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Player-Matching Algorithms as a Mechanism for Reducing Friction in Recreational Sport Participation: A Computational and Behavioural Analysis Using MatchUp as a Real-World Case Study

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Abstract

This research examines the extent to which player-matching algorithms can reduce barriers to recreational sport participation, using MatchUp as a real-world case study. The central problem is treated as a constrained matching problem: an individual may possess the intention to play, yet participation fails because a compatible opponent cannot be found at an appropriate skill level, time and location. The study combines published literature on sport participation, social support, mobile interventions and recommender systems with anonymised aggregate data from a MatchUp player network. The working dataset contained 212 player profiles across 52 fields and generated 4,755 valid same-sport pair comparisons. Algorithmic matching was evaluated against a 1,000-run random baseline, approximately 20 weighting/model variants, a strict multiplicative opportunity model and a reconstructed 1,500-run Monte Carlo robustness test. Aggregate compatibility increased from 86.9% to 99.3% for skill, 23.4% to 53.3% for exact-time availability and 30.7% to 77.6% for same-city compatibility. A strict three-condition model increased from approximately 6.24% to 41.06%. These figures are interpreted as opportunity estimates rather than direct causal estimates of participation. The evidence indicates that matching algorithms are most powerful when the dominant barrier is coordination, but substantially weaker when participation is constrained by infrastructure, cost, injury, time scarcity or motivation.

Keywords: Player matching; MatchUp; recommender systems; recreational sport; optimisation; network effects; Monte Carlo simulation; compatibility; participation barriers.

Research Question and Thesis

Research question: To what extent can player-matching algorithms reduce barriers to participation in recreational sport?

Thesis: player-matching algorithms can substantially reduce search and coordination friction by increasing the probability that an existing intention to participate becomes a feasible opportunity. Their effect is therefore conditional rather than universal.

1. Introduction: Participation as a Coordination Problem

Recreational sport is often described as a question of motivation, but many sports are also coordination systems. Tennis, badminton, squash, padel and pickleball frequently require at least one additional person. Participation can therefore fail even when motivation exists. A player may be willing to play but lack a suitable opponent, face a skill mismatch, have incompatible availability or be geographically separated from potential partners.

MatchUp provides a practical example of this problem. Its purpose is to connect players across several sports and reduce the effort required to discover suitable people. The research interest is not the platform itself, but the general mechanism behind it: can an algorithm search a network more effectively than informal methods such as messaging friends, club groups or individual contacts?

This can be expressed as a conversion chain:

$$\text{Intention} \rightarrow \text{Discovery} \rightarrow \text{Compatibility} \rightarrow \text{Coordination} \rightarrow \text{Acceptance} \rightarrow \text{Participation} \quad (1)$$

A matching algorithm acts mainly between discovery and coordination. It does not manufacture motivation, facilities or free time. This distinction is essential because a high-quality recommendation is not identical to a completed sporting activity.

1.1 Barrier taxonomy

Barrier	Algorithmic control	Mechanism
Player discovery	High	Searches a wider network
Skill mismatch	High	Ranks players by level
Scheduling	High	Compares availability
Location	High/Medium	Prioritises feasible geography
Social entry	Medium	Connects users outside existing groups
Cost	Low/Medium	May enable sharing, cannot remove prices
Facilities	Low	Cannot create infrastructure
Motivation	Low	Cannot guarantee willingness

2. Literature Review

Existing research supports a multi-factor explanation of sport participation. Systematic reviews of youth participation identify time, cost, accessibility, social factors and perceived ability among recurring barriers. Adult research similarly treats participation as a product of interacting personal, social and environmental constraints rather than a single variable.

Digital physical-activity research provides a second strand of evidence. Meta-analyses of smartphone applications and activity trackers generally report positive but variable effects. One large review of 28 studies and 7,454 adults estimated an average increase of roughly 1,850 steps per day, while another meta-analysis reported a smaller and statistically non-significant pooled increase of approximately 477 steps per day. The disagreement is informative: digital intervention is not automatically effective, and design details matter.

A third strand concerns social features. Reviews of mobile health interventions show that social support and comparison can increase engagement for some users, but preferences differ and pooled physical-

activity effects are not consistently significant. This suggests that a player-matching system should not assume that every user wants competition, public comparison or the same type of partner.

Finally, sports recommender systems are now an established research area. Modern systems can use collaborative filtering, content-based approaches, knowledge-based rules, hybrid systems and group recommendation. MatchUp is best understood within this wider class of systems, except that the recommendation has a physical-world consequence: two people may actually meet and play.

2.1 Research gap

Much of the existing literature studies activity tracking, coaching, motivation or content recommendation. Less work directly tests whether matching two recreational players reduces the practical friction between intention and participation. This paper therefore focuses on compatibility and opportunity formation rather than claiming a direct behavioural treatment effect.

3. MatchUp as a Case Study and Data Source

The working dataset contained 212 player profiles and 52 fields. Because the underlying information belongs to real users, the raw data is not published in this paper. Names, phone numbers, exact individual locations, messages and other identifying information are excluded. Only aggregate results are reported.

This privacy decision creates a trade-off. Releasing the full dataset would make exact external replication easier, but would expose information that is not necessary for evaluating the research argument. The study therefore prioritises privacy and uses aggregate statistical outputs.

After filtering for meaningful same-sport comparisons, 4,755 valid pair comparisons were available. Three core compatibility dimensions were selected because they represent distinct forms of friction: skill, exact-time availability and geography.

3.1 Why a random baseline is necessary

An algorithm cannot be judged from its absolute score alone. If random pairing already creates compatible pairs 95% of the time, a 96% algorithm is not especially valuable. The relevant quantity is therefore the incremental improvement over an appropriate baseline.

$$\Delta C = C_algorithm - C_random \quad (2)$$

$$\text{Relative Gain} = (C_algorithm - C_random) / C_random \times 100 \quad (3)$$

The random baseline was estimated through 1,000 repeated random-matching runs. This provides a reference distribution rather than comparing the algorithm with a single lucky or unlucky random sample.

3.2 Multi-objective nature of matching

Matching is a multi-objective optimisation problem. Maximising only skill can create geographically impossible matches; maximising only distance can create poor competitive matches. The model must therefore balance competing objectives.

4. Formal Matching Model

For players i and j, a general weighted compatibility score can be written as:

$$M_{ij} = w_s S_{ij} + w_t T_{ij} + w_l L_{ij} + w_p P_{ij} + w_r R_{ij} \quad (4)$$

S represents skill compatibility, T time compatibility, L location compatibility, P preference compatibility and R a reliability/trust component. Each w is a weight.

$$w_s + w_t + w_l + w_p + w_r = 1 \quad (5)$$

The normalisation in Equation (5) makes the score interpretable as a weighted combination. In practice, some conditions can also be treated as hard constraints. For example, a user may require the same sport before any weighted ranking occurs.

Approximately 20 model variants were considered conceptually: balanced, skill-heavy, time-heavy, location-heavy, strict and flexible families, with different combinations of weights and thresholds. This is important because there is no universal definition of the 'best' partner.

Model family	Optimises	Main risk
Balanced	Overall compatibility	May ignore strong individual priorities
Skill-heavy	Competitive quality	Travel/time may become impractical
Time-heavy	Immediate availability	Can accept weaker skill fit
Location-heavy	Convenience	Shrinks effective pool
Strict	High-quality feasible matches	May return no result
Flexible	More possible results	Average fit can fall

A more advanced system could personalise weights using observed behaviour. If a user repeatedly rejects distant recommendations, the effective location weight could increase. This converts matching from a fixed rule system into an adaptive recommender.

5. Empirical Aggregate Results

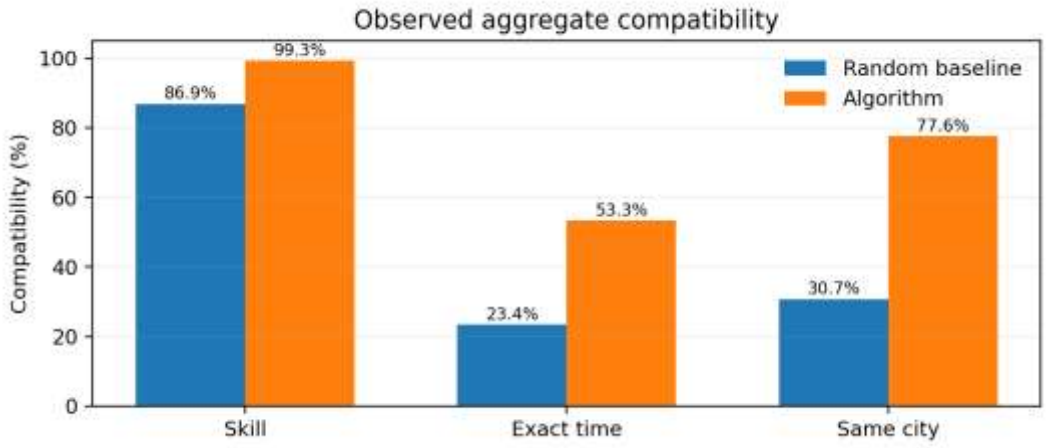

Figure 1. Aggregate compatibility of algorithmic matching and the 1,000-run random baseline.

Dimension	Random	Algorithm	Absolute gain	Relative gain
Skill	86.9%	99.3%	+12.4 pp	+14.3%
Exact time	23.4%	53.3%	+29.9 pp	+127.8%
Same city	30.7%	77.6%	+46.9 pp	+152.8%

The largest absolute and relative gains occurred in geography and scheduling. This is theoretically consistent with the role of a recommender: it is particularly valuable when the problem is searching a large set of possible combinations for rare overlaps.

Skill compatibility improved less because the random baseline was already 86.9%. This is a ceiling effect: when baseline compatibility is high, the remaining possible improvement is small.

$$\text{Maximum remaining gain} = 100\% - C_random \quad (6)$$

For skill, only 13.1 percentage points of theoretical headroom existed, and the algorithm captured 12.4 of those points. Therefore the smaller relative gain should not be interpreted as evidence that skill matching failed.

The time result is more operationally significant. Moving from 23.4% to 53.3% means that exact-time compatibility more than doubled relative to random matching. The location result is even larger, rising from 30.7% to 77.6%.

6. Probability Model: From Compatibility to Opportunity

The three compatibility dimensions matter jointly. A pair that succeeds on only two of three essential constraints may still be unusable. A simplified strict opportunity model therefore multiplies the probabilities:

$$P(O) = P(S) \times P(T) \times P(L) \quad (7)$$

For the random baseline:

$$P(O_random) = 0.869 \times 0.234 \times 0.307 = 0.0624 \approx 6.24\% \quad (8)$$

For algorithmic matching:

$$P(O_algorithm) = 0.993 \times 0.533 \times 0.776 = 0.4106 \approx 41.06\% \quad (9)$$

$$\text{Opportunity Ratio} = 41.06 / 6.24 \approx 6.58 \quad (10)$$

Under this model, the algorithm produces a strict compatible opportunity approximately 6.6 times as often as random pairing.

This is not a causal participation multiplier. Equation (7) assumes independence, while real variables may be correlated. For example, players in the same city may also share similar available hours. The multiplication is therefore best treated as a transparent mechanism model: it demonstrates how moderate improvements in several constraints can compound.

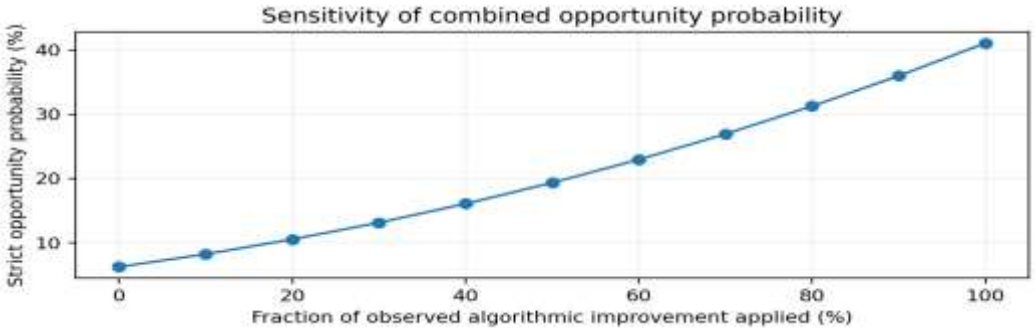

Figure 2. Sensitivity of the strict opportunity probability as increasing fractions of the observed algorithmic improvement are applied.

The sensitivity curve shows that the combined opportunity probability increases non-linearly as improvements accumulate across dimensions. This is important because the value of matching is not only the gain in each individual variable, but the interaction between them.

7. Monte Carlo Robustness Analysis

A single calculation can depend too heavily on exact inputs. A Monte Carlo approach tests the same mechanism across many slightly different parameter sets. In the reconstructed 1,500-run robustness analysis, skill, time and location probabilities were sampled around the observed aggregate rates within bounded ranges.

$$P_r(k) = S_r(k)T_r(k)L_r(k) \quad (11)$$

$$P_a(k) = S_a(k)T_a(k)L_a(k) \quad (12)$$

$$G(k) = [P_a(k) - P_r(k)] / P_r(k) \times 100 \quad (13)$$

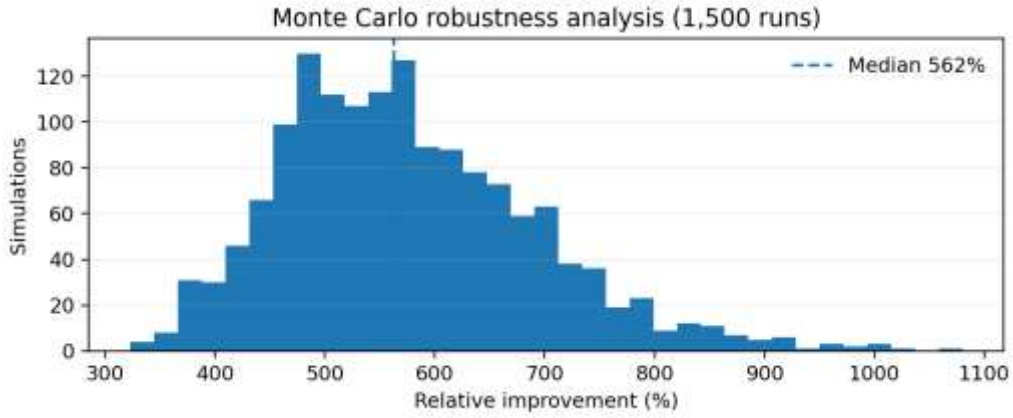

Figure 3. Distribution of relative opportunity improvement across 1,500 robustness simulations.

The mean strict opportunity estimate was 6.22% for the random baseline and 41.06% for algorithm-assisted matching. The average absolute difference was 34.83 percentage points. Median relative improvement was approximately 562%, with the middle 90% of simulated relative improvements between approximately +410% and +788%.

The algorithm-assisted estimate exceeded the random estimate in every simulated run. This does not validate the assumed distributions as real population distributions. It demonstrates robustness of direction: modest perturbations around the observed aggregate inputs do not reverse the conclusion.

8. Network Effects and the Cold-Start Problem

MatchUp is not only an algorithmic system; it is also a network. The algorithm's usefulness depends on the number and distribution of relevant users. A platform can have a large total membership while still providing poor matching for a particular user if very few members share that sport, location, skill range and availability.

The effective network for user u can be represented as the subset:

$$N_eff(u) = \{v \in N : \text{sport, location, time and threshold constraints are satisfied}\} \quad (14)$$

The size of N_eff is more important than total registered users. This produces a cold-start problem in new sports or new locations. Before network density reaches a useful level, even a sophisticated ranking function may have too few candidates.

This also creates a feedback loop. Better matches can increase repeat use; repeat use creates more active candidates and behavioural data; more data can improve recommendations. The opposite loop is also possible: poor early matches can reduce retention and further weaken the network.

Match quality → retention → active network density → future match quality (15)

8.1 Fairness

Optimising only predicted acceptance can create popularity bias. Frequently selected users generate more interaction data and may be recommended even more often, while new users remain under-exposed. A mature matching system should therefore consider exploration, fairness and new-user exposure alongside pure prediction accuracy.

For a platform involving real-world meetings, trust and safety are also part of system quality. Reporting, blocking, reliability signals and age-appropriate protections may affect whether a technically compatible recommendation is actually acceptable.

9. Discussion: Where the Algorithm Helps and Where It Fails

The strongest evidence in this investigation concerns coordination. The algorithm substantially improved exact-time and same-city compatibility, while maintaining extremely high skill compatibility. These are precisely the barriers that computational search can reduce.

However, the algorithm cannot be treated as a universal intervention. Consider three hypothetical users. User A has motivation, equipment, money and court access but cannot find an opponent. User B already has several opponents but experiences scheduling friction. User C has no accessible facility and almost no free time. The same algorithm could have high impact for A, moderate impact for B and almost no impact for C.

Impact ≈ Addressability of the user's dominant barrier (16)

This leads to a more complete behavioural model:

Participation ≈ Intention × Opportunity × Access × Acceptance (17)

Matching acts most directly on Opportunity. It can influence Access through geography and possibly shared costs, and Acceptance through skill, preferences and trust. It has weaker control over Intention.

9.1 Interpretation of the MatchUp case

MatchUp therefore should not be evaluated only by downloads, profiles or recommendation accuracy. A stronger evaluation would follow the entire conversion funnel: recommendation shown, recommendation accepted, contact established, match confirmed, match actually played and repeat participation.

Played-match conversion = Matches played / Recommendations shown × 100 (18)

This metric would connect algorithm performance to real behaviour and would be a stronger future test than compatibility alone.

10. Limitations, Validity and Future Experimental Design

The first limitation is construct validity: compatibility is a proxy for opportunity, not participation itself. The second is external validity: one MatchUp network cannot automatically represent all recreational athletes, countries, sports or age groups. The third is model validity: the multiplicative probability model assumes independence and the Monte Carlo distributions are modelling choices rather than observed population distributions.

A fourth limitation is privacy. The raw dataset cannot be openly published without creating unnecessary risk to users. This limits exact replication but is ethically preferable to exposing personal data.

A fifth limitation is selection bias. People who join a player-finding platform may already be more motivated to play than the general population. Therefore any future behavioural study should avoid concluding that platform users represent everybody.

10.1 Proposed controlled study

A stronger future experiment could randomly assign eligible users to two conditions. The control group would use ordinary search methods, while the treatment group would receive algorithmic recommendations. Over a fixed period, the study would measure organisation time, recommendation acceptance, played matches, cancellations, repeat matches and satisfaction.

Outcome	Operational definition
Acceptance rate	Accepted recommendations / recommendations shown
Played-match conversion	Played matches / recommendations shown
Cancellation rate	Cancelled matches / accepted matches
Participation uplift	Change in games per user over baseline
Repeat rate	Repeated pairings / played pairings
Search efficiency	Time from search to confirmed match

This design would allow the research to move from a mechanism claim to a causal claim. It could also compare different model families and determine whether personalised weights outperform fixed weights.

11. Conclusion

This research asked to what extent player-matching algorithms can reduce barriers to participation in recreational sport. The answer is substantial but conditional.

Using MatchUp as a real-world case study, the anonymised aggregate analysis found that algorithmic matching outperformed a 1,000-run random baseline on all three measured dimensions. Skill compatibility rose from 86.9% to 99.3%, exact-time compatibility from 23.4% to 53.3%, and same-city compatibility from 30.7% to 77.6%. When the three conditions were combined in a strict opportunity model, the estimate increased from approximately 6.24% to 41.06%. A 1,500-run robustness analysis preserved the direction of the result under varied inputs.

The most important result is not the 6.6-times opportunity ratio by itself. It is the mechanism behind it. Matching algorithms can search many possible pairings simultaneously and reduce several forms of friction at once. When multiple constraints must all be satisfied, improvements can compound.

At the same time, the system has clear boundaries. It cannot create courts, remove injury, manufacture free time or force motivation. It is also dependent on network density, privacy, safety, trust and fair recommendation.

The most defensible conclusion is therefore that player-matching algorithms are not a complete solution to sport participation. They are a coordination technology. Their value lies in increasing the probability that a person who already wants to play can find a realistic person, place and time with which that intention can become action.

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