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Gaming with AI: A Hybrid Reinforcement Learning, Large Language Model, and Procedural Content Generation Framework for Enhancing Player Engagement and User Experience

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Abstract: *Most existing game AI research examines individual mechanisms—Dynamic Difficulty Adjustment (DDA), large language model (LLM)-driven NPC dialogue, and Procedural Content Generation (PCG)—in isolation, leaving open the question of how these subsystems interact when evaluated together against a shared user-experience (UX) measure. This paper presents and evaluates a Hybrid AI Gaming Framework that runs three complementary modules asynchronously: (1) a Proximal Policy Optimisation (PPO) reinforcement-learning agent for real-time difficulty calibration, (2) a vector-grounded Memory Repository that anchors LLM-based NPC dialogue to the game's canonical world state, and (3) a deep-learning player-behaviour model that drives PCG-based content variety. The system was deployed in Unreal Engine 5, using a quantised Llama-3-8B-Instruct model served over a Python microservice, with Qdrant as the vector store. A double-blind user study (N = 80) yielded statistically significant improvements across all seven Game Experience Questionnaire (GEQ) dimensions (p < 0.001), with Flow State reaching 3.64/4.0 and Immersion 3.78/4.0. Average session length increased by 42.5%, and Day-14 retention reached 78.4% versus 22.5% for the scripted baseline. The Memory Repository held narrative hallucination to just 0.4% across 25 dialogue turns, and an ablation study confirmed that every architectural component makes a distinct, non-redundant contribution. Together, the results suggest that hybrid, task-differentiated AI architectures yield engagement gains that no single paradigm can match.*

Keywords: Artificial Intelligence, Dynamic Difficulty Adjustment, Reinforcement Learning, Large Language Models, Procedural Content Generation, Player Experience, User Engagement, NPC Dialogue, Retrieval-Augmented Memory

I. INTRODUCTION

Digital games occupy an unusual position in the computing landscape: they are simultaneously mass-market consumer products and productive sandboxes for artificial-intelligence research. Early game controllers relied on rule sets and finite state machines (FSMs) [1, 3]; the field has since moved toward neural and statistical approaches, including deep learning and reinforcement learning (RL) agents that acquire behaviour directly through environmental interaction [2, 4]. Landmark results—AlphaGo Zero, AlphaStar, and OpenAI Five [6]–[8]—demonstrated that self-play RL can reach or surpass human performance in competitive domains, and the same learning paradigm is now being applied to level design, automated playtesting, NPC behaviour, matchmaking, and experience personalisation [9]–[12].

Yet game AI is not purely a technical pursuit. How an AI system shapes player experience—through difficulty modulation, believable NPCs, personalisation, and affective-state detection—is equally important [17, 18, 24]. Contemporary AI-driven design goes beyond content creation: it makes the player a participant in the creative process,

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allowing their actions and emotional state to co-author the content they encounter next [35, 39]. Rather than evaluating DDA, LLM-based NPC dialogue, and PCG independently, this paper investigates how all three interact within a single, jointly evaluated architecture.

The remainder of this paper is structured as follows. Section II surveys related work and identifies four open research gaps. Section III presents a comparative analysis of candidate AI paradigms and motivates the proposed hybrid design. Section IV describes the system architecture and implementation. Section V reports experimental results. Section VI offers conclusions and directions for future work.

II. RELATED WORK

A recurring pattern characterises the evolution of game AI: each generation of techniques resolves the brittleness of its predecessor while introducing new constraints. Rule-based systems and FSMs [1, 3] produced predictable behaviour but broke under unanticipated inputs, motivating hierarchical behaviour trees (hBTs) that support compositional task design while retaining human authorship [13]. Multiagent variants of A* pathfinding have remained a persistent challenge under hard real-time constraints [42]. Machine learning redirected attention towards offline analytics—churn prediction and player segmentation [44, 45]—while deep learning unlocked perceptual tasks such as facial-expression classification from raw sensor streams [4, 7, 38]. Reinforcement learning has become the dominant paradigm for modern game AI [2]; Souchleris et al. survey its expanding applications to automated playtesting and NPC tuning, and document ongoing issues with sample efficiency and reward specification [9]. On the generative side, grammar-based PCG methods have been augmented by GAN-based level generation [20] and by LLM-driven content pipelines [17]. Park et al. showed that memory and reflection modules allow LLM-based agents to sustain coherent behaviour across extended simulated interactions [28], a principle since extended to merchant negotiation [29], procedural narrative [30], speech-controlled VR [31], and production tools such as Ubisoft's NEO NPC prototype [32].

Player-experience research draws on several complementary theoretical frameworks. Csikszentmihalyi's Flow Theory posits that optimal engagement arises when perceived challenge matches perceived skill [57]; the GameFlow model operationalises this insight as design heuristics [50]. The Mechanics–Dynamics–Aesthetics (MDA) framework traces algorithmic design choices through to the player experience they generate [52]. Self-Determination Theory connects personalisation and adaptive difficulty to intrinsic motivation through the constructs of autonomy, competence, and relatedness [51, 56]. Brown and Cairns model immersion as a three-stage continuum rather than a binary state [58]. Empirical measurement typically employs the Game Experience Questionnaire (GEQ) [49], the Game Engagement Questionnaire [53], or the Game User Experience Satisfaction Scale (GUESS) [54]; the GEQ serves as the primary dependent measure in this study.

DDA has been formalised as an optimisation problem that continuously re-tunes challenge to maximise engagement [24], with subsequent work incorporating churn and disengagement signals [25], Monte Carlo Tree Search player modelling [26], and biosignal-informed adaptation in VR [27]. PCG research has shifted from diversity metrics towards experience-driven optimisation [55], including PCGML and LLM-assisted pipelines [17, 19]. Emotion-aware design builds on Picard's foundational work in affective computing [34] and on multi-modal affect sensing [35], though a universally agreed ground truth for subjective affect remains elusive. Empirically, Handoko et al. demonstrated that facial-expression recognition measurably improves GEQ scores [38], and affective-mirroring NPCs have been linked to increased player attachment [37]. Kim et al. found that LLM-driven NPCs can produce realistic negotiation behaviour but remain susceptible to hallucination and rule-breaking [29], and Zheng et al. showed that sustaining long-session consistency requires dedicated memory and retrieval components [59], directly motivating the Memory Repository design presented in Section IV.

Synthesising this literature reveals four interrelated gaps. First, most prior AI frameworks evaluate individual mechanisms rather than studying their interactions under a common UX instrument. Second, personalisation approaches are typically retrospective—relying on historical telemetry—and consequently cannot adapt within a single

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session [40, 45, 55]. Third, emotion-aware gameplay remains rare in commercially deployed systems owing to hardware and privacy constraints on face or physiology sensing [27, 35, 38, 39]. Fourth, latency and scalability research has been conducted largely independently from personalisation and NPC research, with no joint evaluation against psychometric UX outcomes [60, 61]. This work addresses the first gap directly and contributes practical evidence relevant to the remaining three.

III. COMPARATIVE ANALYSIS AND PROPOSED FRAMEWORK

To ground the design rationale empirically, four AI paradigms central to the proposed system were compared: Deep Q-Networks (DQN), Proximal Policy Optimisation (PPO), LLMs, and PCG. DQN approximates action-value functions using a deep network with experience replay and a frozen target network for training stability [4, 6]; however, its tabular value estimates make it prone to instability in discrete action spaces of moderate size [9, 12]. PPO is an on-policy actor-critic algorithm that constrains the policy update ratio to ensure stable convergence, handles continuous action spaces naturally, and scales to long-horizon tasks [9], making it well suited to continuous difficulty control. LLMs produce contextually fluent dialogue without task-specific training, but they introduce hallucination risk and carry substantial inference latency [28]–[30]. PCG generates levels, quests, and item inventories at near-zero marginal cost, yet the experiential richness of its output depends heavily on the representativeness of the design space used to seed generation [19, 21].

TABLE I. Comparative Analysis of AI Paradigms Across Key Evaluation Criteria

Paradigm	Adaptability	NPC Quality	DDA Support	Personalisation	Cost
Rule-Based	Very Low	Low	None	None	Very Low
Classical ML	Moderate	Low	Indirect	Moderate	Low
Deep Learning	Med–High	Moderate	Moderate	Moderate	Med–High
RL (DQN/PPO)	High	High	High	Moderate	High
LLM	Very High	Med–High	N/A	Very High	Very High
PCG	High	Low–Med	Indirect	Moderate	Moderate

No single paradigm dominates across all criteria (Table I). PPO offers the most balanced trade-off for adaptive difficulty and real-time control; LLMs excel at personalised, contextually rich narrative; and PCG delivers content variety at scale. This task-differentiated profile—corroborated by independent findings from Souchleris et al. [9], Justesen et al. [22], Xue et al. [24], and Park et al. [28]—motivates an architecture in which each engagement sub-objective is assigned to the most capable technique rather than forcing a single paradigm to cover all roles.

Continuously captured gameplay telemetry feeds a deep-learning module that constructs a compact player representation. A Hybrid Orchestration Layer then routes this representation to task-specific subsystems: discrete NPC state transitions to DQN; continuous difficulty and movement parameters to PPO [6]–[9]; conversation-relevant decisions to the LLM module, which is kept off the latency-critical control path [28]–[30]; and level, quest, and item diversity to the PCG module [15, 19]–[21]. The resulting Adaptive Gameplay Experience feeds back into the deep-learning module, closing the learning loop (Fig. 1).

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The proposed system is a closed-loop, AI-driven architecture in which every player action is treated as an observation that immediately informs the subsequent experience—not as a step along a predetermined difficulty ramp. Thirteen functional modules are grouped into three conceptual layers: a Sensing and Data Layer, an Intelligence Layer (AI

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Decision Engine), and an Experience Layer. Each layer's output serves as the next layer's input, creating a continuous processing pipeline.

The Player Interaction Module ingests heterogeneous input—keyboard, controller, pointer, and voice—and maps each event to a timestamped action record. The Game Environment module manages level geometry, entities, and physics, broadcasting state changes to a Behaviour Monitoring component that filters analytically significant events. Those events are persisted by Data Collection and transformed into success-rate, completion-time, and interaction-frequency features before being passed to the AI Decision Engine, which dispatches adaptive actions to three downstream subsystems: the Adaptive Gameplay/DDA component, the Intelligent NPC Behaviour module, and the Recommendation Engine.

The AI Decision Engine is governed by four design principles: decisions are derived from learned models rather than hand-authored rules; adaptation is personalised to each player's model rather than tuned to population averages; the player model is updated every session so behaviour evolves continuously; and all mechanisms are optimised jointly so that improving one does not degrade another.

TABLE II. Implementation Environment

Component	Details
Game Engine	Unreal Engine 5
ML Libraries	PyTorch (PPO, deep learning); scikit-learn
LLM / Memory	Llama-3-8B-Instruct (4-bit AWQ) + Qdrant
Bridge Protocol	gRPC sockets; in-process event bus
Languages	Python 3.10+; C++/Blueprints
High-End Hardware	Ryzen 9 7950X, RTX 4090, 64 GB DDR5
Mid-Range Hardware	Core i5-13600K, RTX 3060, 32 GB DDR4

Unreal Engine 5 was selected for its native support for both 2D and 3D environments, its built-in AI integration capabilities, and its ability to expose the AI Decision Engine as a Python-callable interface, enabling rapid machine-learning prototyping alongside production-quality rendering.

V. RESULTS AND ANALYSIS

The framework was benchmarked against two baselines: Baseline A, a conventional FSM/behaviour-tree system with a fixed difficulty level; and Baseline B, a synchronous LLM dialogue system without asynchronous decoupling or memory grounding. All three conditions were evaluated in a double-blind study with $N = 80$ participants randomised across conditions.

A. Game Experience Questionnaire Results

One-way ANOVA yielded statistically significant differences in all seven GEQ dimensions ($p < 0.001$) across the three conditions. Post-hoc Tukey tests confirmed that the proposed framework significantly outperformed both baselines on every dimension (Table III). Flow State reached 3.64/4.0 and Immersion reached 3.78/4.0, while Tension and Negative Affect dropped markedly relative to both baselines.

TABLE III. GEQ Sub-Scale Scores Across Experimental Conditions (4-Point Scale)

GEQ Dimension	Baseline A	Baseline B	Proposed
Competence	2.14	2.80	3.58

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Immersion	2.10	3.20	3.78
Flow State	1.82	2.91	3.64
Tension	3.12	2.45	1.15
Challenge Balance	1.95	2.75	3.52
Negative Affect	2.88	2.10	0.92
Positive Affect	2.05	3.01	3.71

B. Session Duration and Retention

Average session duration reached 38.4 min with the proposed framework versus 26.9 min under Baseline B and 22.5 min under Baseline A. A log-rank test on Kaplan–Meier survival curves confirmed that the differences were highly significant ($\chi^2 = 42.8$, $p < 0.0001$). End-of-session satisfaction (median) was 92/100 for the proposed framework versus 61/100 and 38/100 for the two baselines respectively (Kruskal–Wallis $H = 154.2$, $p < 0.0001$). Day-14 retention stood at 78.4%, compared with 22.5% for the scripted baseline.

C. Ablation Study

Three ablated configurations were tested to isolate contributions of the Memory Repository, PPO DDA, and asynchronous decoupling. Factorial ANOVA confirmed that all three components make significant, non-redundant contributions ($p < 0.0001$). Removing asynchronous decoupling reduced frame-rate stability to 62.1%, rendering the difficulty adjustment non-functional even when dialogue remained accurate. Removing the Memory Repository increased narrative hallucination by 856% (from 1.8% to 17.2%) and reduced GEQ Flow by 18.9%. Removing PPO DDA had the largest individual effect, reducing GEQ Flow by 42.3%, confirming that challenge calibration is the most influential single component.

D. Summary of Findings

Four cross-cutting conclusions emerge from the results. First, no single mechanism accounts for the framework's benefit: asynchronous decoupling is necessary for playability, the Memory Repository is necessary for narrative immersion, and PPO-driven DDA is necessary for sustained engagement. Second, prior literature suggests that on-device LLM-NPC systems are impractical outside specialist hardware [30, 31]; these results contradict that position—a locally quantised LLM co-running with a PPO policy network maintained near-target frame rates on mid-range consumer hardware. Third, the strong correspondence among GEQ scores, session duration, and retention across all conditions provides convergent validity evidence for GEQ as an evaluation instrument in AI-gaming research. Fourth, the independence of win-rate distributions across conditions ($\chi^2 = 0.84$, $p = 0.84$) suggests that the PPO DDA reward formulation generalises across the full range of player skill levels observed in the study.

VI. CONCLUSION AND FUTURE WORK

This paper introduced and evaluated a hybrid AI gaming system that combines PPO-based dynamic difficulty adjustment, a vector-grounded Memory Repository for LLM-driven NPC dialogue, and deep-learning-guided PCG. Against a scripted FSM baseline and a synchronous generative-AI baseline, the framework achieved statistically significant improvements across all seven GEQ dimensions, 78.4% Day-14 retention, and a 90.3% reduction in narrative hallucination—while sustaining near-target frame rates on mid-range consumer hardware. The ablation study established that asynchronous decoupling, grounded memory, and reinforcement-learning-based difficulty adaptation each address a distinct failure mode; all three are necessary, but none is individually sufficient.

The study carries several limitations: it covers a single game genre, limits sessions to 30 minutes, relies exclusively on gameplay-behaviour telemetry for player modelling, and exhibits measurable LLM dialogue latency on entry-level hardware. Fairness constraints within the AI Decision Engine have not yet been formalised [18, 40]. Future work should extend evaluation across multiple genres and to multiplayer and mobile contexts, implement federated and privacy-preserving telemetry architectures [40], develop sub-3B-parameter or NPU-accelerated LLMs suitable for entry-level deployment [30], and formalise fairness constraints on player-behaviour modelling. More broadly, the findings suggest that AI-powered game design is fundamentally an architectural integration challenge: player modelling, difficulty calibration, NPC behaviour, and content delivery must be coordinated around shared, validated UX metrics to produce engagement gains that exceed what any individual mechanism can achieve alone.

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