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Research and Analysis of Intelligent NPC Behavior Modeling Based on Machine Learning: Platform, Method, Metrics, and Quantification of Player Experience

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Abstract. In most games, the Non-Player Characters (NPCs) are designed mainly using a rule-based approach for controllability. For achieving realistic NPC behaviors, usually, a lot of manual fine-tuning is needed for different player types and scenarios. However, machine learning can be adopted to enable NPCs to learn and adjust their behavior over time using data and interaction feedback. Although there are related studies using machine learning to improve NPC behaviors for games, they are scattered across different technical platforms, tasks, evaluation methods and metrics. Therefore, it is impossible to make any cross-study comparisons and draw conclusions. This paper introduces a review framework named PMM (Platform–Method–Metric) which is a method-based classification approach. Using this framework, this paper systematically reviews the existing research and also constructs a unified system for measuring player experience. The future work of this research will contribute to the goal of unifying and automating cross-platform evaluation standards.

Keywords: Intelligent NPCs, Machine Learning, Quantification of Player Experience, PMM Framework

1. Introduction

Non-player characters (NPCs) can be enemies, allies, or interactive objects in the game. They can influence the pace, the perceived balance, the immersion, and the longevity of the game. Current research indicates that although reviews and trend reports on game artificial intelligence have mentioned that "intelligent NPCs" is one of the main topics that game AI researchers should focus on [1, 2]. However, the actual implementation of most games actually adopts the traditional, manually coded (usually rule-based) approach [3]. Research on the development of interactive NPCs indicates that rule-based behavior is controllable, but it may become predictable. Furthermore, it is difficult to expand in different player strategies and scenarios, which has prompted people to adopt data-driven alternatives [4]. However, a key research contradiction lies in the fact that enhancing the abilities of NPCs does not necessarily improve the player experience. In many studies, "better NPCs" have been proposed by merely focusing on the gameplay. The criteria for measurement include win rate, score, and success rate, etc. However, indicators of player experience such as engagement, difficulty appropriateness, frustration, and even trust in the authenticity of NPCs have either not been properly defined or are measured in very inconsistent ways across different games [5, 6]. This creates an assessment gap: a policy for non-player characters (NPCs) that can enhance objective performance does not necessarily mean that players will gain significant, pleasant or sustainable benefits from it [7]. Therefore, finding a unified and repeatable method to link the changes in player behavior with the quantified improvement of the game experience has become a problem that needs to be addressed at present. Due to the fragmentation issue that may arise when comparing different platforms and indicators, in order to enhance the comparability of the review, this paper adopts the PMM (Platform–Method–Metric) framework to organize the literature. Specifically, Platform refers to the game platform, task types, engine environment and data collection methods relied upon by the research institute; Method refers to the NPC behavior modeling and training methods; Metric refers to the indicator system used to evaluate the effectiveness of NPCs and the player experience. Compared to ordinary reviews that classify studies only by technical routes, the PMM framework emphasizes the correspondence among the three components, where a certain method often depends on a specific platform environment to function, and different platforms and tasks determine which metrics are more appropriate for evaluation. The significance of this framework is not only to organize the literature, but also to provide a structural foundation for subsequent standardized evaluation. This article analyzes four aspects of intelligent NPCs which are modeling methods, application platforms, player experience quantification methods, and evaluation system construction. These aspects correspond to behavioral modeling technical routes, platform environment characteristics, experience indicator design, and standardized evaluation processes, respectively.

2. The evolution path of intelligent NPC modeling technology

As shown in Figure 1, intelligent NPC behavior modeling has undergone a gradual evolution from rule control, goal planning, learning adaptation to data generation-driven process. This evolution reflects the overall trend of game artificial intelligence research from "making NPCs usable" to "making NPCs more natural, more intelligent, and better able to improve player experience" [1, 2].

Early rule-driven phases were mainly represented by finite state machines (FSM) and behavior trees. These methods control NPC actions through preset states, conditional judgments and behavior switching. Their advantages are clear logic, simple implementation and strong controllability. Therefore, they were widely used in early game and industrial development [1-3].

Based on this, research has gradually entered the goal-driven stage. Representative methods in this stage include GOAP (Goal-Oriented Action Planning) and Utility AI. Unlike simply relying on fixed rules, goal-driven methods emphasize that NPCs plan actions or make utility trade-offs around specific goals, giving them a certain dynamic decision-making ability [1, 2].

Subsequently, with the development of machine learning methods, NPC research entered the learning-driven stage. The most representative technologies in this stage are reinforcement learning and imitation learning [3, 6, 7]. At the same time, research has also explored player-centered adaptation mechanisms, such as dynamic difficulty adjustment and behavior adaptation based on player states [8, 9].

In recent years, NPC modeling has further entered the data and generation-driven stage. On the one hand, this stage inherits the decision-making ability of deep reinforcement learning in complex environments, and on the other hand, it introduces large language models, generative agents and multi-module hybrid frameworks, enabling NPCs to show greater potential in dialogue generation, context understanding, long-term memory and behavioral consistency [10-12].

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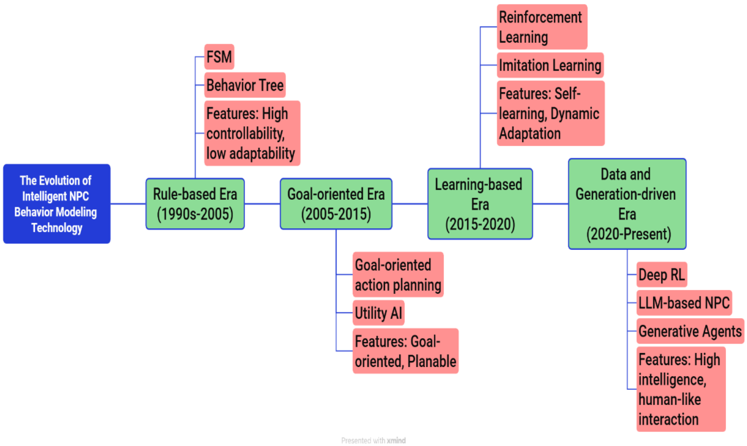

Figure 1. Evolutionary diagram of intelligent NPC behavior modeling technology. (picture credit: original)

3. Representative research case matrix

Table 1. Comprehensive matrix of PMM cases

Research Case	Platform, P	Method, M	Metric, M	PX Dimension
[5]	3D RPG prototype + User Research	Conversational/ Interactive NPC (context-aware dialogue)	GEQ/Godspeed (scale) + participation/agency related indicators	Narrative immersion, emotional engagement, sense of challenge/ agency
[3]	2D fighting game environment (RL training + in-game tiering)	RL (Responsibility Learning) skills + difficulty tiers	Win rate / reward / survival time (performance) → Further mapping challenge matching CM	Levels of difficulty and fairness of challenge (experience agency)
[9]	Educational/training serious game (facial expressions + physiological sensing)	Affective adaptation	Affect (emotional state) + flow/motivation + learning performance	Flow, Motivation and Participation Frustration Control
[4]	Interactive demonstration process + FPS prototype/Gym-like environment	HITL/IL Interactive Training	Demonstration/interaction rounds, training efficiency, coverage/stability (training cost metrics)	Controllability, development efficiency, naturalness/credibility (experience proxy)
[8]	EA Commercial Mobile Games + Online DDA Service + Large-Scale Telemetry/A-B	Experience-Driven Adaptation (DDA)	Engagement/retention/session (telemetry) + Challenge Matching (Win Rate Range)	Long-term engagement, frustration/boredom control, challenge matching
[11]	Unity: MindEscape (serious game/escape room)	Personalization/personalization (DRL + persona)	Completion time/stability/performance + personality consistency	Credibility, role consistency, Presence (proxy)
[12]	Generative agent dataset + RPG dialogue corpus	Hybrid framework (Gen agents + dialogue + RL)	Immersion, narrative consistency, interactive diversity, responsiveness	Immersion, narrative consistency, and interactive diversity

Table 1 presents the results of the PMM case study comparison in the form of a case matrix. The data in the matrix demonstrate substantial differences in platform environment, research methods, and evaluation indicators among the individual case studies.

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From the perspective of the essence of the metrics, the evaluation methods used in different studies can be broadly classified into three categories: Objective indicators based on behavioral logs (such as participation rate, retention rate, etc.), proxy indicators based on performance (such as winning rate, reward value, etc.), and subjective experience indicators based on questionnaires or interviews (immersion, presence, and satisfaction, etc.). These metrics respectively reflect player behavior, system performance and subjective perception, but their measurement dimensions and interpretative meanings are not consistent.

The problem that arises is that such differences in metrics prevent direct comparisons between different works in the field. On the one hand, behavioral log data is typically gathered by means of large online experiments and is highly reproducible; on the other hand, questionnaire-based metrics heavily depend on sample size and experimental design. Performance metrics are easy to calculate but do not necessarily translate to better player experience; therefore, even studies that claim to have "improved the performance of NPCs" cannot be compared directly.

In this context, the design of the PMM framework integrates platform conditions, method selection and indicator systems into a unified analytical framework, thereby revealing the intrinsic connections and sources of differences among different studies. In this way, although the results of different types of research still cannot be directly aligned, they can be explained and summarized within a same context. This lays the foundation for the subsequent establishment of a standardized evaluation system.

Table 2. Quantitative framework for player experience indicators and applicable scenarios

Metric Category	Commonly Used Metrics	Calculation Method	Data Source	Applicable Scenarios	Representative Literature
Engagement	Average session duration, retention rate, churn rate, number of key interactions	The individual indicators are calculated and then weighted to form the Engagement Score.	Telemetry logs and behavior records	DDA, long-term online gaming, and rich scenarios of behavior logs	[8]
Experience	Immersion, enjoyment, presence, fairness, credibility, likeability	Scale average score + normalization + weighted summation	Questionnaires, interviews, and dialogue logs	RPG dialogue, narrative games, and AI character interaction scenarios	[5, 6]
Challenge Matching	Win rate deviation, skill gap, survival time, and reward stability	Construct match scores based on target win rate or skill difference.	Game results, training logs, simulation data	Competitive games, DDA, training/serious games	[8, 9]
Performance	Win rate, average reward, task completion rate, training efficiency	Direct statistics or average by round/task	Simulation environment, training logs	RL (Responsive Logic) and Skill-Based Agent Assessment	[3, 10, 11]
Behavioral Quality	Diversity, novelty, consistency controllability interpretability	Observational statistics + visualization + manual interpretation	Behavioral logs, visual analysis, expert review	Complex behavior assessment, generative NPC, interpretive analysis	[7, 12]

Table 2 shows that the current quantitative methods of intelligent NPC research are no longer limited to "whether the win rate is higher", but have gradually developed into an evaluation system with multiple indicators such as participation, experience quality, challenge matching degree, performance and behavior quality. In the future, the assessment of NPCs will need to take into account both the objective performance and the subjective experience [6, 7].

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4. Quantitative and standardized evaluation of player experience

In order to improve the quality and comparability of research results on the effect of NPCs on player experience, it is necessary to measure player experience using more than one quantitative indicator, and to establish a unified evaluation process based on a comprehensive description of relevant player behaviors and experiences from multiple perspectives. Based on three core dimensions including player engagement, experience quality and challenge match degree, this paper systematically describes relevant indicators and established a standardized evaluation process.

4.1. Engagement

Player engagement is used to measure the degree of players' involvement in the game process, and it is an important metric for evaluating whether NPCs can continuously attract players. In actual research, engagement is usually characterized through behavioral logs, such as average session duration, retention rate, churn rate, the number of key interactions and so on. These metrics respectively reflect the players' short-term investment, long-term retention, and the level of their interaction activity. The average session duration can be defined as follows: $\overline{d} = \frac{1}{N}\sum_{i=1}^{N} d_i$. Retention rate and churn rate are respectively used to describe the continuous participation of players within a certain time window. To comprehensively reflect information from different dimensions, a weighted engagement metric can be constructed: $E = \alpha \cdot \mathrm{Norm}\left(\overline{d}\right) + \beta \cdot \mathrm{Norm}\left(R\right) + \gamma \cdot \mathrm{Norm}\left(I\right) - \delta \cdot \mathrm{Norm}\left(C\right)$. Where $\overline{d}$ represents the average session duration, R represents the retention rate, C represents the churn rate, I represents the number of key interactions, and α, β, γ, and δ are weighting parameters. Through this metric, the level of player participation can be evaluated on a unified scale.

4.2. Experience

Player experience is a measure of how a game is experienced by the player, typically evaluated through subjective experiences and perceptions of immersion, presence, satisfaction and fairness. This is different from engagement which is commonly measured quantitatively using metrics such as time played or number of sessions. Player experience is typically evaluated using Likert-type scales and questionnaires such as the Game Experience Questionnaire (GEQ) or the validated Godspeed player experience questionnaire.

In the quantification process, the Likert scale is often used to score multiple items, During the quantification process, the Likert scale is often used to score multiple items, and the score of a certain experience dimension is obtained by calculating the average: $S_m = \frac{1}{K}\sum_{j=1}^{K} s_j$. In the multi-dimensional experience scenario, it is possible to further integrate different dimensions through weighting, thereby generating an overall experience score: $X = \sum_{m=1}^{M} w_m \cdot \mathrm{Norm}\left(S_m\right)$. Where S_m represents the score of the m-th experience dimension, and w_m is the corresponding weight. In absence of subjective information, it is possible to resort to behavioral proxy metrics.

In particular, by analyzing some data concerning the player behavior (depth of the dialogue, frequency of exploration actions, interaction rate with NPCs, active choices made by the player) it is possible to build an immersion index for the behavior agent: $Imm_b = \lambda_1 \cdot \mathrm{Norm}\left(Q\right) + \lambda_2 \cdot \mathrm{Norm}\left(E_x\right) + \lambda_3 \cdot \mathrm{Norm}\left(N_i\right) + \lambda_4 \cdot \mathrm{Norm}\left(B\right)$. This approach is

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more flexible and easily scalable to large online gaming environments, where it is often difficult to collect sufficient data from questionnaires.

4.3. Challenge matching

Challenge matching is how well the abilities of NPCs are matched against the abilities of a player. Challenge matching is one of the key elements of game design that impact player experience. A game that is too difficult can be frustrating, while a game that is too easy can be without challenge. Therefore, in order to enhance players' engagement and satisfaction, an appropriate challenge matching degree is of great significance.

A common approach is to evaluate based on win rate bias: $CM_1 = 1 - \left|w - w^*\right|$.

Where w represents the player's actual win rate, and w^* represents the target win rate. This method achieves a balanced experience by controlling win rate deviations. Another method is based on the skill gap between players and NPCs: $\Delta s = |s_p - s_n|$, and further define the challenge matching degree as $CM_2 = e^{-k\Delta s}$. Where k is an adjustment parameter. The smaller the skill gap, the higher the matching degree. Furthermore, the challenge matching situation can be indirectly measured by reward stability. Let the average reward be μ and the reward variance be σ^2, then the stability index can be expressed as: $\text{Stability} = \frac{1}{1+\sigma^2}$. This metric reflects the degree of fluctuation in the game process, and indirectly reflects the balance of the experience.

4.4. Standardized evaluation process

Based on the above indicator system, a unified and standardized evaluation process can be established. First of all, it is necessary to clearly define the evaluation goals, such as increasing player engagement, improving the quality of the experience, or achieving challenge matching. Secondly, based on the assessment objectives, select the corresponding indicator system and determine the data sources, including behavioral logs, questionnaire data, or simulation results, etc.

During the specific evaluation process, an objective performance assessment should be conducted first, such as indicators like win rate, rewards, completion time and training efficiency, to determine the technical performance of the NPC. Subsequently, subjective experience evaluations will be conducted, such as indicators like immersion, satisfaction, and sense of fairness, to reflect the actual feelings of the players. Based on this, the objective indicators and subjective indicators can be integrated through a weighting method, thereby obtaining the comprehensive assessment result: $\text{Eval} = \rho \cdot O + (1 - \rho) \cdot S$. Where O represents the objective evaluation score, S represents the subjective experience score, and ρ is the weighting parameter. Furthermore, in order to enhance the robustness of the evaluation results, a stratified analysis can be conducted for different types of players (such as beginners and experts), and the final results can be normalized to uniformly map them into the range of [0,1]. The final assessment results not only can reflect the performance of the NPC in all aspects, but also can be used to determine its applicable scenarios and target audience, thereby providing guidance for the design and optimization of the NPC.

4.5. From PMM mapping to final evaluation

Let's further elaborate on how to summarize the intelligent NPC evaluation process based on the PMM framework into a systematic flow from input to output. Firstly, using existing literature and research cases as the input, people will structure and organize them, and classify them from three

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dimensions: platform (Platform), method (Method), and metric (Metric), thereby forming an initial PMM mapping relationship.

Based on this, the research is further decomposed and summarized. On one hand, different platform types are classified. On the other hand, the NPC modeling methods are categorized. At the same time, group the evaluation metrics.

Subsequently, through the correlation analysis of the above three types of elements, the applicability of different methods in specific platform environments can be identified, as well as the roles of various indicators in the assessment process. Thus, a mapping relationship between "platform - method – metric" can be established. Based on this, a more comprehensive set of comparable cases can be further constructed, providing a unified foundation for subsequent analysis.

During the unified assessment stage, the corresponding indicator system is selected based on the research objectives. For instance, indicators for participation or challenge matching can be constructed. Subsequently, the data sources were integrated, including behavioral log data, questionnaire data, and experimental results, and the data were standardized and normalized for calculation to ensure the comparability of different metrics.

During the evaluation process, both objective assessment and subjective assessment need to be carried out simultaneously. By comprehensively analyzing the results of both types, a more comprehensive assessment conclusion can be obtained.

Finally, during the output stage, a horizontal comparison is conducted on the performance of different NPC models under different platform conditions. The strengths and weaknesses of each model, as well as their applicable scenarios, are analyzed, and based on this, different research questions are answered. Through this process, a systematic transformation from PMM to the final assessment result can be achieved.

5. Conclusion

Intelligent behavior of NPCs is a significant research focus in the field of game NPC behavior modeling based on machine learning methods. The paper conducts a detailed review of existing research on intelligent NPC technology, and then summarize and analyze the results based on the PMM (Platform–Method–Metric) review framework in order to find out the existing problems in intelligent NPC behavior modeling research. The paper finds that intelligent NPC technology has developed from rule-based methods to reinforcement learning methods, and has further evolved into the field of personalization-based methods and generative hybrid methods for improving player experience. In addition, the paper finds that the choice of method and indicators is significantly affected by different platforms and task environments, and the superiority or inferiority of NPCs cannot be evaluated independently. This article further points out that existing research lacks a unified indicator standard for evaluating intelligent NPC behavior models, such as the participation level of players, immersion, and the degree of challenge match. Based on this finding, this paper attempts to define the core indicators and an evaluation process. The aim of this paper is to establish a basic and comparable experimental data for follow-up studies that aim to improve intelligent NPC behavior models in order to guarantee that the player experience is genuinely and stably improved.

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