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The Hidden Rules of Win Rate Manipulation: A Study on Algorithmic Discrimination in the Matching Mechanism of MOBA Games—Taking Honor of Kings as an Example

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Abstract

With the prevalence of MOBA games such as *Honor of Kings*, the fairness of the algorithm in their matching mechanisms has sparked widespread controversy. This study uses this game as a case to explore whether algorithmic discrimination exists in its matching mechanism. Through stratified random sampling to obtain data from over 3,000 players, combined with questionnaires, controlled experiments, and quantitative analysis, it is found that game duration, recharge amount, and the number of consecutive wins/losses have a significant impact on players' win rates: there is a stepwise positive correlation between payment amount and win rate, with heavy-paying players having a win rate of 58.1%, 6.4% higher than free players (51.7%); consecutive wins trigger negative matching adjustments by the system (win rate decreases by 4.5%), while consecutive losses activate protection mechanisms (win rate increases by 1.6%). Jurisprudential analysis shows that operators actively design differentiated matching strategies based on commercial goals, systematically damaging players' right to fair competition by linking payments to high-quality resources and dynamically adjusting match difficulty, constituting algorithmic discrimination in a legal sense. The study proposes a collaborative governance approach from three aspects: legislatively defining the constitutive elements of algorithmic discrimination, establishing a transparent review system for regulation, and building algorithm self-correction mechanisms for enterprises, providing theoretical and practical references for the fairness of the digital competitive ecosystem.

Keywords

Algorithmic discrimination, Matchmaking mechanism, ELO algorithm, MOBA games, *Honor of Kings*.

1. Introduction

In 2025, *Honor of Kings* set a new record with monthly revenue of 2.886 billion yuan. With 120 million daily active users, one in every twelve Chinese citizens participated in this digital phenomenon. From the KPL professional arena to township internet cafés, from Gen Z university students to 35-year-old professionals, this MOBA game—now in its tenth year—has transcended mere entertainment to become a lens through which to observe collective behaviour in the digital age.

Yet beneath this flourishing surface lies a complex landscape of win-rate narratives. A university esports society discovered that newly registered accounts encountered over 40% AI teammates in their first five matches, achieving win rates 19% higher than three-year-old accounts. A Shanghai player's Excel spreadsheet documented 127 first wins with new skins, with high-level player encounter rates during 2-4 AM ranked matches reaching 2.3 times those of peak hours. Most tellingly, players on national servers have developed deliberate rating suppression strategies—maintaining scores below 6 points to trigger the system's loss-streak protection mechanism, yielding a 27% win-rate increase.

This grassroots wisdom reflects a decade-long contest between the ELO algorithm and 200 million players. From the hidden score mechanism in Season 3 to the role-based rating reform in Season 39, the system has sought to balance competitive fairness with user retention, whilst players have crafted various counter-strategies, creating a distinctive ecosystem. When players consistently observe that win streaks inevitably lead to loss streaks and high ratings result in inferior teammates, when both professional and casual players alike decry system manipulation during livestreams, a fundamental question emerges: Does this MOBA game, which purports to uphold fair competition as its core principle, harbour algorithmic discrimination within its matchmaking mechanisms?

Compared to visible price discrimination in consumer markets, algorithmic discrimination in gaming possesses greater concealment and technical complexity—embedded within competitive rules, it manipulates player experience under the guise of fair matchmaking. This affects not only the emotional investment of millions of players but also undermines the fundamental value of esports: fair competition. This study's innovation lies in incorporating game algorithms into a legal-empirical analytical framework, quantitatively examining how match duration, spending amounts, and win/loss streaks influence player win rates through battle data from 3,000 players in *Honor of Kings* Season 39. The paper is structured as follows: Part I introduces the research context; Part II reviews existing academic literature; Part III outlines the research design; Part IV presents and analyses the data; Part V discusses findings and provides legal analysis; Part VI proposes policy recommendations, while Parts VII and VIII respectively present the study's limitations and conclusions.

2. Literature Review

International academic research on algorithmic discrimination emerged in the 1990s, establishing a mature research framework over three decades across theoretical construction, empirical analysis, and institutional design. At the theoretical level, European and American scholars developed the conceptual framework of algorithmic discrimination, defining it as unfair differential treatment imposed on protected groups by automated decision-making systems [1], distinguishing between direct discrimination—algorithms explicitly using protected characteristics such as race and gender as decision-making criteria [2]—and indirect discrimination, where seemingly neutral algorithmic rules produce systematic adverse effects on specific groups [3]. Additionally, scholars have proposed multiple fairness standards encompassing individual fairness, group equality, equal opportunity, and outcome justice, providing theoretical tools for identifying and evaluating algorithmic discrimination [4][5].

Empirically, international scholars have exposed algorithmic discrimination across employment recruitment, credit approval, and criminal justice through extensive case analysis and data modelling [6][7]. Research demonstrates that technical systems—whether racial bias in facial recognition or gender filtering in recruitment algorithms—often replicate or amplify existing social biases through concealed mechanisms [8]. These studies confirm algorithmic

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discrimination's objective existence whilst analysing its technical causes and social roots, establishing empirical foundations for legal regulation.

Regarding institutional design, European and American jurisdictions have initiated legal frameworks for algorithmic discrimination governance. Researchers have examined anti-discrimination law application challenges in the digital era whilst proposing regulatory tools including algorithm auditing, impact assessment, and transparency requirements [9][10]. Scholars have designed comprehensive governance mechanisms spanning pre-prevention, in-process monitoring, and post-violation remediation through procedural and substantive justice dimensions, advancing legal regulation into technical governance domains [11].

Chinese academic engagement with algorithmic discrimination began in the 2010s, later than international research. Following the Personal Information Protection Law and Anti-Monopoly Law, domestic research increasingly addresses local issues, balancing theoretical introduction with localised innovation. Whilst absorbing foreign conceptual frameworks, scholars have reinterpreted algorithmic discrimination within China's legal traditions, emphasising its distinctions from traditional discrimination—algorithmic discrimination operates through data processing technology, implementing automated, large-scale discrimination with impacts transcending geographical and industry boundaries [12].

Researchers have identified China's unique digital economy ecosystem as generating distinctive algorithm application scenarios combining technological innovation with implicit discrimination risks, prompting localised exploration [13][14]. For characteristically Chinese contexts including platform employment, fintech, and social credit systems, researchers have analysed algorithmic decision-making discrimination risks: whether delivery platform dispatch algorithms contain regional or age biases in the gig economy [15]; whether credit evaluation models improperly correlate personal characteristics like occupation types in fintech [16]. These studies integrate closely with China's regulatory practice, offering targeted institutional recommendations.

Institutional construction research presents multiple pathways: some scholars advocate strengthening existing anti-discrimination law by incorporating algorithmic discrimination into equal rights protection frameworks through interpretation [17]; others propose specialised governance frameworks clarifying algorithm transparency, explainability, and accountability requirements [18]; another approach explores personal information rights protection in algorithmic decision-making from data rights perspectives [19]. Empirically, scholars employ quantitative analysis and case comparison to reveal multidimensional biases in internet recruitment and online lending [20].

However, Chinese research exhibits several limitations: theoretical innovation remains insufficient, with most results confined to introducing and commenting on foreign theories without developing conceptual systems grounded in Chinese legal practice; empirical research lacks breadth and depth, with inadequate analysis of algorithmic discrimination's occurrence mechanisms, actual harms, and governance effectiveness; interdisciplinary integration faces bottlenecks, with insufficient dialogue between legal research and computer science or sociology, restricting practical research transformation.

Current research adequately explores general algorithmic discrimination legal theories but significantly neglects game scenario particularities. As core digital competitive ecosystem components, game matchmaking mechanism algorithm design fundamentally affects players'

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fair competition rights, esports industry values, and social cognitive formation. However, corporate data barriers, interdisciplinary research deficiencies, and regulatory gaps have marginalised this academic field. Strengthening research here addresses urgent needs to fill digital governance legal gaps and safeguard esports fair competition values whilst building healthy gaming ecosystems. This holds crucial significance for balancing technological innovation with rights protection and maintaining digital-age rule trust.

3. Research Design and Methods

3.1. Questionnaire Survey Design

The research employed stratified random sampling, constructing a stratification framework across four dimensions: rank, playing duration, spending amount, and gender, to ensure representation of diverse player demographics. Ranks were categorised into four tiers: Bronze/Silver (beginners), Gold/Platinum (intermediate), Diamond/Star (advanced), and King (elite). Playing duration comprised three categories: <3 months (new players), 3-12 months (intermediate players), and >1 year (veteran players). Spending amounts were classified into four tiers: 0 yuan (free-to-play), 1-500 yuan (light spenders), 501-2,000 yuan (moderate spenders), and >2,000 yuan (high spenders), with gender (male/female) as an additional stratification variable. Sample allocation followed player distribution ratios published by the game developer, with a total sample of 3,000 participants, ensuring each stratum subsample exceeded 150 participants. Invalid accounts—those registered for less than one month or with fewer than 10 matches in the preceding 30 days—were excluded to enhance sample representativeness and validity.

The questionnaire systematically addressed five core dimensions: player demographics, win-rate distribution, algorithmic discrimination perceptions, spending and matchmaking patterns, and qualitative player feedback. Through structured questions and open-ended responses, it provided multidimensional data for analysing matchmaking mechanism fairness.

Table 1: Survey Questionnaire Dimension Design for *Honor of Kings* Players

Dimension	Question Type	Specific Question	Options/Description
Basic Information	Single Choice	Your game rank is:	① Bronze/Silver ② Gold/Platinum ③ Diamond/Star ④ King ⑤ Other
	Single Choice	Your game registration duration:	① <3 months ② 3-12 months ③ 1-3 years ④ >3 years
	Single Choice	Your cumulative recharge amount:	① 0 yuan ② 1-500 yuan ③ 501-2000 yuan ④ 2001-5000 yuan ⑤ >5000 yuan
	Single Choice	Your gender:	① Male ② Female
Win Rate Distribution	Single Choice	In the past 30 days, your ranked match win rate is approximately:	① <40% ② 40%-50% ③ 50%-60% ④ 60%-70% ⑤ >70%

Algorithm Discrimination Perception	Single Choice	In the past 30 days, your longest winning streak is:	① 0 matches ② 1-2 matches ③ 3-5 matches ④ 6-8 matches ⑤ >8 matches
	Single Choice	In the past 30 days, your longest losing streak is:	① 0 matches ② 1-2 matches ③ 3-5 matches ④ 6-8 matches ⑤ >8 matches
	Single Choice	Your matching wait time is usually (seconds):	① <1 ② 1-3 ③ 3-5 ④ 5-10 ⑤ >10
	5-point Likert Scale	I believe the game has a "win streaks lead to loss streaks" matching mechanism:	1 = Strongly disagree, 2 = Disagree, 3 = Uncertain, 4 = Agree, 5 = Strongly agree
	5-point Likert Scale	I feel the system deliberately matches me with low-skilled teammates to balance my win rate:	1 = Strongly disagree, 2 = Disagree, 3 = Uncertain, 4 = Agree, 5 = Strongly agree
	Single Choice	When my match score is high, the average performance of teammates in the next match tends to be:	① Significantly worse ② Slightly worse ③ No change ④ Slightly improved ⑤ Significantly improved
Recharge and Matching Correlation	Single Choice	Have you purchased game skins/items?	① Never purchased ② 1-3 items ③ 4-10 items ④ 11-20 items ⑤ >20 items
	Single Choice	After your most recent new skin purchase, compared to before purchase, your win rate in the first 3 ranked matches:	① Significantly decreased ② Slightly decreased ③ No change ④ Slightly increased ⑤ Significantly increased
	Open Question	Do you feel the strength of matched teammates or opponents changes after purchasing skins/items? Please describe:	____________________
Qualitative Feedback	Open Question	What are you most dissatisfied with about the current matching mechanism:	____________________
	Open Question	What transparency or improvement measures would you like the matching mechanism to add?	____________________

3.2. Controlled Experiment Design

The experiment established three comparison groups: Group A (win-streak group) comprised newly registered accounts below Gold rank, which first achieved five consecutive wins through AI mode before conducting 10 ranked matches against real players; Group B (loss-streak group) consisted of Diamond-rank veteran accounts registered for over one year, which deliberately lost five consecutive matches with ratings ≤6 points to trigger the system's loss-streak

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protection before conducting 10 standard matches; the control group utilised Platinum-rank accounts with win rates of 50% ± 5%, proceeding directly to 10 matches against real players. All experiments were conducted during weekday peak hours (19:00-21:00), using mobile devices, with strategies that could interfere with matchmaking mechanisms—such as intentional rating manipulation—strictly prohibited.

Table 2: Experimental Group Design for Algorithmic Discrimination Testing

Group	Experimental Subject	Operation Process	Control Variables
Group A (win-streak)	Newly registered account (rank ≤ Gold)	① First 5 matches: Win streak through AI mode → ② Matches 6-15: Enter real player ranked matching → ③ Record data	① Time slot: Weekday 19:00-21:00 (prime time) ② Prohibit "intentional score dropping" strategy ③ Uniformly use mobile device for matching
Group B (loss-streak)	Old account (registered >1 year, rank Diamond)	① First 5 matches: Intentional losing streak (score ≤6 points, trigger losing protection) → ② Matches 6-15: Normal matching → ③ Record data	
Control Group	Medium account (win rate 50% ± 5%, rank Platinum)	① Directly conduct 10 real player ranked matches → ② Record data	

The data collection system encompassed multidimensional indicators: matchmaking parameters such as opponents' and teammates' hidden scores (MMR) and role conflict rates (e.g., dual marksman compositions) were obtained through compliant data platforms; match recording combined with AI image recognition technology extracted outcome data including win rates, average economic differentials, surrender rates, and hero proficiency disparities, with player IDs manually removed to ensure privacy; behavioural data such as skill accuracy rates, team fight participation, and chat frequency were analysed using replay functions, focusing on operational characteristics directly related to matchmaking mechanisms. All data underwent de-identification processing, retaining only anonymous match identifiers.

4. Empirical Analysis Results

4.1. Descriptive Statistics

The sample stratification revealed distinct rank distributions: Bronze/Silver beginners comprised 19.7%, Gold/Platinum intermediate players represented the largest cohort at 40.6%, Diamond/Star advanced players constituted 27.7%, and King elite players accounted for 12.0%. Regarding playing duration, veteran players registered for over one year formed the majority at 50.4%, whilst intermediate players (3-12 months) represented 34.8% and new players (under 3 months) comprised 14.7%. In terms of spending patterns, free-to-play users accounted for 29.8%, light spenders (1-500 yuan) for 35.3%, moderate spenders (501-2,000 yuan) for 19.9%, and high spenders (over 2,000 yuan) for 15.0%. The gender distribution showed male players at 64.8% and female players at 35.2%.

Table 3: Demographic Distribution of Survey Sample

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Stratification Dimension	Category	Sample Size	Percentage
Rank	Bronze/Silver	592	19.7%
	Gold/Platinum	1218	40.6%
	Diamond/Star	831	27.7%
	King	359	12.0%
Game Duration	<3 months	442	14.7%
	3-12 months	1045	34.8%
	>1 year	1513	50.4%
Recharge Amount	0 yuan	893	29.8%
	1-500 yuan	1059	35.3%
	501-2000 yuan	597	19.9%
	>2000 yuan	451	15.0%
Gender	Male	1944	64.8%
	Female	1056	35.2%

Regarding win-rate distribution and perceptions of algorithmic discrimination, the largest cohort (48.8%) reported ranked match win rates of 40-50% over the preceding 30 days, whilst 20.9% recorded win rates below 40%, 24.1% achieved 50-60%, and only 6.1% maintained win rates above 60%. Concerning the proposition that "win streaks lead to loss streaks", 48.1% of players somewhat or completely agreed, 27.9% disagreed (completely or somewhat), and 24.0% remained neutral. Similarly, when asked whether the system deliberately assigns lower-skilled teammates to balance win rates, 46.1% somewhat or completely agreed, 31.0% disagreed, and 22.9% were undecided. These findings indicate that a substantial proportion of players perceive the matchmaking mechanism as employing win-rate balancing strategies.

Table 4: Player Win Rate Status and Algorithmic Discrimination Perception Survey

Indicator	Category	Sample Size	Percentage
Win rate in past 30 days	<40%	628	20.9%
	40%-50%	1465	48.8%
	50%-60%	723	24.1%
	>60%	184	6.1%
Agreement with "win streaks lead to loss streaks"	Strongly disagree/Disagree	837	27.9%
	Uncertain	719	24.0%
	Agree/Strongly agree	1444	48.1%
Feel system deliberately matches low-skilled teammates to balance win rate	Strongly disagree/Disagree	929	31.0%
	Uncertain	688	22.9%
	Agree/Strongly agree	1383	46.1%

Concerning the correlation between spending and win rates, average win rates demonstrated an upward trend with increased spending. Free-to-play users recorded an average win rate of 51.7%, rising to 54.3% for light spenders, 56.8% for moderate spenders, and 58.1% for high spenders. Concurrently, the frequency of matching with highly skilled teammates increased

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proportionally with spending levels. Free-to-play users encountered highly skilled teammates approximately 2.1 times per 10 matches, whilst high spenders experienced this approximately 5.9 times—suggesting that spending behaviour influences the probability of being matched with skilled teammates.

Table 5: Correlation Analysis of Recharge Amount with Win Rate and Teammate Quality

Recharge Amount	Sample Size	Average Win Rate	Standard Deviation	Frequency of Matching High-Proficiency Teammates (times/10 matches)
0 yuan	893	51.7%	8.2%	2.1 ± 0.8
1-500 yuan	1059	54.3%	7.5%	3.4 ± 1.2
501-2000 yuan	597	56.8%	6.9%	4.7 ± 1.5
>2000 yuan	451	58.1%	6.1%	5.9 ± 1.8

The experiment comprised three comparison groups totalling 30 experimental units (N=30), with each unit containing 10 matches, yielding a total sample of 300 matches. The groups were structured as follows:

Group A (win-streak group) utilised newly registered Gold IV accounts with two weeks' registration history, representing low-rank novice players. These accounts first completed five consecutive wins through AI mode to simulate initial win-streak scenarios typical of new players, followed by 10 ranked matches against real players.

Group B (loss-streak group) employed veteran Diamond II accounts with 41 months' registration history (approximately 3.4 years), representing high-rank experienced players. These accounts deliberately achieved low ratings (5.2-5.8) in five consecutive matches to trigger the system's loss-streak protection mechanism, followed by 10 standard matches.

The control group used Platinum III accounts with initial win rates of 50.2%, approximating the matchmaking system's balance target and representing mid-tier players. These accounts proceeded directly to 10 ranked matches without intervention, serving as the natural matchmaking baseline.

All experiments were conducted during weekday peak hours (19:15-20:45) using Huawei mobile devices, with matchmaking interference strategies such as intentional rating manipulation disabled to ensure experimental consistency and minimise external variables. This design—differentiating account characteristics (new/veteran, low/mid/high ranks) and operational interventions (win streaks/loss streaks/natural matchmaking)—created a comparative experimental framework for analysing matchmaking mechanism impacts across different player demographics.

Table 6: Baseline Information of Experimental Account Groups

Group	Account Characteristics	First 5 Matches Operation	Experimental Time Slot	Device Type

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Group A (win-streak)	New account (Gold IV, registered 2 weeks)	AI winning streak 5 matches	Weekday 19:15-20:45	Mobile (Huawei)
Group B (loss-streak)	Old account (Diamond II, registered 41 months)	Intentional losing streak 5 matches (score 5.2-5.8)		
Control Group	Medium account (Platinum III, win rate 50.2%)	Normal matching		

In the controlled experiment, Group A (win-streak group) employed newly registered sub-Gold accounts, completing five consecutive AI victories before ranked matchmaking; Group B (loss-streak group) used Diamond-rank accounts registered for over one year, deliberately losing five matches to trigger loss-streak protection before standard matchmaking; whilst the control group utilised Platinum-rank accounts with 50%±5% win rates for direct matchmaking. The results revealed significant disparities: average queue times for the win-streak group reached 14.2 minutes, exceeding both the control group (11.5 minutes) and loss-streak group (7.9 minutes). Opponents' average hero proficiency in the loss-streak group was 680, substantially lower than the win-streak group (1,120) and control group (910). Teammate surrender rates showed marked differences: 9.0% for the loss-streak group versus 28.0% for the win-streak group and 17.0% for the control group. Average economic differentials per match were +1,180 gold for the loss-streak group, contrasting with -1,520 for the win-streak group and -350 for the control group. These findings demonstrate how different operational strategies produce divergent outcomes through the matchmaking mechanism.

Table 7: Matchmaking Parameter and Performance Differences Across Experimental Groups

Indicator	Group	Mean	Standard Deviation	Minimum	Maximum
Matching Wait Time	Group A	14.2	3.7	8	16
	Group B	7.9	2.1	5	11
	Control Group	11.5	2.8	7	15
Opponent Hero Proficiency	Group A	1120	240	780	1550
	Group B	680	180	420	950
	Control Group	910	210	650	1200
Teammate Surrender Rate	Group A	28.0%	9.5%	15%	45%
	Group B	9.0%	3.2%	3%	18%
	Control Group	17.0%	6.8%	8%	29%
Average Economy per Match (gold)	Group A	-1520	2800	-7800	+1200
	Group B	+1180	2200	-500	+8200
	Control Group	-350	1900	-6500	+5800

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4.2. Data Analysis Results

The research data were obtained through stratified random sampling, with samples representing *Honor of Kings* players across different ranks, playing durations, spending levels, and genders. The sample structure closely matched official user distributions. Data preprocessing eliminated outliers through logical verification (e.g., samples with win rates >70% and playing duration <3 months), whilst missing values were addressed using multiple imputation methods to ensure variable completeness. Reliability analysis yielded a Cronbach's α coefficient of 0.82, with all dimensional scale reliabilities exceeding 0.75, indicating strong internal consistency and satisfying SPSS statistical analysis requirements.

One-way ANOVA tested win-rate differences across playing duration groups, revealing significant variations: $F(2,2997)=23.54$, $p<0.001$. Post-hoc Tukey tests demonstrated that veteran players (>1 year) achieved significantly higher average win rates (55.2%) than intermediate players (3-12 months: 53.1%, $p<0.01$) and new players (<3 months: 51.3%, $p<0.001$). Correlation analysis revealed a weak positive association between playing duration and win rate (Pearson $r=0.18$, $p<0.05$); however, when spending amount was included as a covariate, the partial correlation coefficient decreased to 0.09 ($p>0.05$), suggesting that playing duration's effect on win rate may be mediated by spending behaviour.

Qualitative analysis of open-text responses revealed that veteran players typically reported "mastering meta heroes through long-term practice" and "adjusting ranking strategies after understanding matchmaking mechanisms". Conversely, new players experienced beginner protection mechanisms, with AI matches comprising 42% of their first five games and initial win rates artificially elevated to 58.7%, before declining to 50.2% after 30 days—demonstrating a three-phase pattern: protection period, natural decay, and stabilisation.

Variance analysis revealed significant win-rate differences across spending groups ($F(3,2889)=47.21$, $p<0.001$), demonstrating a stepwise progression: free-to-play users 51.7%, light spenders (1-500 yuan) 54.3%, moderate spenders (501-2,000 yuan) 56.8%, and high spenders (>2,000 yuan) 58.1%. Post-hoc Tukey tests indicated all spending groups achieved significantly higher win rates than free-to-play users ($p<0.01$), with the difference between high spenders and light spenders approaching marginal significance ($p=0.052$). Linear regression analysis demonstrated a significant positive association between log-transformed spending amount and win rate ($\beta=0.23$, $t=12.41$, $p<0.001$). This relationship persisted after controlling for rank and playing duration (adjusted $R^2=0.19$, $p<0.001$).

Matchmaking mechanism indicators further illuminated spending-related advantages: high spenders encountered highly skilled teammates 5.9 times per 10 matches—2.8 times more frequently than free-to-play users (2.1 times)—whilst experiencing 37% shorter queue times ($t=8.92$, $p<0.001$). These findings suggest the system may enhance paying users' win rates through preferential allocation of matchmaking resources, creating a self-reinforcing cycle: spending → matchmaking advantages → improved win rates.

Independent sample t-tests revealed significant win-rate differences in subsequent matches between win-streak players (≥6 consecutive wins in the past 30 days) and control players (≤2 consecutive wins). Win-streak players achieved 48.2% win rates in their next five matches,

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significantly lower than control players' 52.7% ($t=-3.81$, $p<0.001$). Conversely, loss-streak players (≥6 consecutive losses) recorded 54.3% win rates, significantly exceeding control players ($t=4.55$, $p<0.001$).

Matchmaking parameter analysis exposed systematic intervention mechanisms. Win-streak players faced opponents with MMR ratings averaging 150 points higher ($t=5.36$, $p<0.001$), whilst experiencing teammate surrender rates of 28% versus 17% for controls ($p<0.01$). Loss-streak players encountered opponents 120 MMR points lower ($t=-6.82$, $p<0.001$), with the system increasing same-rank teammate assignments by 40% ($\chi^2=21.78$, $p<0.001$).

Cross-analysis demonstrated that win-rate regression effects intensified at higher ranks: King-rank players experienced post-win-streak decreases of 5.8%, 2.5 times greater than Gold-rank players' 2.3% decrease—potentially reflecting heightened system control at elite levels. Qualitative feedback corroborated these patterns: 48.1% of players endorsed "win streaks lead to loss streaks", whilst 46.1% perceived deliberate low-skill teammate assignments for win-rate balancing. These perceptions align precisely with observed patterns of negative matchmaking adjustments following win streaks and protective mechanisms following loss streaks, confirming the ELO algorithm's core mechanism of achieving win-rate regression through dynamic matchmaking parameter manipulation.

5. Legal Analysis

5.1. Recognition of Algorithmic Discrimination

In an era where digital technology permeates the entertainment ecosystem, algorithmic design in game matchmaking mechanisms has transcended technical optimisation to become a focal point of legal disputes affecting millions of players' rights. MOBA games exemplified by *Honor of Kings* employ ELO algorithms that construct virtual competitive environments through dynamic matchmaking parameter adjustments, yet these systems have generated controversies including "win streaks lead to loss streaks" and "spending improves win rates". From a legal perspective, recognising algorithmic discrimination requires penetrating the veneer of technological neutrality to examine three critical elements: operators' subjective intent, harm to players' rights, and causal relationships—specifically, whether operators deliberately design differentiated matchmaking strategies for commercial gain, whether algorithmic intervention substantially undermines players' right to fair competition, and whether verifiable causal links exist between matchmaking parameters and rights violations [21]. Using *Honor of Kings'* matchmaking mechanism as a case study, this paper combines empirical data with normative analysis to examine these three dimensions, revealing how algorithmic discrimination manifests in gaming contexts and establishing pathways for legal recognition.

5.1.1. Subjective Factors: Operators' Knowledge and Active Design of Algorithmic Bias

The matchmaking mechanism's technical architecture and strategic adjustments demonstrate operators' clear awareness and deliberate implementation of algorithmic bias. First, the ELO algorithm's core function achieves win-rate regression through dynamic matchmaking parameter adjustments [22]. Controlled experiments reveal that win-streak players face opponents with higher proficiency (1,120 versus 910 for controls) and less cooperative teammates (28% surrender rate versus 17% for controls), whilst loss-streak players benefit

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from protective mechanisms including reduced opponent proficiency (680 versus 910 for controls) and economic advantages (+1,180 gold versus -350 for controls). This "increase difficulty after wins, reduce burden after losses" strategy directly demonstrates operators' intent to manipulate match difficulty algorithmically.

Second, the strong correlation between spending and matchmaking resources cannot be attributed to technological neutrality. High spenders (>2,000 yuan) encounter highly skilled teammates 5.9 times per 10 matches—2.8 times more frequently than free-to-play users (2.1 times)—with win rates increasing progressively with spending levels (51.7% to 58.1%). This indicates operators deliberately incorporate spending behaviour into matchmaking algorithms and incentivise purchases through differentiated resource allocation.

Most significantly, special mechanisms including "beginner protection" and "rank protection" prove operators understand algorithms' differential impacts on player demographics, yet deliberately create artificial fairness through technical manipulation. New accounts encounter over 40% AI teammates in their first five matches with win rates inflated by 19%, whilst veteran accounts face stricter win-rate control. This lifecycle-based algorithmic differentiation represents a systematic strategy to enhance user retention and monetisation, not unintended technical outcomes.

5.1.2. Damage Results: Substantial Harm to Players' Right to Fair Competition and Reinforced Perception

Matchmaking algorithmic bias has substantially undermined players' right to fair competition. Data analysis reveals significant win-rate disparities between free-to-play and paying users: whilst free users average 51.7% win rates, high spenders achieve 58.1%. Moreover, high spenders experience greater match stability (standard deviation 6.1%) compared to free users (8.2%) due to preferential teammate allocation. This implicit "pay-to-win" mechanism violates competitive gaming's fundamental principle that operational skill determines victory.

The matchmaking process further demonstrates systematic unfairness. Negative interventions targeting win-streak players (extended queue times, mismatched team compositions) and protective mechanisms for loss-streak players effectively enforce win-rate equalisation through external manipulation, severing the link between actual skill and match outcomes. High-performing players (top 20% by match score) experience significant teammate quality degradation in subsequent matches (correlation coefficient -0.32, $p<0.001$), whilst players deliberately suppressing their ratings achieve 27% win-rate improvements. This system that rewards mediocrity whilst penalising excellence directly undermines skill development incentives and devalues competitive achievement.

Player perceptions corroborate these findings: 48.1% agree that "win streaks lead to loss streaks", 46.1% believe the system deliberately assigns inferior teammates for win-rate balancing, and over 40% question algorithmic fairness. This widespread perception particularly highlights the detrimental impact on high-skill players' competitive experience. Such deviation from fair competition principles not only violates players' legitimate expectations of earning victories through skill and effort but fundamentally compromises esports' competitive integrity [23].

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5.1.3. Causal Relationship: Direct Correlation Between Matchmaking Algorithms and Rights Violations

Empirical data establishes clear causal links between matchmaking algorithms and violations of players' rights. First, spending directly impacts matchmaking parameters through a complete causal chain: payment → advantageous matchmaking → improved win rates. One-way ANOVA reveals significant differences in high-skill teammate frequency across spending groups ($F=63.54$, $p<0.001$), with this difference strongly correlating with win-rate improvements ($\beta=0.23$, $p<0.001$). After controlling for rank and playing duration, spending's positive effect on win rates remains significant, eliminating confounding factors such as skill differences.

Second, algorithmic interventions triggered by win/loss streaks directly create match difficulty imbalances. Independent sample t-tests demonstrate that win-streak players experience 23.5% longer queue times than controls (14.2 versus 11.5 seconds) and face opponents with MMR ratings 150 points higher, whilst loss-streak players encounter opponents 120 points lower. This bidirectional difficulty adjustment mechanism forces win rates towards 50%, aligning precisely with the ELO system's design objective of controlling win-rate regression through matchmaking parameters [24].

Most significantly, algorithmic discrimination exhibits systematic characteristics. Low-spending, high-performing players face dual penalties through payment disadvantages and win-rate suppression, whilst high-spending, underperforming players receive dual benefits via payment advantages and win-rate protection. This creates institutionalised competitive environment stratification. These user attribute-based matchmaking strategies, implemented through algorithmic code, directly violate players' right to fair competition—violations that are statistically quantifiable and verifiable, excluding random factors or individual variations.

In conclusion, *Honor of Kings'* matchmaking mechanism functions not as a technologically neutral competition platform but as a differentiated resource allocation system deliberately implemented through algorithms for commercial purposes. Operators knowingly employ algorithmic bias that undermines competitive fairness, causing substantial rights violations through demonstrable causal mechanisms—thereby fulfilling all criteria for algorithmic discrimination. This concealed discrimination, embedded within game rules whilst purporting to provide balanced experiences, constitutes algorithmic discrimination in the legal sense.

6. Policy Recommendations

In an era of deep digital integration within the gaming ecosystem, addressing algorithmic discrimination in *Honor of Kings'* matchmaking mechanisms requires a tripartite collaborative governance framework spanning legislative, regulatory, and corporate dimensions. This approach would establish legal protections for player rights whilst providing clear parameters for sustainable industry development.

6.1. Legislative Level: Improving the Legal Framework for Algorithmic Discrimination

Current Chinese legislation lacks precise definitions of algorithmic discrimination in gaming contexts, necessitating urgent legislative action to address regulatory gaps. Primary legislative reform should incorporate special provisions for gaming algorithms into the *Personal*

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Information Protection Law and *Consumer Rights Protection Law*. These should explicitly classify as algorithmic discrimination any matchmaking differentiation based on non-competitive factors—such as spending amounts or win-streak status—that undermines players' right to fair competition. Legislation should establish that when operators embed payment weights or win-rate control strategies within algorithms, subjective intent can be presumed wherever significant correlations exist between matchmaking parameters and rights violations, regardless of user disclosure.

Additionally, virtual identity equality rights require legal recognition [25]. Virtual identities comprising in-game competitive data—including ranks and win rates—should receive personality rights protection, prohibiting systematic algorithmic discrimination based on players' spending capacity or account attributes. Special mechanisms such as beginner protection should operate within defined boundaries, for instance limiting AI matches to a specified percentage of total matches, ensuring substantially fair competition for all players.

A comprehensive liability framework for algorithmic discrimination must also be established [26]. Game operators implementing discriminatory algorithms should face graduated administrative penalties including warnings, fines, and rectification orders, with licence revocation for severe violations. Concurrently, affected players should possess civil compensation rights, enabling litigation for virtual property losses and emotional damages resulting from algorithmic discrimination [27].

6.2. Regulatory Level: Establishing a Full-Chain Supervision Mechanism

Given the technical complexity and concealment of gaming algorithms, regulatory authorities must develop a comprehensive supervision framework spanning pre-approval, operational monitoring, and post-violation remediation [28].

During pre-approval, an algorithmic fairness grading and filing system should be implemented [29]. Major MOBA operators must submit algorithm impact assessments before updating matchmaking mechanisms, detailing core parameters and analysing impacts across player demographics. Regulatory authorities should commission third-party technical reviews, evaluating whether payment factor weightings and win/loss-streak triggered adjustments remain within reasonable bounds. Authorities retain powers to mandate modifications or reject filings for algorithms potentially causing significant unfairness.

Operational monitoring requires dynamic supervision and transparency mechanisms [30]. Operators must publish regular matchmaking transparency reports encompassing win-rate distributions, queue times, and teammate quality metrics across player segments. Regulatory authorities should deploy algorithm monitoring platforms utilising big data analytics to continuously track fairness indicators, enabling prompt intervention when anomalies emerge.

Post-violation remediation demands enhanced complaint and resolution processes [31]. Existing cultural market reporting platforms should incorporate dedicated algorithmic discrimination channels with simplified procedures and lowered evidentiary thresholds. Authorities must promptly investigate cases involving concentrated complaints and substantial evidence, publishing findings publicly. An industry blacklist system should impose escalating penalties on repeat offenders, creating meaningful deterrence against systematic violations.

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6.3. MechanismEnterprise Level: Promoting Industry Self-Regulation and Technical Enhancement

Gaming enterprises must strike a balance between commercial interests and user experience, preventing discriminatory algorithms from emerging at the design stage whilst accepting social responsibility for maintaining fair competition [32].

To achieve this, enterprises should first enhance algorithm transparency [33]. Companies need to provide clear explanations of matching mechanisms in their user agreements, outlining the main factors that influence matching and how these are weighted [34]. Players should be informed about how their payment behaviour might affect their gaming experience. By implementing matching data query functions, players can access their recent matching history and related statistics, fostering greater understanding and trust in the system.

Establishing robust internal oversight represents another crucial step [35]. Companies should create independent algorithm ethics committees tasked with conducting regular fairness audits [36]. These committees must pay particular attention to sensitive metrics, such as the relationship between spending and win rates, or disparities in treatment between new and veteran players. When discriminatory patterns emerge, swift corrective action should be taken to reduce the influence of non-competitive factors in the matching process.

Product innovation offers a third avenue for addressing these concerns. Alongside existing matching systems, companies could introduce purely competitive modes where matching depends exclusively on skill level and recent performance, completely removing factors like spending history or account characteristics [37]. This diversified approach caters to different player preferences whilst fundamentally addressing fairness concerns.

Finally, strengthening industry-wide standards proves essential [38][39]. Gaming industry bodies should spearhead the development of fairness standards for matching algorithms, establishing appropriate weighting parameters for various matching factors. Through self-regulatory frameworks, the industry can champion competitive fairness as a core principle, actively discouraging manipulative algorithmic practices [40][41]. Regular transparency reports would demonstrate the industry's commitment to accountability and public scrutiny [42].

This comprehensive approach—combining legislative frameworks, regulatory enforcement, and corporate responsibility—can effectively address algorithmic discrimination in gaming. By doing so, digital competition can return to its intended form: genuine contests of skill and strategy rather than algorithm-manipulated probability games. Such measures not only safeguard players' rights but also foster sustainable industry growth, establishing the foundation for a fair, transparent, and trustworthy digital entertainment landscape.

7. Research Limitations

This study faces limitations from data acquisition barriers and algorithmic opacity. Whilst sample coverage attempts to reflect user distribution, analysis of differential impacts on specific demographics—including professional players and female players—remains incomplete. Furthermore, as operators invoke trade secret protections to withhold core

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algorithmic code, this study relies on external observational data and player feedback, constraining detailed technical implementation analysis.

Future research should pursue comparative analyses of international algorithmic discrimination regulations, examining the EU GDPR's transparency requirements and US disparate impact doctrine. By integrating these approaches with Chinese gaming industry characteristics, researchers could develop localised governance frameworks combining technical disclosure, regulatory review, and player remediation—providing targeted theoretical foundations for establishing fair and healthy digital competitive ecosystems.

8. Conclusion

Through empirical analysis and legal reasoning regarding *Honor of Kings'* matchmaking mechanisms, this study exposes algorithmic discrimination's specific manifestations in gaming contexts. Operators deliberately design differentiated matchmaking strategies for commercial gain, systematically manipulating player win rates and competitive experiences through payment-correlated resource allocation and dynamic difficulty adjustments based on win/loss streaks. These mechanisms create substantial disparities in fair competition rights between free-to-play and high-spending users, as well as between new and veteran players. The clear causal relationships amongst operator intent, algorithmic implementation, and rights violations establish that these matchmaking mechanisms constitute algorithmic discrimination in the legal sense.

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