more immersive, educational, and engaging gaming experiences.

In summary, while NPC behavior research has made significant strides, there is still ample room for growth and improvement. By exploring new algorithms, integrating educational and social dynamics, and leveraging advanced technologies, researchers and developers can create NPCs that enhance gameplay and contribute to broader applications in education and training.

7. Limitation

The systematic literature review (SLR) on NPC behavior using evolutionary algorithms has several limitations. Firstly, the review is dependent on the availability and scope of existing literature, which means it might miss out on recent unpublished studies or emerging trends that have not been extensively documented. The review period, limited to 2008–2024, might also exclude relevant studies published outside this timeframe that could offer valuable insights.

Additionally, there is an inherent risk of selection bias despite applying inclusion and exclusion criteria, as the subjective judgment in interpreting these criteria can affect the objectivity of the review. The rapid advancements in AI and gaming technology further mean that the findings could quickly become outdated, necessitating continuous updates to maintain relevance.

Moreover, the complexity and diversity of game types and scenarios mean that the results may not be universally applicable across all contexts. Finally, the SLR's dual approach of combining quantitative and qualitative analyses, while comprehensive, might still not capture the full spectrum of NPC behaviors influenced by evolutionary algorithms, particularly in niche or highly specific game environments.

CRediT authorship contribution statement

Hendrawan Armanto: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Harits Ar Rosyid:** Writing – review & editing, Supervision. **Muladi:** Writing – review & editing, Supervision. **Gunawan:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to get words that are more precise and comfortable to read. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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