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Constructing Hybrid-Driven Agents for MOBA Through Player Modeling: Integrating Behavioral Analysis and Narrative Persona in Human-Centered AI

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ABSTRACT

To address the challenges of rigid behavioral patterns, lack of semantic consistency, and insufficient emotional interaction in current MOBA game AI agents, this study proposes a Persona-Driven Game AI Agents (PDGAIA) framework based on the Human-Centered AI (HCAI). The framework integrates Dual-Channel Player Profiling, a Narrative Consistency Engine, and Hierarchical Reinforcement Learning (HRL) to enhance the personalization, immersion, and tactical adaptability of game AI. Using Tencent's MOBA game *Honor of Kings* as a case study, player personas are constructed from large-scale match logs and survey data. By combining objective behavioral indicators and subjective psychological modeling, core player personality dimensions and their tactical preferences are identified. Based on narrative strategies, the player-modeled character prototypes are transformed into AI agents with consistent personas, leveraging Hunyuan LLMs for multimodal expression. An HRL framework is then employed to decouple tactical decision-making from action execution, enabling the development of stylized AI combat systems. This framework successfully ensures a coherent persona expression across combat behavior, voice tone, and tactical communication. Experimental results demonstrate that the dual-path approach, which combines data-driven modeling and narrative persona construction, significantly improves anthropomorphism and social presence, delivering a more immersive and intelligent gaming experience. The proposed framework provides a reusable HCI methodology for constructing Game AI agents.

Keywords: MOBA games, Player modeling, Hierarchical reinforcement learning (HRL), Narrative persona, Human-centered AI

INTRODUCTION

In recent years, breakthroughs in Large Language Models (LLMs) and deep learning-driven game bot technologies have facilitated a paradigm shift in game AI agent design, transitioning from static rule-driven NPCs to dynamic, personalized, and socially intelligent agents (Alvarez & Vozaru, 2019; Chen et al., 2024). This transformation signifies the transition of game AI from a mere task execution tool to an emotional interaction partner. Due to its game mechanics involving multi-agent competition and cooperation, imperfect information, complex action control, and a vast state-action space, Multiplayer Online Battle Arena (MOBA) games are regarded as a prime testbed for artificial intelligence research (Silva & Chaimowicz, 2017; Robertson & Watson, 2014). Representative MOBA games include *Honor of Kings*, *League of Legends*, and *Dota 2*.

However, traditional AI systems based on Behavior Trees and Supervised Learning still exhibit significant limitations in MOBA scenarios (Berner et al., 2019). First, single-objective optimization frameworks (e.g., maximizing win rate) result in rigid behavioral patterns, lacking stylized tactical expression (Ye et al., 2020). Second, the separate training of action execution modules and language generation systems leads to a lack of semantic consistency between combat behavior and tactical communication. Finally, traditional NLP-based dialogue models struggle to support open-domain personalized interactions, resulting in a deficiency in emotional engagement.

To address these challenges, this study proposes the Persona-Driven Game AI Agents (PDGAIA) framework, grounded in the Human-Centered Artificial Intelligence (HCAI) paradigm (Shneiderman, 2022). The framework enables a transition from functional to personality-driven game AI through three key technological innovations. First, Objective Behavioral Metrics and Subjective Psychological Modeling are integrated into a Dual-Channel Player Profiling mechanism. Second, a Narrative Consistency Engine is employed to transform player-modeled character prototypes into AI agents with coherent personas. Finally, a Hierarchical Reinforcement Learning (HRL) architecture is constructed to support hierarchical behavioral simulation (Song et al., 2021).

RELATED WORKS

Existing research on MOBA-specific player modeling primarily focuses on extracting behavioral insights from game data. Zhang et al. (2021) employed deep neural alignment models to train AI agents that exhibit human-like teammate behavior, demonstrating human-agent adaptivity in *Honor of Kings*. Similarly, Ahmad et al. (2019) applied spatio-temporal clustering and Interactive Behavior Analytics (IBA) in games like Dota 2 to extract strategic decision-making and team coordination metrics. Expanding on this modeling approach, Santos et al. (2019) and Habibi et al. (2023) incorporated psychological analysis of in-game behaviors, proposing methods to infer personality traits from gameplay telemetry and affective cues. These studies highlight potential pathways for integrating emotional and psychological dimensions into MOBA AI agents.

Parallel advancements in interactive storytelling and narrative persona adaptation aim to align AI decision-making with player personas by adjusting in-game narratives based on individual preferences. Dynamic storytelling systems can adapt in real time according to player engagement patterns (Thue et al., 2007), while Ramirez and Bulitko (2012) extended this approach by incorporating player emotions and AI agents into adaptive narrative trajectories. Although these systems effectively customize interactive storytelling experiences in role-playing games (RPGs), their applications in MOBA environments remain underexplored, where real-time strategic decision-making dictates structured narrative sequences.

Additionally, Holmgård et al. (2014) introduced procedural personas as a means of simulating player archetypes for predictive decision modeling, emphasizing the potential of narrative persona-driven AI behavior adaptation in MOBA games.

To integrate these advancements with Human-Centered AI, recent studies have explored AI-human collaboration frameworks within MOBA environments. Gao et al. (2023) introduced the Meta-Command Communication framework, an interpretable AI system designed to enhance coordination and adaptability in MOBA team dynamics. Building on this, Gao et al. (2024) proposed Reinforcement Learning from Human Gain (RLHG), shifting the AI optimization paradigm from performance-driven to human experience-driven enhancement. These approaches underscore the role of explainability and human alignment in MOBA AI. Moreover, incorporating emotional states into NPC decision-making has proven effective, marking a shift toward adaptive, emotionally responsive AI entities capable of delivering more immersive and intelligent gaming experiences.

METHODOLOGY

This section describes our method in dual-channel player portrait construction and AI agent construction. Data and results are also presented.

Dual-Channel Player Portrait Construction

Objective Behavioral Metrics

User behavior data is extracted from the match logs and activity traces of *Honor of Kings*' billion-level users. A system of indicators comprising nine major dimensions and more than 260 sub-items has been constructed (Table 1). Most of the listed indicators originate from long-accumulated business logging needs, making them micro-level and discrete. Due to inconsistencies in standardization, these indicators are difficult to integrate into a mixed model for effectively clustering different typical player groups. To address this issue, a motivation model based on players' real responses and focusing on macro categories is introduced as the ground truth for selecting classification algorithms.

Table 1: Objective behavioral indicator system.

Dimension	Core Indicators (Examples)	Data Source
Combat Characteristics	Hero Niche Preference, Playstyle Preference	Match Logs
Social Patterns	Communication Willingness Preference, Speech Style Preference	Speech Semantic Recognition, Behavior Logs
Economic Strategy	Skin Collection Rate, Payment Conversion Rate	Account Transaction Data
…	…	…

Subjective Psychological Model

Incorporating expert knowledge from game designers, Nick Yee's (2006) model of player motivations in online games (Table 2) has been improved. A questionnaire including seven basic information items and twelve 11-point Likert scale items is developed. Through stratified sampling, 13,201 valid responses were collected, with low-confidence samples removed based on response duration. To verify data quality, imbalance rates and Gini coefficients of individual scale data distributions are calculated to assess response sparsity. The core validation metrics are presented in Table 3.

Table 2: MOBA player motivation model.

Dimension	Game Motivation	Game Behavior	High-Score Tendency	Low-Score Tendency
Action	Combat	Playstyle	Aggressive Offense	Conservative Growth
	Control	Hero Selection	Showcasing Skills	Simple and Direct
Mastery	Strategy	Pre-Match Planning	Tactical Mastery	Passive Approach
		In-Match Tactics	Unconventional Moves	Stable Execution
Social	Competition	Mode Selection	Striving for the Top	Play for Fun
		Communication Style	Active Commanding	Cooperative Following
	Cooperation	Playstyle Coordination	Team Collaboration	Solo Play
Achievement	Collection	Resource Collection	Complete Set Collection	Casual Collection
Immersion	Aesthetics	Aesthetic Pursuit	Emphasis on Aesthetics	Focus on Gameplay
	Narrative	Narrative Engagement	Story-Driven	Mechanism-Focused
Creativity	Design	Personal Expression	Individual Sharing	Fixed Participation
	Exploration	New Content Expansion	Early Adopter	Loyal Focus

Table 3: Category balance of subjective motivation model.

Dimension	Game Motivation	Question ID	Imbalance Rate	Gini Coefficient
Action	Combat	Playstyle Q4	16.91	0.38
	Control	Hero Selection Q5	5.61	0.28
Mastery	Strategy	Pre-Match Planning Q6	9.19	0.34
		In-Match Tactics Q7	5.06	0.28
Social	Competition	Mode Selection Q8	12.10	0.40
		Communication Style Q9	9.25	0.34
	Cooperation	Playstyle Coordination Q10	32.38	0.47

Consistent AI Agent Construction Based on Dual-Channel Hybrid Modeling

Character Archetype Mining

Using the 216 objective behavioral metrics of questionnaire respondents as feature inputs, the model fits the twelve subjective scale items. A reverse-construction mining model is implemented to achieve a complete prediction of any user's subjective motivation tendencies without requiring questionnaire responses while identifying the importance distribution of various gaming behaviors. A five-fold cross-validation is performed, and the classification results' top and bottom 30% are mapped using 0–1 normalization, yielding an average AUC of 0.8408 (Table 4).

Table 4: Mining model cross validation.

Questionnaire Code	Game Behavior	Accuracy Mean	F1 Mean	AUC Mean
q4	Playstyle	0.7628	0.7955	0.8492
q5	Hero Selection	0.8039	0.7927	0.8883
q6	Pre-Match Planning	0.7630	0.7460	0.8516
q7	In-Match Tactics	0.7632	0.7660	0.8523
q8	Mode Selection	0.7577	0.6976	0.8441
q9	Communication Style	0.7905	0.6690	0.8633
q10	Playstyle Coordination	0.7278	0.7545	0.8187
q11	Resource Collection	0.7787	0.6506	0.8382
q12	Aesthetic Pursuit	0.7469	0.6970	0.8333
q13	Narrative Engagement	0.7544	0.5870	0.8092
q14	Personal Expression	0.7346	0.6385	0.8148
q15	New Content Expansion	0.7464	0.6562	0.8267

Subsequently, by comparing clustering results from dual-channel data and incorporating expert knowledge from narrative designers, a four-dimensional, thirty-six-quadrant character archetype matrix is identified, including introversion-extroversion (with neutral), high skill-low skill, emotional value-individualism (with neutral), and serious speech-humorous speech. Additionally, a five-role (crash, jug, supp, mid, farm) by three-style (radical, converse, grow) model is cross-mapped.

Narrative Expression

First, ten differentiated AI character archetypes are extrapolated from the edge quadrants of the character matrix (Figure 1). Designers then draft background stories based on the selected archetypes, systematically constructing more than twenty persona elements, including personality tags, playstyle, voice characteristics, language habits, signature lines, narrative background, and dialogue templates. This framework simultaneously guides voice feature selection and dialogue style prompt generation. Ultimately, personalized voices are generated using the GiiNEX engine's zero-shot voice cloning technology, while scenario-based dialogue generation is achieved through Tencent Hunyuan LLMs (Li et al., 2024) 7B-MoE-RolePlay. The process forms a complete closed-loop from character archetype design to narrative template generation and multimodal expression.

Behavioral Expression

Hierarchical Reinforcement Learning (HRL) is a reinforcement learning method that decomposes complex tasks into more manageable subtasks, simplifying the learning process through a hierarchical structure (Nachum et al., 2018). Referring to HRL, a dual-network structure is designed to decouple tactical decision-making from strategic style (Figure 2). The upper-level style network (planner) samples human data based on the clustering results obtained from dual-channel portrait modeling and constructs a diverse StyleGenerator using imitation learning methods. A Meta-RL framework is adopted to dynamically adjust the policy space, while the value network references interactive Mission interventions to weigh combat behavior Task decisions. The lower-level operation network (executor) is constructed based on the micro-operation reinforcement learning paradigm developed by Ye et al. (2020). Specifically, the upper-level Task is decomposed into Where, What, How triplets (Silver, 2019) as feature inputs to dynamically adjust reward weights, thereby influencing model decisions.

	Introverted Newbie	Introverted Pro	Neutral Newbie	Neutral Pro	Extroverted Newbie	Extroverted Pro
Emotional Value Humorous Speech	A Emotionally stable, humorous meme jokester		B Full emotional support cheerleader			C Witty optimist with reverse psychology
Emotional Value Serious Speech		D Gentle healing pediatrician				E Sunny talkative sports college student
Neutral Humorous Speech						
Neutral Serious Speech	F Tsundere girl (cold exterior/ warm heart)	G Professional emotionless researcher				
Individualism Humorous Speech						H Self-deprecating meme streamer
Individualism Serious Speech		I Ruthless jungle dominator				J Energetic foodie gamer girl

Figure 1: AI character matrix.

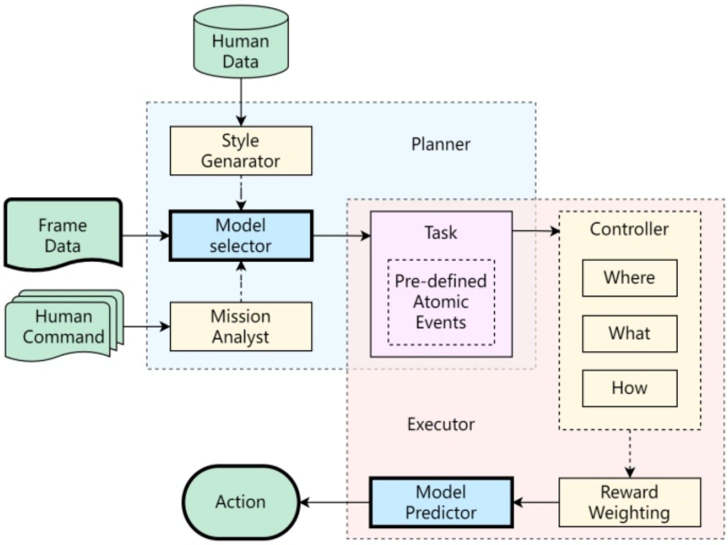

Figure 2: PDGAIA HRL model structure.

EXPERIMENTS AND EVALUATION

Behavioral Divergence Verification

By segmenting matches into early, mid, and late stages based on time, we developed over 20 combat behavior feature indicators across three dimensions: strategic direction, behavioral tendencies, and activity range. In 10,000 self-play matches, the 10 AI character types generated by this framework exhibited significant differences from the baseline model. For instance, in terms of early-game support actions, converse_supp style (0.82) outperformed radical_jug style (0.79), grow_farm style (0.68), and the baseline (0.53). Similarly, in team command response rate, character E (93%) ranked highest, followed by character G (78%), the baseline (66%), and character I (42%).

Player Perception Evaluation

Building on the integration of Flow Theory (Csikszentmihalyi, 1990) and the Three-Factor Theory of Anthropomorphism (Epley et al., 2007), a theoretical foundation for evaluating player perception of game AI was established. Flow Theory explains the dynamic mechanism of narrative immersion through Challenge-Skill Balance (Csikszentmihalyi, 1990), while Anthropomorphism Theory distinguishes the synergy between Hot Cognition Resonance (emotional needs) and Cold Cognition (teamfight decision-making) (Caporael & Heyes, 1997). Together, these theories support the perception of Social Presence in AI, avoiding the traditional dichotomy between mechanical behavior and human-like interaction. This framework aligns with the improved player motivation model proposed in this study and is suitable for evaluating player perception. Specifically, the Godspeed Anthropomorphism Scale (Bartneck et al., 2009), validated in esports settings, and the Social Presence subscale of the Game Experience Questionnaire (GEQ) (IJsselsteijn et al., 2013) were adopted, with modifications made to accommodate the characteristics of MOBA games.

A total of 120 experienced *Honor of Kings* players (rank mean x = Starry Glory I, with an sub-rank standard deviation $\sigma > 5$) were recruited. Under double-blind conditions, each participant played 15 standard matches in teams with either the PDGAIA-generated AI (experimental group) or the behavior tree AI (control group). After each match, a dynamic anchoring rating method was employed, using professional player recordings as the benchmark of fully human (5 points) and traditional SL bot as the benchmark of mechanical behavior (1 point). Players were required to rate AI performance in real-time on a 5-point Likert scale. Data analysis revealed that the experimental group significantly outperformed the control group in Anthropomorphism ($M = 4.62$ vs. 4.05, $p < 0.001$, Cohen's $d = 0.92$) and Social Presence ($M = 3.81$ vs. 2.97, $p < 0.001$), supporting the hypothesis that the PDGAIA-generated AI is superior to the behavior tree AI agent.

CONCLUSION

This study proposes and validates a hybrid-driven construction paradigm for MOBA Persona-Driven Game AI Agents (PDGAIA). The triadic HCAI architecture—integrating *dual-channel persona-narrative enhancement* with *hierarchical behavior design*—overcomes the limitations of traditional single-objective MOBA AI optimization. For the first time, it achieves dynamic alignment between AI behavioral styles and narrative personas, offering a novel approach to anthropomorphic game AI design. Experimental results show that PDGAIA-generated AI characters (10 distinct types) exhibit significantly stronger behavioral differentiation than baseline models. Additionally, this framework enhances both the human-like qualities of AI agents and player immersion, while establishing an extensible technical foundation for human-centric game AI. Future work will focus on dynamic personality evolution and cross-game character adaptation, promoting the continuous evolution of game AI from instrumental intelligence to emotional intelligence.

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