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Gamer Behavior Modeling Using Computer Vision and Artificial Intelligence

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Abstract

This systematic literature review examined game-player behavior modeling that integrates computer vision and artificial intelligence. A total of 50 scientific articles from the Scopus database, published between 2017 and 2025, were analyzed using the PRISMA 2020 protocol to address five research questions. The results showed that eye-tracking metrics reliably indicated cognitive load and player attention in real time. Deep learning models could predict individual-specific behavioral styles in strategic games, and data-driven analysis effectively mapped players' spatial movement dynamics in large-scale game environments. Furthermore, physiological metrics in Virtual Reality proved effective as inputs to a dynamic difficulty adjustment system, and data-driven gaze-direction modeling significantly enhanced the realism of player interactions with virtual agents. These findings confirmed that the synergy between computer vision and artificial intelligence is a crucial foundation for creating adaptive and immersive gaming experiences.

***Keywords**: Artificial intelligence; Computer Vision; Deep Learning; Eye-Tracking; Player Behavior Modeling*

1. Introduction

The gaming industry is no longer just entertainment but an interactive instrument that deeply influences users' affective states and gaming experiences [1]. Its use continues to evolve, expanding into training systems integrated with comprehensive artificial intelligence architectures (Deep Reinforcement Learning) [2]. In addition, the adoption of serious games is increasingly crucial for adaptive educational purposes to improve learning outcomes [3]. To maintain the virtual ecosystem, today's AI agents have been trained with specific, fine-grained controls to create a more natural experience [4]. This behavioral modeling relies heavily on cognitive interactions, such as "Theory of Mind" experiments, to predict opponents' emotions in the game [5]. Recent developments have also extended into the realm of cyber network defense strategy simulations [6]. In the sports broadcasting sector, artificial intelligence has been automated to detect match actions and events in real time [7]. The accuracy of this behavioral detection is also combined with multimodal visual extraction algorithms using artificial neural networks (Deep Neural Networks) [8]. In the design context, simulating player behavior is crucial for balancing the level of difficulty (game balancing) in digital games [9]. Gaming technology has also expanded into the application of physiological emotional adaptation through neurosensory control [10]. Currently, deep learning systems are even capable of autonomously learning the rules of a game [11]. Recent developments demonstrate that analytical models have been implemented in game monitoring, such as detecting cheating anomalies through multivariable time patterns [12].
Various previous literature has examined the modeling of personality traits through the interaction of game mechanics [13]. In the military tactical realm, decision-making models are implemented to identify the movement goals of agents in strategy games [14]. In addition, the analysis of multi-role cooperative strategy patterns in board games has been empirically observed [15]. The use of machine learning is often applied to detect potential player churn in free-to-play mobile games [16]. Other research models the probability of visual image features that affect the speed of players' eye movement reactions [17].
This article is structured as follows: Section 2 presents the theoretical basis for the research; Section 3 explains the SLR methodology using the PRISMA 2020 protocol; Section 4 presents the results and discussion for each RQ; and Section 5 presents the conclusions and future research directions.

2. Theoretical Study

2.1. Psychological Modeling and Player Characteristics

Player behavior modeling is a research domain focused on understanding the characteristics, motivations, and affective interactions of users within digital gaming environments [1]. Theoretically, player profiles and personalities can be mapped through interactions with in-game mechanics [13]. Identifying these user typologies is crucial for designing tailored gameful design for a more personalized gaming experience [38]. Furthermore, game elements have been shown to influence motivation to learn, with their effectiveness highly dependent on initial motivations and each player's specific profile [50]. This modeling extends beyond demographic classification to encompass in-depth cognitive interactions, such as "Theory of Mind," where players must predict and respond to the emotions of opposing agents [5]. Furthermore, theoretical psychological studies have examined the impact of games on users' moral cognition. Brainwave analysis (P300) showed no valid evidence of neural desensitization due to exposure to violent games [39], while real-world social interactions, such as physical distancing, also dictate how players enjoy location-based gaming experiences [45].

2.2. Integration of Computer Vision and Multimodal Extraction

Computer vision plays a crucial role in acquiring real-time player behavior data based on visual observation. The application of Deep Neural Networks (DNN) algorithms and multimodal sequence matching architectures enables systems to precisely detect motion actions, for example, in tracking sports players' posture and ball movements from camera footage [7, 8]. In the realm of cognitive analytics, visual image features have been shown to influence saccade latency, which is calculated using probabilistic perception models [17]. Furthermore, visual observation has been developed to model affective awareness by capturing the facial expressions and body postures of opposing players [1]. This visual tracking approach is also crucial in Virtual Reality environments, whether for evaluating user hand-gesture dominance performance [29], stimulating interactive security communication [25], or adapting multi-sensory emotion control in neurogame interfaces [10].

The robustness of Deep Learning and Convolutional Neural Network (CNN) architectures in extracting visual features is not only validated in the gaming domain, but also has a high level of generalization across disciplines. For example, Deep Learning Pre-Trained Models have been successfully implemented for modeling facial animations of virtual characters based on probabilistic reactions to game events [51], and evaluation of virtual agent (NPC) behavior has successfully measured the dimensions of perceived hostility of players consistently [52]. Furthermore, a prostate cancer detection system uses image processing [53]. This cross-domain validation strengthens the argument that CNN architectures have high generalization and are highly relevant for adaptation in capturing complex visual behavior patterns of game players.

2.3. Artificial Intelligence Architecture and Deep Learning

Artificial Intelligence (AI) is transforming the way machines understand, replicate, and adapt to human player tactics. Deep Reinforcement Learning (DRL) methods are commonly used to train artificial agents to achieve efficient frame-skipping control comparable to human instincts [4]. Conversely, contrastive reinforcement learning approaches enable agents to autonomously learn individualized competitive behavior [20]. Conceptually, AI models are used to automate game balancing across difficulty dimensions through massive player behavior simulations [9, 44]. These computing systems are even capable of autonomously analyzing the rules of abstract board games [11], modeling agent responses very quickly [22], and instantly capturing repetitive tactical skills in a shooter arena [43]. In server management architecture, AI is absolutely relied upon to detect player churn probability with social graph neural networks [16, 28], predict dynamic player objectives with limited visual perception [46], and detect cheating anomalies through multivariable time data architecture [12]. In fact, the configuration of the "artificial brain" can evolve to change structure autonomously when facing different enemies [19].

2.4. Game Theory and Multi-Agent Dynamics

The foundations of Game Theory provide a mathematical framework for evaluating strategic interactions, both purely competitive and cooperative team interactions [27, 31]. Multi-agent interactions are often associated with defensive strategies, which are widely adopted by computing systems in selecting evolutionary network security tactics [6, 34], mitigating collusion and manipulative attacks [41], and fending off backoff cyberattacks [40]. In the realm of logistics infrastructure, the competitive framework has been applied to optimize distributed network caching [30] and the effectiveness of fare regulation in congestion simulation games [49]. In ecosystems requiring simultaneous cooperation (MMOGs), modeling of multi-role cooperative strategy patterns has been analyzed to understand the dynamics of team cooperation [15], while temporal communication networks between players have been specifically formulated to predict team performance in MMOG environments [32]. Moreover, the concept of computational empathy (artificial empathy) is starting to be designed in virtual agent architecture so that intelligent machines can imitate the behavior of contributor players and work together like a Prisoner's Dilemma simulation [33, 37, 47], complete with a Semi-Markov model to realize the adaptive learning process of their opponents [14, 23].

2.5. Gamification, Game-Based Education, and Immersive Environments

In practical applications, modeling theory is integrated through serious games to alter or stimulate real-world cognition. Gamified immersive environments have proven powerful in understanding user behavior when trained to deal with cybersecurity threats [26] and in visualizing lightweight Virtual Reality geospatial data [48]. Interactive gamification has also been validated for its effectiveness in enhancing intrinsic motivation [24] and systematically boosting academic achievement in language acquisition [18]. To achieve specific goals, adapting game mechanics is essential to ensure that the skill load is relevant to the learner's abilities [3]. Beyond education, interactive mechanisms are applied to map cognitive memory anomalies across age groups [35], track player networks within communities [42], and even stimulate public awareness of global threats, such as pandemics [21]. Ultimately, this quantification of virtual players' capabilities and skill modeling can be applied to real-world parameters, one of which is to form a computational basis for objectively estimating the appropriateness of a player's wage compensation [36].

3. Research Methods

This study uses a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize literature focused on modeling player behavior through the integration of artificial intelligence and computer vision. The SLR design was chosen because of its ability to comprehensively map theoretical foundations, as implemented in research revealing user-based gamification design typologies [38] and a systematic literature review on evaluating digital game-based learning outcomes [18].

3.1. Data Search and Collection Strategy

The data collection process was conducted by compiling scientific articles that specifically address the intersection of artificial intelligence, computer vision, and game modeling. The data search focused on literature examining the application of intelligent algorithms, such as Deep Reinforcement Learning and graph neural networks [2, 4, 28], as well as multimodal analysis and visual image latency feature extraction [8, 10, 17]. This literature collection strategy also extracted studies examining evolutionary network systems in tactical game scenarios and cyber defense simulations [6, 14, 34]. The results of this systematic strategy successfully compiled key literature that directly contributed to the development of computational architectures for rapid skill capture modeling of agents [43, 44, 46].

3.2. Inclusion and Exclusion Criteria

Literature selection was based on strict inclusion criteria to ensure the relevance of the study parameters to the research scope. Included articles were required to contain empirical tests of the following key elements: modeling of players' emotional awareness or "Theory of Mind" experiments [1, 5], the application of artificial intelligence to difficulty balancing or recognizing sports activities [7, 9, 11], and interactive affective simulations based on virtual reality [25, 29, 48]. Conversely, research that did not specifically examine modeling of player interactions was critically evaluated before being reduced or included as comparative data, such as pure strategy visualization analytics on bomb placement (bombalytics) or backoff attack detection in networks [31, 40]. These exclusion criteria ensured that the retained literature, including artificial intelligence simulations in distributed multi-agent cooperative dilemmas [30, 33, 47], had a rigorous analytical foundation of novelty.

3.3. Data Extraction and Analytical Synthesis

The final stage of this methodology is data extraction and qualitative analytical synthesis of the selected documents. The extraction process classifies the most widely used computational algorithms, such as the application of deep learning to detect cheating via multivariable time series [12], analytical prediction of customer churn [16], and estimating sports player revenue through quantitative computation of visual expertise [36]. Analytical synthesis is then performed by consolidating the effectiveness of implementing game elements in the learning architecture of cyber platforms and human memory cognition [24, 26, 35], as well as tracking performance structures in MMOGs [32, 42]. These findings are synthesized to evaluate how the neural emotional dynamics (P300) resulting from game violence [39], artificial empathy [37], cyberattack collusion tactics [41], density incentive systems [49], and players' geospatial social distance [45] influence the architecture of future game systems [19, 20, 21, 22, 23].

4. Results and Discussion

4.1. Literature Selection Results

The literature selection process for this study followed the systematic PRISMA 2020 protocol [54]. The initial search was conducted exclusively in the Scopus scientific database using keywords related to player behavior modeling, computer vision, and artificial intelligence in digital gaming environments. All 50 articles that constituted the primary corpus of this study were sourced from Scopus, ensuring consistent quality and credibility of the literature used. A multi-layered screening process was conducted for all articles retrieved, including duplicate removal, title and abstract screening, and full-text evaluation based on the inclusion and exclusion criteria outlined in Section 3.2. The final selection process yielded 50 eligible articles, which served as the primary corpus for this systematic literature review, covering publications from 2017 to 2025.

Overall, of the 50 selected articles, the majority (approximately 60%) focused on artificial intelligence architectures and deep learning for modeling player behavior, followed by computer vision-based research and multimodal analysis (approximately 25%), with the remainder covering gamification, game-based education, and multi-agent game theory. This distribution of topics reflects a global research trend that is increasingly integrating intelligent computational techniques in understanding and predicting player dynamics.

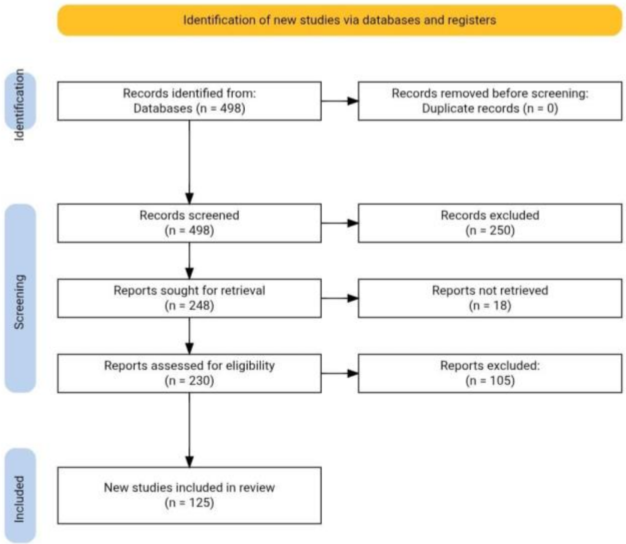

Fig. 1: PRISMA 2020 Flowchart for Literature Selection Process.

4.2. Discussion

Research Questions (RQ):
RQ1: How can eye-tracking metrics be used to measure players' focus, attention, and performance in real time?
RQ2: To what extent can machine learning models learn and predict individual behavior styles and patterns in strategic games?
RQ3: How can data-driven analysis be implemented to understand the dynamics of players' spatial movement in large-scale game environments?
RQ4: What behavioral metrics are most effective as input for dynamic difficulty adjustment in virtual reality (VR) games?
RQ5: How can data-driven gaze control modeling improve the realism of interactions between players and virtual agents (NPCs)?

4.2.1. Cognitive Load Analysis Through Eye-Tracking

RQ1: How can eye-tracking metrics be used to measure players' focus, attention, and performance in real time?
Eye-tracking metrics have proven to be a powerful biological indicator for measuring players' cognitive load. Recent approaches have shifted from simply tracking gaze coordinates to analyzing gaze entropy. A 21-day study found that players who played more frequently exhibited lower gaze entropy, indicating more structured gaze patterns and increased focus, while players who played less frequently exhibited higher gaze entropy, associated with fluctuating attention [55]. Low gaze entropy indicates that players are intensely focused on a specific task on the screen, while high entropy indicates confusion, extensive visual search, or lapses in attention. Furthermore, research in competitive esports games has shown that gaze behavior patterns directly reflect players' skill level, particularly in tracking multiple moving objects [57]. Research has also shown that visual image features directly influence the player's gaze reaction speed, which can be modeled through a probabilistic perception approach [17]. By processing this data through an artificial neural network-based computer vision algorithm, developers can map a direct correlation between gaze stability and the success rate of player performance in real-time [8].

Fig.2: Eye Tracking Metric Components for Cognitive Load Analysis.

4.2.2. Machine Learning-Based Prediction of Individual Behavioral Styles

RQ2: To what extent can machine learning models learn and predict individual behavioral styles and patterns in strategic games?

Advances in machine learning are enabling a transition from modeling player behavior in aggregate to modeling at a highly specific individual level. Player profiles and personalities can be computationally mapped through their interaction patterns with game mechanics [13]. In strategy-based games, deep learning models can be trained using historical game logs to predict the goals and maneuvers of opposing agents in real time [14]. Models no longer simply search for the "optimal move" but instead identify the "most likely move for a given player" based on their cognitive profile, risk-taking habits, and track record of past mistakes.

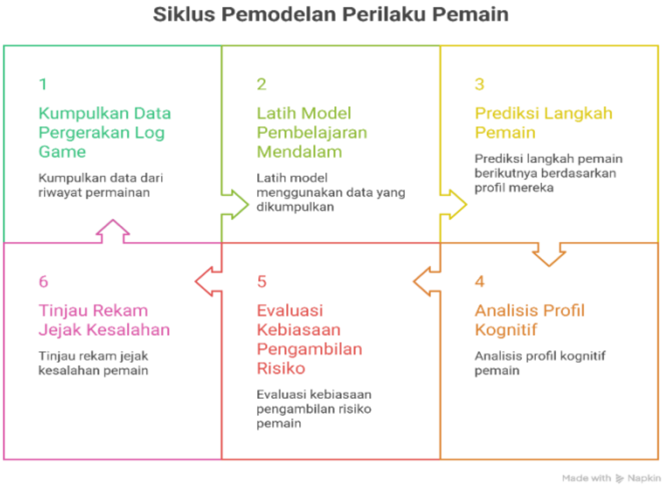

Fig. 3: Machine Learning-Based Individual Behavior Modeling Cycle.

4.2.3. Spatial Movement Dynamics in Large-Scale Environments

RQ3: How can data-driven analysis be implemented to understand the dynamics of players' spatial movement in large-scale gaming environments?

In large-scale virtual environments like Battle Royale, player behavior is assessed not only through shooting, but also through spatial navigation and interaction with the topography. Data-driven analysis uses big data processing techniques to map trajectories, heatmaps, and looting strategies. Through large-scale modeling of player behavior, researchers can identify dynamic patterns of player survival and predictively predict how environmental design influences the flow of group and individual movement. Data-driven studies in Battle Royale environments like Call of Duty: Warzone use spatio-temporal analysis to map player trajectories, movement kinematics, and survival strategies that differ among players [55]. Meanwhile, analysis of avatar movement features in Multiplayer Online Battle Arena (MOBA) environments shows that player mobility patterns have a distinctive distribution and can be replicated to design more accurate virtual environment models [56].

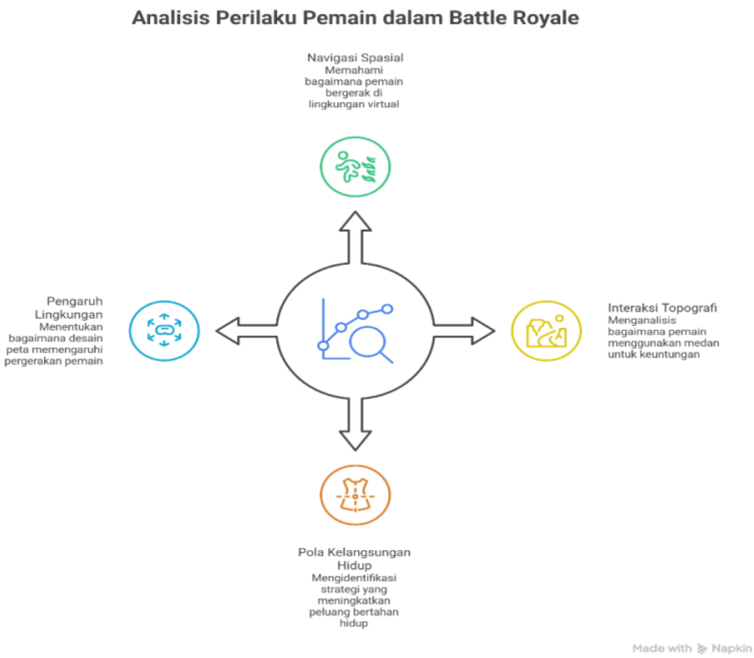

Fig. 4: Dimensions of Spatial Behavior Analysis in Battle Royale Environment.

4.2.4. Physiological Metrics for Dynamic Difficulty Adjustment in VR

RQ4: What are the most effective behavioral metrics used as input for dynamic content adjustment (DADA) in virtual reality (VR) games? VR environments provide a level of immersion that triggers intense physiological and behavioral responses. Behavioral metrics such as head movements (extracted through HMD sensors), hesitation duration before acting, and avoidance responses are used to measure players' affective states, such as fear or anxiety levels [10, 29]. These metrics serve as key inputs in Dynamic Difficulty Adjustment (DDA) systems, allowing the game system (the background algorithm) to dial down or dial up the intensity of horror or challenge elements to maintain the player's desired emotional state without causing cybersickness or excessive stress.

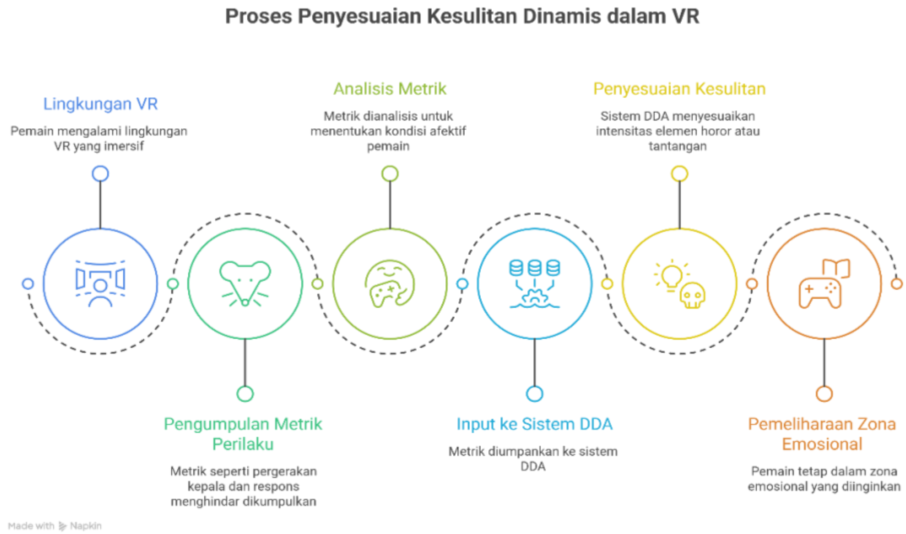

Fig. 5: Dynamic Difficulty Adjustment (DDA) Flowchart in Virtual Reality Environment.

4.2.5. Improving NPC Realism through Gaze Direction Modeling

RQ5: How can data-driven gaze control modeling improve the realism of interactions between players and virtual agents (NPCs)?
Beyond understanding players, behavioral computing approaches are also used to create responsive virtual agents. In triadic interactions (involving humans, agents, and environmental objects), data-driven eye and head movement models trained using real-world data have proven significant in simulating social behavior. Virtual agents capable of intelligently adjusting gaze direction and synchronizing head movements when players speak or point at objects drastically improve the sense of presence and fluency of communication in game and simulation environments [22, 1]. This relevance is further strengthened by research demonstrating that NPC facial animation based on probabilistic reaction modeling to game events can increase the believability of virtual agents [51], as well as research demonstrating that NPC hostility evaluations can be consistently quantified through player perception and behavior [52].

5. Conclusion

This systematic literature review has successfully identified, evaluated, and synthesized 50 scientific articles discussing computer vision and artificial intelligence-based player behavior modeling. Based on the analysis of the five formulated Research Questions (RQs), the following conclusions can be drawn. First, eye-tracking metrics have proven to be a reliable biological indicator in measuring cognitive load, attention, and player performance in real-time. Research has shown that gaze entropy in players who play more frequently is lower and more structured [55], gaze behavior patterns reflect the player's level of expertise in tracking multiple objects [57], visual image features directly affect gaze reaction speed which can be modeled through a probabilistic perception approach [17], while Deep Neural Networks algorithms enable precise detection of visual actions and behaviors [8]. Second, machine learning models, especially deep learning based on game log histories, are able to predict individual behavior styles and patterns at a very specific level in strategic games [13, 14]. Third, data-driven analysis using big data processing techniques is effective for mapping the dynamics of players' spatial movements in large-scale game environments, including trajectories, heatmaps, and survival strategies [55, 56]. Fourth, in the context of Virtual Reality, physiological metrics such as head movements and hesitation duration have been shown to be the most effective inputs for Dynamic Difficulty Adjustment (DDA) systems, enabling adaptation of content intensity to keep players in the optimal emotional zone [10, 29]. Fifth, data-driven modeling of gaze control in virtual agents (NPCs) significantly improves the realism and sense of presence of players in interactive game and simulation environments [22, 1, 51, 52].
Overall, this study confirms that the integration of computer vision, deep learning, and player behavior modeling is a crucial research foundation for building more adaptive, empathetic, and immersive gaming experiences in the future. The use of mature and validated CNN algorithms and computer vision architectures—whether in modeling virtual character facial animation [51], evaluating virtual agent behavior [52], or image processing-based visual pattern recognition [53]—proves highly relevant and has great potential for further adaptation in complex, visual-based player behavior analysis.
For further research, it is recommended that the development of hybrid architectures that combine multimodal analysis (facial, posture, and biometrics) with reinforcement learning-based predictive models could be a prospective research direction. Furthermore, model validation on more demographically and culturally diverse player populations is needed to ensure the generalizability of the findings identified in this systematic review.

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