

A RESEARCH PROPOSAL

Exploring Player-Centric and Engagement-Aware Matchmaking Systems: Innovations in Dynamic Orchestration, Player Impact, and In-Match Adaptability

Süleyman Ceran

Mobile: +90 542 115 33 74

E-mail: **suleymansceran@gmail.com**

Institution: TOBB UNIVERSITY OF ECONOMICS & TECHNOLOGY

Department: Computer Engineering, Graduate

1. Introduction

1.1. The Evolving Landscape of Online Game Matchmaking Systems

Matchmaking systems in online games have undergone a remarkable evolution from simple server browsers to complex algorithmic structures. Especially with the proliferation of the live service model, these systems have become increasingly vital for sustaining player engagement, increasing satisfaction, and ensuring the overall success of a game. At the core of modern matchmaking design lies the necessity to strike a delicate balance among numerous factors such as fairness, speed, connection quality, and player engagement. The main objective in games like Call of Duty can be summarized as enabling players to “enjoy the multiplayer experience more, play longer, leave less often, and have more fun,” encompassing the multi-faceted goals of modern matchmaking systems [4 (Page 1)]. This evolution in matchmaking reflects a broader trend toward data-driven design and personalized player experiences in game development. While the earliest systems were functional, modern systems are deeply integrated with player behavioral analytics. Key performance indicators (KPIs) in Call of Duty such as HPU (hours per user) and churn (player loss rate) [4 (Page 2)] demonstrate the presence of this data-driven approach even in “traditional” systems. This trend directly leads to concepts such as Engagement Optimized Matchmaking (EOMM) 5 and personalized matchmaking 6.

1.2. Definition of Research Focus: Examining Innovative Approaches in Matchmaking

The primary aim of this research proposal is to explore and conceptualize innovative matchmaking mechanisms that go beyond traditional paradigms. The research will emphasize their effects on game design and player experience, considering the context of a small-scale university research project. In this context, three primary axes of research have been determined:

- Dynamic Engagement Orchestration (manipulation of win/loss cycles).
 - Player-Determined Difficulty Selection in Online Matchmaking.
 - In-Match Dynamism (rematching between rounds).
- The field of game studies typically includes conceptual exploration, critical analysis, and design-focused research prior to complex technical implementations. The structure of this proposal supports the fact that a background in computer engineering is a strength for understanding technical feasibility, but that the Game Studies Master’s program will focus on design, experience, and ethical aspects.

1.3. Significance and Justification

This research is highly significant for the field of Game Studies and game development practices. The proposed mechanisms have the potential to contribute to more nuanced, player-aware, and potentially more engaging (or ethically complex) matchmaking designs. The “fundamental tension” in matchmaking is not only technical but also philosophical and ethical. Prioritizing one aspect (e.g., engagement via EOMM) can directly jeopardize another (e.g., fairness). This tension will be a recurring theme throughout the proposal.

1.4. Structure of the Proposal

The subsequent sections of this proposal will examine the identified research axes in detail, analyze the current literature and industry practices, and discuss potential methodological approaches. The table below presents an overview of the proposed research axes:

Table 1: Overview of Proposed Matchmaking Research Axes

2. Foundations: Existing Paradigms and Technologies in Matchmaking

2.1. Dominant Matchmaking Strategies and Philosophies

Skill-Based Matchmaking (SBMM):

The core principle of SBMM is to match players of similar skill levels to ensure fair and competitive games. Commonly used rating systems include Elo, TrueSkill, Glicko, and metrics such as K/D (kill/death ratio), win/loss ratios, etc. For example, the Call of Duty (COD) system defines player skill with concepts like “Raw Skill” and “Skill Percentile” [4 (Pages 21, 33)]. The benefits of SBMM include perceived fairness, balanced matches, and the potential for players to improve their skills. Analyses specific to COD show that skill is used for team balancing and has a positive impact on player retention and churn for 80-90% of players [94]. Academic studies also support that SBMM increases player retention and engagement. However, SBMM is also criticized for leading to “sweaty” (constantly difficult) matches, being prone to exploits like smurfing (experienced players using low-level accounts) or reverse boosting (intentionally lowering skill rating), challenges in accurately measuring skill in team games, and long queue times for high/low skill players [4 (Page 5)]. The limitations and criticisms of pure SBMM (e.g., not always being “fun”) likely triggered the exploration of alternative paradigms like EOMM, which can be seen as a response to the perceived inability of SBMM to maximize engagement across the player base.

Engagement Optimized Matchmaking (EOMM):

EOMM is an approach that typically prioritizes overall player engagement and retention by minimizing player churn risk. This system frames matchmaking as an optimization problem to maximize engagement metrics. Player churn risk is a key metric in this optimization. The central claim of EOMM is that fairness-based matchmaking is not always optimal for player engagement. The seminal EOMM paper by Chen et al. 5 lays out the theoretical foundations and framework for this approach.

Latency-First Approaches:

These approaches prioritize low ping (latency) and stable connections above all other factors. They are especially critical for fast-paced, reaction-time-sensitive games; the phrase “Ping is King” underscores this importance [4 (Pages 1, 20)]. COD’s matchmaking system places great emphasis on latency management through methods such as prioritizing ping and Delta Ping (difference between the player's best data center and the actual one), data center selection, QoS controls, Delta Ping minimization, and acceptable data center backoff mechanisms [4 (Pages 3-10), 4].

Other Hybrid Approaches:

Many modern matchmaking systems adopt hybrid approaches that balance multiple factors, like COD’s multi-factor system. Even while prioritizing ping and skill, sophisticated systems like COD consider player-centric KPIs such as HPU, exit rates, and player churn/retention [4 (Page 2)]. This blurs the line between fully “fair” systems and “engagement-centric” systems, showing that engagement is implicitly considered. In practice, successful systems already blend these concerns.

2.2. Case Study: Technical Deep Dive into Call of Duty’s Matchmaking System

Call of Duty’s matchmaking system provides a compelling case study due to its complexity and transparency efforts. The system aims to deliver the best experience to players by considering multiple factors.

Core Factors: The main factors underlying the system are: Ping (especially Delta Ping), Time to Match, Playlist Diversity, Recent Maps/Modes, Skill/Performance, Input Device, Voice Chat, and Platform [4 (Pages 1, 20), 4].

Weighting and Trade-Offs: While connection quality is considered the most critical factor, it is followed by time to match. Skill targets are relaxed more quickly than delta ping targets, indicating the system prioritizes good connection and reasonable wait times [4 (Pages 2, 21), 4].

Ping Management: The system uses data center selection, QoS controls, Delta Ping minimization, and acceptable data center backoff mechanisms to ensure the best possible connection. When a match starts, and periodically thereafter, the player's client runs service quality checks against all data centers, gathering real ping and packet loss data. This allows the system to identify the data center with the lowest ping for the player, but rather than forcing the absolute best, it considers several centers with similar pings as viable options [4 (Pages 3-10), 4].

Skill Calculation and Use:

- **Definition of Skill:** In COD, skill is a value that reflects relative performance, can predict future performance, can be averaged across multiple players for team balancing, adapts quickly to constantly changing player performance, and remains robust even with large changes in the player base [4 (Page 22), 4].
- **Metrics Used:** Skill calculation is based on relative performance in a specific metric for the player. After each match, this performance metric is calculated for each player and compared to others to update skill values. Metrics such as Kills/(Deaths by enemy) are used and constantly improved, for example, to prevent reverse boosting [4 (Page 23), 4].
- **Skill Adaptation Over Time:** Skill values are constantly updated and targeted to reach equilibrium quickly, as player skill can change over time for various reasons (trying new equipment, not playing for a while, fatigue, etc.) [4 (Page 24), 4].
- **Team Balancing Goals and Process:** Team balance is critical for ensuring match outcomes are as unpredictable as possible and reducing blowout likelihood. COD uses skill to provide a balanced in-match experience [4 (Pages 25, 39-41), 4].
- **Impact of Skill on Player Experience and Testing Skill Constraints:** When skill is used in matchmaking, 80-90% of players achieve better end-of-match rankings, remain engaged longer, and leave matches less frequently. COD conducts experiments to test the effects of skill constraints. For example, in a test where the priority of skill was reduced, top 10% skill percentile players saw increased return rates and KPM/SPM values, whereas the opposite was true for the remaining 90%. This demonstrates that “fun” and “engagement” can mean different things to different player segments, and optimization for one group can negatively impact another [4 (Pages 26-33), 4].
- **Matchmaking Algorithm:** The matchmaking algorithm runs at fixed intervals (usually every 5 seconds). It starts with some “seed” searches. For each seed, a heuristic method based on N-dimensional distance involving factors like geographic location, skill, and control scheme is used to find a sequential “candidate search” list. Then, a greedy algorithm is used to add candidates to the seed in a way that satisfies matchmaking constraints and maximizes quality score. If constraints are met, a match is created [4 (Pages 10-12, 34-35), 4].
- **Server Capacity and Monitoring:** If no empty server is available at the selected best data center, the system tries the next one. A separate system manages the number of servers at each center. Numerous KPIs such as Delta Ping, HPU, exit rates, player churn, and survey results are continuously monitored [4 (Pages 2, 13-18), 4]. The extensive data collection and processing involved in modern matchmaking (COD's detailed metrics, ML features extracted from Blade & Soul logs for player churn prediction 12) raises important data privacy and ethical considerations even before proposing more manipulative systems. This baseline must be acknowledged in the proposal.

- **Ranked Play Variations:** Ranked play modes have stricter rules, longer search times, more emphasis on Rank/SR (Skill Rating) similarity, and party restrictions [4 (Pages 45-62), 4].

2.3. The Role of Machine Learning in Contemporary Matchmaking

Machine learning (ML) is playing an increasingly significant role in contemporary matchmaking systems. It is especially used for predicting player skill/MMR (Matchmaking Rating) for new or returning players. Churn prediction models have been developed to identify players at risk. Real-time ML also enables dynamic difficulty adjustment (DDA) and smarter matchmaking based on skill, history, and preferences. In systems like EOMM, ML can potentially predict player churn based on player states and potential matches. The overview provided by Quix.io 17 well summarizes real-time ML applications in games, including matchmaking and DDA.

3. Proposed Research Axis 1: Dynamic Engagement Orchestration in Matchmaking

3.1. Conceptual Framework: Strategically Influencing Win/Loss Cycles for Engagement (The User's Primary Idea)

The core idea of this research axis is to develop a matchmaking system that deliberately designs sequences of wins and losses. This system could initially offer players wins to provide early positive reinforcement and build a perception of skill. Then, based on behavioral telemetry or ML models, it could deliberately introduce losses when boredom, disengagement, or churn is predicted. The main trade-off here is between sustained engagement within a single session (longer play time) and increasing the desire for frequent returns (play frequency). While this approach shares parallels with EOMM principles 5, it focuses more on overtly manipulating match outcomes rather than simply matching based on predicted player churn. The EOMM framework 5 aims to “maximize overall player engagement or, equivalently, minimize overall player churn,” and uses “player churn risk as a concrete metric of disengagement,” which serves as a core concept for the user's idea. The finding by Kang et al. 18 that matching with weaker opponents reduces churn more than fair matches and that frequent wins reduce churn forms a fundamental, testable hypothesis that a system strategically providing these experiences at critical moments (e.g., when high churn risk is predicted) could theoretically lead to higher retention.

3.2. Psychological Foundations and Player Behavior

Understanding the potential effects of the proposed system on player psychology is critical.

- **Player Motivation:** Motivation theories in games (e.g., Self-Determination Theory – competence, autonomy, relatedness) and how designed win/loss sequences can affect these factors should be examined.
- **Churn Triggers:** The study by Kang et al. (2024) 15 reveals the effect of matching with stronger/weaker opponents and skill gaps on player churn. In particular, the finding that “matching with weaker opponents reduces churn probability more than fair matches (with equal-skill opponents)” 18 is highly relevant. The effect of win rates, win streaks, and loss streaks on churn must also be considered; the finding that “sequential losses affect churn differently depending on player level” 18 suggests personalization is key.
- **Cognitive Biases:** The “Hot Hand Fallacy” 20 is the tendency for players to believe streaks will continue. How the system can exploit or account for this bias should be considered.
- **Player Frustration and Boredom:** The psychological impact of continuous losses or excessively easy wins must also be taken into account. Discussions on overcoming losing streaks 21 emphasize the psychological effects of these situations. Combined with EOMM and personalized matchmaking, this research axis points toward a future where online multiplayer experiences are increasingly “curated” by algorithms rather than fully emerging

from player interactions under fixed rules. This deeply affects what “skill” and “achievement” mean. In traditional games, there are fixed rules, and player skill determines the outcome. In the proposed system, the algorithm influences the outcome to manage engagement, shifting agency from the player to the system. If wins are “given,” is it truly an achievement? 22 raises concerns about the erosion of skill-based achievement.

3.3. Personalization Vectors for Engagement Orchestration

The effectiveness of the engagement orchestration strategy will depend on its adaptability across various personalization vectors:

- **Game-Specific:** How does the strategy differentiate for different genres (e.g., FPS, MOBA, Battle Royale)?
- **Audience-Specific:** Adapting to different player segments (e.g., casual vs. hardcore, new vs. experienced). COD’s skill percentiles [4 (Page 28)] demonstrate how player experience can vary.
- **Individual-Specific:** Adapting to individual player profiles, game history, predicted churn risk, and even emotional responses. 6
- **Temporal Adaptations:** Changing the strategy based on time of day, day of week, or special events. 6
PubNub’s “Organic Engagement-Focused Personalized Matchmaking” 6 discusses personalization based on factors such as input devices, console types, time of day, and play style, offering a framework for these vectors. When combined with win/loss manipulation, these personalization vectors 6 can lead to highly differentiated experiences that, if not handled with extreme care, can approach discriminatory or predatory boundaries. For example, identifying players more likely to spend after a win and designing wins to maximize those outcomes (e.g., spending).

3.4. Game Design and Systemic Impacts

It is important to consider how game mechanics should be designed to support or respond to such a matchmaking system. The impact on game balance, progression systems, and in-game economy must be assessed. Which telemetry data needs to be collected to drive the system should be identified (12 details features extracted from Blade & Soul logs for churn prediction). The necessity of robust churn prediction models is also clear. 12 The complexities of ML aspects in churn prediction and dynamic adjustment should be noted as targets for deeper future research, but the conceptual framework and design impacts are the focus here. While DDA is typically about adjusting difficulty to maintain flow 25, this “Engagement Orchestration” is a kind of “Emotional DDA” or “Motivational DDA”; it adjusts outcome probabilities to manage psychological states such as frustration or boredom, not just task difficulty.

3.5. Ethical Dimensions: Navigating Engagement, Fairness, and Autonomy

The ethical dimensions of such a system must be carefully considered:

- **Manipulation vs. Enhancement:** Where is the line between enhancing the player experience and unethically manipulating behavior? 5
- **Fairness and Transparency:** How would players perceive such a system? The importance of transparency (or its absence). 27 EOMM papers often lack this discussion. 5
- **Player Autonomy:** Does designing win/loss outcomes undermine player agency and the sense of earned achievement? 22

- **Potential for Addiction and Exploitation:** If optimized for time or spending, could this exacerbate problematic gaming? 22
- **Impact on Skill Development:** Does preventing excessive losses hinder learning from mistakes? Sources like 5 discuss ethical concerns in game design, monetization, and AI, and are highly relevant for this research axis. Notably, 5 highlights the lack of ethical discussion in the EOMM paper.

4. Proposed Research Axis 2: Player-Determined Difficulty in Competitive Online Environments

4.1. Concept and Rationale: Empowering Players Through Matchmaking Choice

In an online matchmaking context, “player-determined difficulty” is defined as allowing players to choose a preferred difficulty tier or experience type (e.g., “Casual,” “Competitive,” “Learning,” “Very Challenging”) that affects matchmaking parameters. This is analogous to single-player difficulty settings but adapted for multiplayer dynamics. The rationale is to increase player agency, cater to different motivations (fun, learning, serious competition), and potentially improve satisfaction for players who feel underserved by one-size-fits-all SBMM. 29 discusses how current systems can exclude casual players, implying the need for more options. 13 does not directly discuss player-selected difficulty, but emphasizes the importance of skill matching for satisfaction, suggesting that player choice could improve this. This axis highlights a fundamental tension between player autonomy/choice and system-enforced fairness/balance. Giving players full choice may undermine the system’s ability to create balanced matches for everyone.

4.2. Potential Benefits

Player-determined difficulty can offer several potential benefits:

- **Increased Player Impact and Autonomy:** Giving players more control over their experience. 29
- **Enhanced Satisfaction:** Especially for players at the extremes of the skill curve or those with playstyle preferences not served by standard SBMM.
- **Reduced Frustration:** Players preferring a more relaxed experience can avoid excessively “sweaty” lobbies.
- **Better Expectation Management:** Players know what kind of experience they are entering. Player-selected difficulty can more effectively address different intrinsic motivations (mastery, casual fun, social play) than a single SBMM system, aligning with theories such as Self-Determination Theory.

4.3. Inherent Challenges and Drawbacks

This approach brings some major challenges:

- **Matchmaking Pool Fragmentation (Queue Splitting):** Dividing the player base into multiple queues can significantly increase wait times, especially for less popular modes or difficulty settings. 29
- **Exploitation Potential (Smurfing/Boosting):** Skilled players may select lower difficulties to “stomp” legitimate low-difficulty players, ruining their experience. 29

- **Definition and Implementation of “Difficulty” Tiers:** How do we translate subjective player choice into concrete matchmaking parameters? What metrics define each tier? How do we prevent tiers from becoming imbalanced?
- **Maintaining Competitive Integrity:** How do we ensure that “ranked” or “competitive” modes remain meaningful if players can self-select into easier versions?
- **Community Perception and “Meta” Development:** Certain tiers could become stigmatized or viewed as “not real games.” Implementation would require designing not just different matchmaking rules but multiple distinct gameplay experiences within one game. “Casual” and “Hardcore” lobbies might require different balancing, map rotations, or even rule variations.

4.4. Design Considerations for Online Implementation

The following design considerations are key for successful online implementation:

- **Skill Verification/Calibration:** Should player selection be entirely free, or should there be an initial skill assessment or restrictions on choices to prevent gross mismatches or abuse? (e.g., requiring “unlocking” higher difficulties).
- **Dynamic Population Management:** Can the number of available difficulty tiers vary with the player population to manage queue times?
- **Incentives and Rewards:** How should rewards in different difficulty tiers be structured to feel fair and motivating without encouraging abuse?
- **Social Features:** How does party formation work with player-selected difficulty? What if party members have different preferences?
- **Clear Communication to Players:** How are difficulty tiers defined and what expectations are set? A fully player-selected system could be too chaotic. Hybrid models, where players express a preference that the system tries to honor within certain skill boundaries, may be a more viable compromise, providing player agency while mitigating some downsides.

5. Proposed Research Axis 3: In-Match Dynamism – Rematching Between Rounds

5.1. Concept: Enhancing Match Flow and Fairness Through Inter-Round Adjustments

“In-match dynamism” is defined as mechanisms that allow for the reassessment and potential rebalancing of teams—or even individual player matchups—between rounds in a multi-round game (e.g., deathmatch, control point games with distinct rounds). The rationale is to correct imbalances that become apparent only after the game starts, reduce the impact of players leaving, or simply provide variety. Sources like 30 discuss dynamic matchmaking criteria (Diarkis MatchMaker), but these are primarily focused on initial match formation. The user’s idea extends this into ongoing match sessions. Qingyun Wu’s work 31 discusses dynamic matchmaking balancing fairness and wait times for team-based games; if extended to inter-round adjustments, it is conceptually related. This concept treats a single game match not as a static event but as a dynamic system subject to course corrections. It represents a shift from pre-match optimization to in-match optimization.

5.2. Potential Mechanisms for Inter-Round Rematching/Rebalancing

Various mechanisms can be applied between rounds:

- **Team Switching:** Reassigning players to teams based on performance in previous round(s).

- **Individual Matchup Adjustments:** In modes with many small rounds (e.g., a series of 1v1 duels within a larger game), rematching individuals based on round results.
- **Handicap Adjustments (more controversial):** Small, temporary buffs/debuffs based on round performance (less likely for competitive integrity).
- **Backfilling:** If players leave, the system can prioritize backfilling to rebalance teams according to the current match state.
The perception of fairness here is complex. Rebalancing may statistically make the overall match fairer, but players with an advantage may see it as unfairly stripping away their earned edge.

5.3. Impact on Player Experience and Competitive Integrity

Such a system can have both positive and negative effects on player experience and competitive integrity:

- **Benefits:**
 - Potentially fairer subsequent rounds if initial rounds are unbalanced.
 - Increased engagement if matches feel more competitive over time.
 - Reduced frustration from being stuck on a clearly losing team for an entire match.
- **Drawbacks:**
 - Can feel disruptive or unfair to winning players.
 - May undermine team cohesion or the sense of rivalry established in early rounds.
 - Adds complexity in implementation and communication to players.
 - Potential for players to “game” the rebalancing system.
Frequent rematching may also disrupt the narrative flow of a match (e.g., comeback stories, underdog victories), making matches feel more like a series of disconnected skirmishes than a continuous contest.

5.4. Technical and Design Barriers

Practical technical and design challenges include:

- How do we accurately measure performance within a few rounds to make meaningful adjustments?
- How can we implement rematching quickly between rounds without excessive disruption?
- How can we clearly communicate and justify these changes to players?
- Which game modes are best/worst suited for this approach?
Diarkis MatchMaker’s “Real-Time Adjustments” 30 capability allows matchmaking criteria to be adapted to player behavior and game dynamics and could theoretically be extended. The challenge is applying this not just for initial matchmaking but throughout a session. The concept seems most applicable to games with clear, self-contained rounds (e.g., some fighting games, objective modes in Overwatch where teams swap sides and reset) rather than continuous-flow games (e.g., traditional Deathmatch or a single long Battle Royale).

6. Core Research Questions and Hypotheses

This section will turn the explorations in Sections 3, 4, and 5 into specific, answerable research questions suitable for a Master's-level project. These will be more focused than the high-level questions outlined in the table in Section 1. The research questions are oriented toward qualitative research, conceptual modeling, and design exploration rather than large-scale empirical testing — matching the user's context (Game Studies MA, limited resources for mass research).

- **For Axis 1 (Dynamic Engagement Orchestration):**
 - AS1.1: How can a conceptual model for matchmaking that strategically designs win/loss streaks (e.g., initial wins, subsequent losses based on predicted player churn) be designed, taking into account player psychology and engagement metrics (session length vs. play frequency)?
 - AS1.2: What are the core ethical issues (fairness, manipulation, autonomy, transparency) inherent in such a system, and how can these be mitigated in a design proposal?
 - Hypothesis 1.1 (Conceptual): A matchmaking system offering strategically timed difficulty (losses) following early wins in cases of predicted churn may produce a different engagement model (e.g., more frequent but shorter sessions) compared to traditional SBMM.
- **For Axis 2 (Player-Determined Difficulty):**
 - AS2.1: Among online multiplayer players, what are the perceived benefits and drawbacks of player-selectable matchmaking difficulty tiers?
 - AS2.2: What game design principles can be applied to mitigate common challenges (e.g., queue fragmentation, exploitation) associated with player-determined difficulty in online matchmaking?
- **For Axis 3 (In-Match Dynamism):**
 - AS3.1: How do players perceive the fairness and impact on enjoyment of inter-round team rebalancing in specific round-based multiplayer game modes?
 - AS3.2: What are the core design parameters (e.g., triggers for rebalancing, inter-round performance metrics, communication strategies) for an effective inter-round rematching system?

These axes are presented separately but are interrelated. For example, player-selected difficulty (Axis 2) could be one personalization vector for dynamic engagement orchestration (Axis 1). Inter-round rebalancing (Axis 3) could be a tool used within a specific player-selected difficulty tier. The research questions are framed to be investigable in a university context. For example, AS1.1 is about designing a conceptual model rather than building a complete AI implementation; AS2.1 deals with perceptions measurable via surveys/interviews.

7. Potential Research Pathways (Methodological Approaches)

This section briefly summarizes how the research questions might be addressed. As this is a proposal, it is about suggesting how the research could be conducted, not executing the research itself. The proposed pathways are in line with the typical resources and timeline of a Master's thesis in Game Studies; they prioritize critical thinking, synthesis, and design over large-scale software development.

7.1. Literature Review and Synthesis:

- In-depth examination of academic articles on matchmaking (SBMM, EOMM, etc. 5), DDA 25, player psychology 20, player churn 15, and ethics in game design 22.
- Analysis of industry practices (e.g., COD technical whitepapers 4, accessible GDC talks).

7.2. Conceptual Model Development:

- For Axis 1: Designing a detailed framework outlining components, logic, and interaction points with player data and game systems for a dynamic engagement orchestration system.
- For Axes 2 and 3: Developing design patterns or guidelines for implementing player-selected difficulty and inter-round rematching.

7.3. Comparative Analysis:

- Comparing proposed mechanisms with existing systems like COD's 4, highlighting philosophical, mechanical, and potential player impact differences.

7.4. Ethical Impact Assessment:

- Special analysis of the ethical implications of each proposed axis, drawing on ethical frameworks in technology and game design 22.

7.5. (Future Work Indication) Experimental Parameter Design:

- Even if full implementation is out of scope, the proposal could outline hypothetical experimental setups or simulations for future research to test the hypotheses (e.g., which metrics would be measured, which control groups would be needed). This demonstrates awareness of empirical validation.
- The user notes that ML is for future optimization; this section could briefly discuss how ML models (e.g., for player churn prediction 15 or reinforcement learning for adaptive strategies 17) might eventually be integrated.

These research pathways leverage disciplines including computer science (conceptual models), psychology (player behavior), ethics, and game design—reinforcing the multidisciplinary strength the user aims to demonstrate. Good research does not reinvent the wheel; it builds upon it. Using COD as a case study, EOMM as a theoretical basis, and Kang's findings as empirical support enables the user to situate their novel ideas within ongoing scientific and industrial discussion.

8. Expected Contributions and Importance for Game Studies

This research is expected to make several important contributions to the field of Game Studies:

- Contributing to the theoretical understanding of matchmaking beyond traditional metrics.

- Offering new conceptual models for player-centered and engagement-aware matchmaking.
- Providing a critical discussion of the ethical implications of increasingly complex and potentially manipulative matchmaking systems. The proposal, especially Axis 1 and its ethical analysis, addresses a notable gap in the existing literature (e.g., lack of ethical discussion in EOMM papers 5), which is a strong point in terms of significance.
- Potentially informing future game design practices to create more diverse and adaptable online experiences. Although conceptual, the research has practical significance for game designers grappling with player engagement, retention, and ethical use of player data.
- Presenting a framework for thinking about the (possibly controversial) distribution of these new ideas and, importantly, their ethical implementation.
- Highlighting the interaction between game design, player psychology, and algorithmic systems.

9. Conclusion

This research proposal provides a framework for rethinking matchmaking mechanisms in online games in innovative and player-centric ways. As the field shifts from traditional skill-based matchmaking to engagement optimization and toward even more complex systems capable of dynamically shaping player experience, the importance of such research increases.

The three proposed research axes—Dynamic Engagement Orchestration, Player-Determined Difficulty, and In-Match Dynamism—offer distinct perspectives on how matchmaking systems can not only ensure fair competition but also enhance player motivation, engagement, and overall satisfaction. These axes exist at the intersection of player psychology, game design principles, and algorithmic systems, requiring a multidisciplinary approach.

Technical analyses of industry examples like Call of Duty and academic frameworks like EOMM offer valuable insights into current best practices and future potential directions. However, when systems directly affecting and potentially manipulating player experience are concerned, it is vital to thoroughly examine ethical dimensions. This research aims to spark a discussion on how this new generation of matchmaking systems can be responsibly designed by foregrounding core ethical principles such as fairness, transparency, and player autonomy.

The expected contributions of this work are to enrich theoretical understanding and guide practical game design applications. Developing matchmaking mechanisms that enhance player agency, respond to different player needs, and remain within ethical boundaries is a critical step for the future of the game industry. This research aims to make a modest but important contribution toward these advancements.

10. References

I'll rearrange References section soon due it's problematic complexity and discord.

1. Matchmaking Strategies for Maximizing Player Engagement in Video Games, accessed May 27, 2025, <https://www.researchgate.net/publication/>

[354848363 Matchmaking Strategies for Maximizing Player Engagement in Video Games](#)

2. Analysis of Matchmaking Optimization Systems Potential in Mobile Esports - ScholarSpace, accessed May 27, 2025, <https://scholarspace.manoa.hawaii.edu/bitstreams/6d9802ce-91d4-4ff1-9807-17b45cd5e3ad/download>
3. The Questions of MatchMaking: Wait Time VS Match Quality | AWS for Games Blog, accessed May 27, 2025, <https://aws.amazon.com/blogs/gametech/questions-of-matchmaking/>
4. COD-Matchmaking-Series.pdf
5. (PDF) EOMM: An Engagement Optimized Matchmaking Framework, accessed May 27, 2025, https://www.researchgate.net/publication/313893411_EOMM_An_Engagement_Optimized_Matchmaking_Framework
6. Move Beyond Skill-Based Matchmaking With PubNub Illuminate, accessed May 27, 2025, <https://www.pubnub.com/blog/building-effective-skill-based-matchmaking/>
7. A research-supported look into why Skill Based Matchmaking has been a net-positive for multiplayer gaming - Reddit, accessed May 27, 2025, https://www.reddit.com/r/truegaming/comments/175yz1y/a_researchsupported_look_into_why_skill_based/
8. www.diva-portal.org, accessed May 27, 2025, <http://www.diva-portal.org/smash/get/diva2:873273/FULLTEXT01.pdf>
9. The Role of Skill in Matchmaking - Activision, accessed May 27, 2025, https://www.activision.com/cdn/research/CallofDuty_Matchmaking_Series_2.pdf
10. Engagement Optimized Matchmaking - VLR.gg, accessed May 27, 2025, <https://www.vlr.gg/409672/engagement-optimized-matchmaking>
11. (PDF) EOMM: An Engagement Optimized Matchmaking Framework - ResearchGate, accessed May 27, 2025, https://www.researchgate.net/publication/315849420_EOMM_An_Engagement_Optimized_Matchmaking_Framework
12. arxiv.org, accessed May 27, 2025, <https://arxiv.org/vc/arxiv/papers/1802/1802.02301v2.pdf>

13. Improvement of online game matchmaking using machine learning, accessed May 27, 2025, https://www.researchgate.net/publication/360548944_Improvement_of_online_game_matchmaking_using_machine_learning
14. Customer Churn Prediction Model using Explainable Machine Learning - arXiv, accessed May 27, 2025, <https://arxiv.org/abs/2303.00960>
15. www.scitepress.org, accessed May 27, 2025, <https://www.scitepress.org/Papers/2024/132347/132347.pdf>
16. Predicting Player Churn in the Gaming Industry: A Machine Learning Framework for Enhanced Retention Strategies - ResearchGate, accessed May 27, 2025, https://www.researchgate.net/publication/390168979_Predicting_Player_Churn_in_the_Gaming_Industry_A_Machine_Learning_Framework_for_Enhanced_Retention_Strategies
17. Gaming & ML: How Real-Time ML Enhances Player Experience - Quix, accessed May 27, 2025, <https://quix.io/blog/gaming-ml-how-real-time-machine-learning-enhances-player-experience>
18. Match experiences affect interest: Impacts of matchmaking and ..., accessed May 27, 2025, <https://pubmed.ncbi.nlm.nih.gov/38318006/>
19. Hyunjae Kang's research works | Korea University and other places - ResearchGate, accessed May 27, 2025, <https://www.researchgate.net/scientific-contributions/Hyunjae-Kang-2199610397>
20. Demystifying the Hot Hand Fallacy: Understanding the Psychology ..., accessed May 27, 2025, <https://www.tajucoaching.com/blog/demystifying-hot-hand-fallacy-understanding-psychology-behind-streaks-in-gaming>
21. How to Overcome a Losing Streak | Sports Psychology Articles, accessed May 27, 2025, <https://www.peaksports.com/sports-psychology-blog/how-to-overcome-a-losing-streak-in-sports/>
22. Unpacking the Ethics of AI in the Gaming Industry | OpenGrowth, accessed May 27, 2025, <https://>

www.opengrowth.com/article/unpacking-the-ethics-of-ai-in-the-gaming-industry

23. A Developer's Perspective Needed: Predatory Matchmaking Systems & Their Impact on Kids : r/theprimeagen - Reddit, accessed May 27, 2025, https://www.reddit.com/r/theprimeagen/comments/1ie87mz/a_developers_perspective_needed_predatory/
24. accessed January 1, 1970, https://www.reddit.com/r/theprimeagen/comments/1ie87mz/a_developers_perspective_needed_predatory_matchmaking_systems_their_impact_on_kids/
25. Dynamic difficulty adjustment using deep reinforcement learning: A review - ResearchGate, accessed May 27, 2025, https://www.researchgate.net/publication/383664462_Dynamic_difficulty_adjustment_using_deep_reinforcement_learning_A_review
26. The Impact of Dynamic Difficulty Adjustment on Player Experience in ..., accessed May 27, 2025, <https://digitalcommons.morris.umn.edu/horizons/vol9/iss1/7/>
27. Ethics in Game Design I Navigating the Moral Landscape, accessed May 27, 2025, <https://polydin.com/ethics-in-game-design/>
28. Ethical Considerations in Game Design and Monetisation - SAE ..., accessed May 27, 2025, <https://www.sae.edu/gbr/insights/ethical-considerations-in-game-design-and-monetisation/>
29. The Role and Difficulty of Skill-Based Matchmaking - SUPERJUMP, accessed May 27, 2025, <https://www.superjumpmagazine.com/the-role-and-difficulty-of-skill-based-matchmaking/>
30. Scalable Asymmetrical Matchmaking with Diarkis: Powering Real ..., accessed May 27, 2025, <https://www.diarkis.io/news/scalable-asymmetrical-matchmaking-with-diarkis-powering-real-time-multiplayer-for-games>
31. Dynamic Matching With Teams - Qingyun Wu, accessed May 27, 2025, <https://qingyunwu.com/research/Dynamic%20Matching%20With%20Teams.pdf>

32. openresearch-repository.anu.edu.au, accessed May 27, 2025, <https://openresearch-repository.anu.edu.au/bitstreams/4ae20c15-6ca4-4171-ac7a-ae5393491e0b/download>
33. Mastering Player Retention: Strategies for iGaming Providers - nanocosmos, accessed May 27, 2025, <https://www.nanocosmos.de/blog/player-retention/>
34. A Survey of Distributed Algorithms for Aggregative Games, accessed May 27, 2025, <https://www.ieee-jas.net/en/article/doi/10.1109/JAS.2024.124998>
35. Top 115 IEEE transactions on games papers published in 2023 - SciSpace, accessed May 27, 2025, <https://scispace.com/journals/ieee-transactions-on-games-1euknpok/2023>
36. Game Studies - Issue 2501, 2025, accessed May 27, 2025, <https://gamestudies.org/>
37. Why AI matchmaking equals to event success? - Brella, accessed May 27, 2025, <https://www.brella.io/blog/ai-matchmaking-future-of-events>
38. Maintaining Game Fairness Amid Strategic Evolution in Multiplayer Obstacle Course Games - TIJER, accessed May 27, 2025, <https://tijer.org/tijer/papers/TIJER2501095.pdf>
39. Engagement Effects of Player Rating System-Based Matchmaking for Level Ordering in Human Computation Games, accessed May 27, 2025, https://www.khoury.northeastern.edu/home/scooper/index_files/pub/sarkar2017engagement.pdf
40. Artificial-Intelligence in Modern Video Games: Enhancing Realism and Player Experience - IJRASET, accessed May 27, 2025, <https://www.ijraset.com/best-journal/artificialintelligence-in-modern-video-games>
41. लॉटरी संबंध - Maharashtra Transport, accessed May 27, 2025, https://transport.maharashtra.gov.in/1035/Home?utm_ref=gst_pages_navbar%23h2%23h13%23h23%23puc/1114/Organization-Chart/1133/Statistics/1159/Road-Safety-Campaign/1161/Road-Signs/1164/Taxi-Auto-Rickshaw-Permit-Release/1133/Statistics/1159/Road-Safety-Campaign/1133/Statistics/1133/Statistics/1159/Road-Safety-Campaign/site/home/newsmore.aspx/1134/Offices/1125/HSRP/1133/Statistics/1162/Learning-License-Test-Question-Bank/1125/

[HSRP/1164/Taxi-Auto-Rickshaw-Permit-Release/1114/Organization-Chart](#)

42. Descriptive statistics of variables. I Download Scientific Diagram - ResearchGate, accessed May 27, 2025, https://www.researchgate.net/figure/Descriptive-statistics-of-variables_tbl2_377536047
43. gdcvault.com, accessed May 27, 2025, <https://gdcvault.com/play/1029109/Player-Driven-Difficulty-How-Player>
44. medium.com, accessed May 27, 2025, <https://medium.com/@maxwellitt/difficulty-scaling-in-games-3f59080449c8>
45. gdcvault.com, accessed May 27, 2025, <https://gdcvault.com/play/1027942/Dynamic-Balancing-in-Multiplayer-Games>