JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 38, XXX-XXX (2022)
DOI: 10.6688/JISE.20220X_38(X).00XX

AI-Enhanced Multi-Criteria Decision-Making in Ultimate Frisbee: Advancing Precision Athlete Evaluation through Grey Relational Informatics

WU-SHIUN Tao[1], SHENG-HSIANG CHEN[2], KAI-LIN HUANG[3] AND CHE-WEI CHANG[3*]

[1]*Department of Ball Sport, National Taiwan University of Sport, No. 16, Sec. 1, Shuangshi Rd., North Dist., Taichung City 404401, Taiwan (R.O.C.)*
[2]*National Taiwan University of Sport, Department of Sport Information and Communication, No. 16, Sec. 1, Shuang-Shih Road, Taichung, 404, Taiwan, R. O. C.*
[3]**National Taiwan University of Sport, Department of Recreational Sport No. 16, Sec. 1, Shuang-Shih Road, Taichung, 404, Taiwan, R. O. C.*
**Correspondence author:* chewei@gm.ntus.edu.tw

This study aims to establish key evaluation criteria for athlete selection in Ultimate Frisbee through a scientifically grounded and systematic framework. First, the origin and historical development of Ultimate Frisbee are reviewed, followed by an analysis of its current global and Taiwanese landscape. The importance of talent selection and the challenges faced in current practices are then discussed. A two-stage selection model is constructed using the Modified Delphi Method and Grey Relational Analysis (GRA). In the first stage, expert consensus is achieved via the Modified Delphi Method to define the selection process and evaluation indicators. In the second stage, GRA is applied to develop a screening procedure, culminating in the construction of a selection matrix based on grey relational degrees and comprehensive athlete evaluation scores. The results reveal that athletes can be categorized into four performance tiers: elite, excellent, advanced, and reserve; based on their physical attributes and grey relational indicators. These classification outcomes provide concrete guidance for team training, resource allocation, and role assignment in Ultimate Frisbee development.

Keywords: Ultimate Frisbee, Sports Talent Identification, Modified Delphi Method, Grey Relational Analysis (GRA)

1. INTRODUCTION

Ultimate Frisbee (UF) originated in the 1970s as a campus-based team sport in the United States, integrating elements from basketball, soccer, and American football. Over time, it has evolved into a competitive team sport that emphasizes physical fitness, technical skills, and tactical coordination [1]. One of its most distinctive features is the self-officiating system, governed by an ethical framework known as the Spirit of the Game (SOTG), which promotes mutual respect, fair play, and conflict resolution without external referees. Athletes are expected to embody this spirit by navigating formal rules and informal norms, thereby fostering a participatory ethic that challenges conventional models of sports governance. As such, UF combines athletic performance with moral reflection, serving not only as a high-intensity sport but also as an educational tool for cultivating ethical awareness and social cohesion [2].

With the establishment of the World Flying Disc Federation and the promotion of international competitions, UF has rapidly gained global popularity [3]. In Taiwan, the sport has developed for over four decades, but it was only officially recognized as a competitive event in 2001. Despite this progress, the general public still largely perceives it as a recreational activity, and systematic standards for competitive athlete selection remain lacking. This gap in systematic selection is a common challenge in sports science. As highlighted in a systematic review by Johnston et al. [4], many sports disciplines still suffer from a "snapshot" approach, relying heavily on isolated physical performance metrics or subjective coaching assessments. This over-reliance on subjective experience is problematic, as coach intuition often lacks the inter-rater reliability and long-term predictive validity necessary for elite selection. Furthermore, focusing solely on singular physiological traits fails to account for the dynamic interactions between technical, tactical, and psychological factors that are intrinsic to multidimensional sports like Ultimate Frisbee. In recent years, as participation rates and competitive levels have increased, the scientific identification of potential athletes has become a critical issue for enhancing team performance and strategic effectiveness.

Athlete selection in UF involves multiple dimensions, including physical attributes, technical skills, psychological traits, and teamwork capabilities. However, current selection practices often rely heavily on coaching experience, lacking objective evaluation tools and data-driven analysis. Identifying key selection indicators and developing a method to screen starting players that align with team efficiency and tactical needs has become a pressing challenge for coaches. This study proposes an analytical matrix model for athlete selection, offering an objective framework to comprehensively assess player performance and assist coaches in identifying elite starting players. First, the Modified Delphi Method is employed to integrate expert opinions and determine the core selection indicators for UF athletes. Subsequently, Grey Relational Analysis (GRA) is applied to construct a selection indicator matrix, providing coaches and team managers with concrete, data-informed selection criteria.

2. LITERATURE REVIEW

2.1 Athlete Selection Methods

Research on athlete selection has employed various methodologies, including cross-sectional surveys, literature reviews, descriptive studies, and conceptual analyses, to reveal the limitations of current selection mechanisms and propose future directions. Kaynar [5] through cross-sectional surveys and semi-structured interviews, found that most athletes in Turkey had not undergone formal selection testing, with selection largely based on natural observation. He recommended integrating physical, psychological, physiological, and genetic assessments to enhance scientific rigor. Extending this empirical approach, Suryadia [6] adopted a descriptive study combined with the “Sport Search” model to validate early talent identification in grassroots physical education, emphasizing the role of teacher involvement and purposive sampling in talent development. Muniroglu and Subak [7] conducted a literature review based on Bompa’s three-stage model to construct a systematic selection framework, integrating physiological, psychological, skill-based, and genetic as-

sessments, and introducing several international standardized tools to reinforce the scientific foundation of selection. Baker et al. [8] and Barraclough et al. [9] through narrative reviews, critiqued prevailing assumptions in athlete selection, highlighting the neglect of nonlinear development and environmental influences. They advocated for longitudinal, multidisciplinary, and ecologically valid testing designs, distinguishing between symbolic and sample-based assessments to improve predictive validity. Ko [10] employed historical and policy analysis to review Korea's 30-year KISS selection strategy, demonstrating how institutionalized selection and tool development contribute to national athletic competitiveness. Bar-Eli et al. [11] used conceptual analysis to integrate subjective evaluations, objective testing, and big data analytics, critiquing traditional heuristic selection for its susceptibility to bias. They proposed cross-method integration and algorithmic modeling to build more systematic and predictive selection frameworks.

Collectively, these studies suggest that future athlete selection should move toward multi-source data integration, long-term tracking, and ecological rationality to improve the accuracy of potential identification and decision-making effectiveness. However, several methodological limitations persist. Cross-sectional designs often overlook long-term and nonlinear athlete development and suffer from limited sample representativeness and temporal relevance. Literature reviews, while integrating diverse models, may struggle to translate heterogeneous data into operational tools. Heuristic and subjective selection methods are prone to cognitive bias and lack standardized procedures. Psychological testing faces ethical and practical challenges, particularly in grassroots implementation. Institutionalized selection improves efficiency but may lack flexibility to adapt to emerging sports and societal changes. Moreover, some testing tools lack sufficient validity to reflect actual athletic performance in selection contexts.

2.2 Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA), proposed by Deng [12], is widely applied in decision-making and performance evaluation across various domains due to its ability to handle small samples and incomplete information systems. In sports research and educational evaluation. Connor et al. [13] demonstrated that stature, 10-m sprint velocity, and lower-body explosive power (jump height) are the primary determinants differentiating selected and non-selected national team players. Their findings suggest that while technical skills are foundational, physiological traits—specifically acceleration—possess high discriminative power in elite selection. This justifies the inclusion of physical and explosive power metrics within our proposed evaluation framework. This aligns with Wang et al. [14], who analyzed trends in football education in Chinese universities, both demonstrating GRA's theoretical value in quantitative analysis. In technical performance evaluation, Zhu & Wang [15] analyzed trampoline scores from the Tokyo Olympics, identifying "flight time" and "difficulty level" as key performance factors. Their findings complement Chen et al. [16], who studied the second support phase in women's discus technique, jointly validating GRA's potential in technical diagnostics and training optimization. Wang [17] further developed a tactical evaluation model for tennis, proposing a "three-stage indicator assessment" to strengthen the link between technical performance and match outcomes, showcasing GRA's predictive power in complex competitive systems. In comprehensive performance evaluation and athlete ranking, Chuang et al. [18] used GRA to predict World

Baseball Classic outcomes, demonstrating its accuracy in competition forecasting. Pradhan [19] applied GRA to rank NBA players based on game statistics, identifying key performance indicators, while Oral [20] analyzed financial performance of Turkish sports clubs, all highlighting GRA's empirical value in sports management and resource allocation.

In digital platform and industry integration analysis, Lan et al. [21] combined GRA with ANP to build a competitiveness model for esports streaming platforms, quantifying factors such as "network externalities," "social demand," and "psychological well-being." This methodology was extended by Sun et al. [22] in their study on the integration of China's digital economy and sports industry, demonstrating GRA's applicability in multi-dimensional strategic analysis and industrial structure identification. Additionally, Yan et al. [23] applied GRA to assess the resilience of public services in rural China, revealing correlations among education, healthcare, and infrastructure. This complements Ecemis et al. [24], who used entropy weighting to evaluate Turkish football teams, both emphasizing GRA's cross-disciplinary potential in identifying systemic weaknesses and enhancing evaluation objectivity.

In summary, GRA demonstrates high precision in technical sports analysis, educational evaluation, and performance forecasting, while also offering robust quantitative support in digital strategy, public service resilience, and industrial integration. Its adaptability to small samples and incomplete data systems underscores its broad applicability and theoretical contribution.

2.3 Modified Delphi Method (MDM)

The Modified Delphi Method (MDM) is an enhanced version of the traditional Delphi technique, omitting the initial open-ended questionnaire in favor of structured surveys to improve efficiency and response rates [25]. Dalkey [26] emphasized the richness of information and reliability of expert opinions, while Murray and Hammons [27] argued that group decision-making surpasses individual judgment. Quartiroli [28] systematically reviewed 5,036 studies from 2000 to 2024, identifying inconsistencies in methodological application and proposing the SEPP (Sport, Exercise, and Performance Psychology) framework to improve design and reporting transparency. Costa [29] conducted a three-round Delphi study with 17 global sport management scholars to explore disciplinary maturity and future development. Sadeqi-Arani and Ghahfarokhi [30] applied MDM during the COVID-19 crisis to develop 94 resilience strategies across marketing, processes, resources, and actions, demonstrating its practical and strategic effectiveness in crisis management. Kuvaldina et al. [31] addressed Olympic sport needs during the Ukraine conflict by engaging 42 experts in three consensus rounds to identify ten priority areas, reinforcing international aid strategies. Parent et al. [32] focused on interpersonal violence in sports, achieving consensus on 49 items through three anonymous rounds with 52 scholars, covering reporting mechanisms and educational interventions to enhance research sensitivity and policy relevance.

Hashemi Mad et al. [33] integrated Fuzzy Delphi with MDM to extract seven core dimensions of public relations competencies among sports education administrators at Islamic Azad University, validated through Likert-scale confirmatory factor analysis, demonstrating its effectiveness in indicator precision and theory-practice linkage. Keegan et al. [34] combined expert workshops and online surveys in defining physical literacy in

Australia, facilitating consensus formation. Quyen [35] applied a hybrid Delphi approach in university governance research, collecting expert input through discussions, questionnaires, and interviews to propose a comprehensive indicator and weighting system. This mixed-method strategy effectively integrates diverse data collection techniques, fosters expert consensus, and highlights MDM's suitability in educational policy and governance research.

3. METHODOLOGY

This study proposes a two-stage athlete evaluation model for selecting UF players for competitive participation. In the first stage, expert consensus is achieved through the Modified Delphi Method (MDM) to identify key evaluation criteria for athlete selection. Experts were recruited based on the following qualifications: over four years of experience in UF, participation in more than five collegiate-level tournaments, and possession of official coaching or refereeing certification. These experts participated in case interviews and literature analysis to consolidate the core selection indicators. In the second stage, Grey Relational Analysis (GRA) was applied to examine the relationship between each indicator and the performance of 20 athletes from the National Taiwan University of Sport. A selection indicator matrix was constructed to assess individual strengths and weaknesses. The overall research process is illustrated in Figure 1.

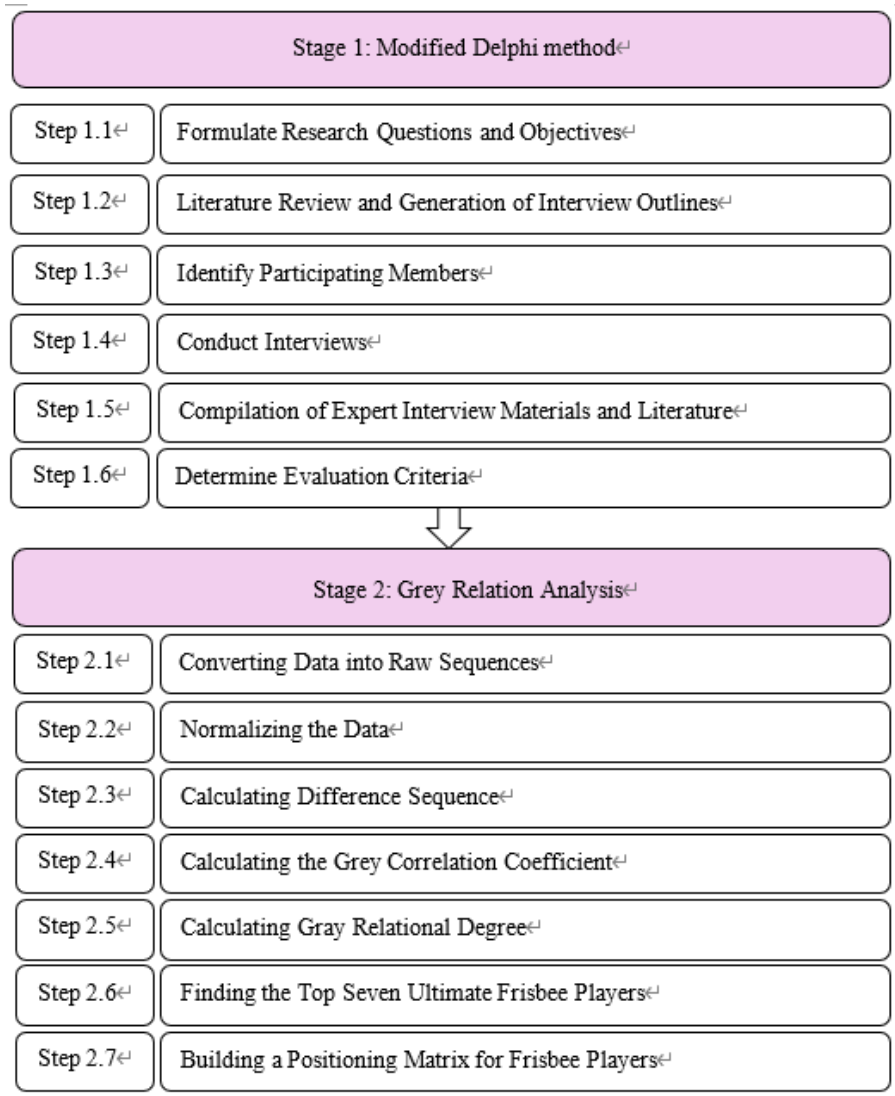


Fig. 1. Research Flow Chart

Stage 1: Modified Delphi Method

In official UF competitions, each team fields seven players. Depending on the division, teams may be composed of all-male, all-female, or mixed-gender groups. In mixed-gender formats, the male-to-female ratio typically follows a 3:4 or 4:3 configuration [3]. The standard playing field is a rectangular area measuring 100 meters by 37 meters. At each end of the field lies an end zone measuring 37 meters by 18 meters. The central area, known as the playing field proper, spans 64 meters by 37 meters. Positioned 20 meters from each end zone line within the playing field are cross-shaped markers referred to as

"Brick Marks," which designate the starting point for out-of-bounds pulls. The field layout is depicted in Figure 2.

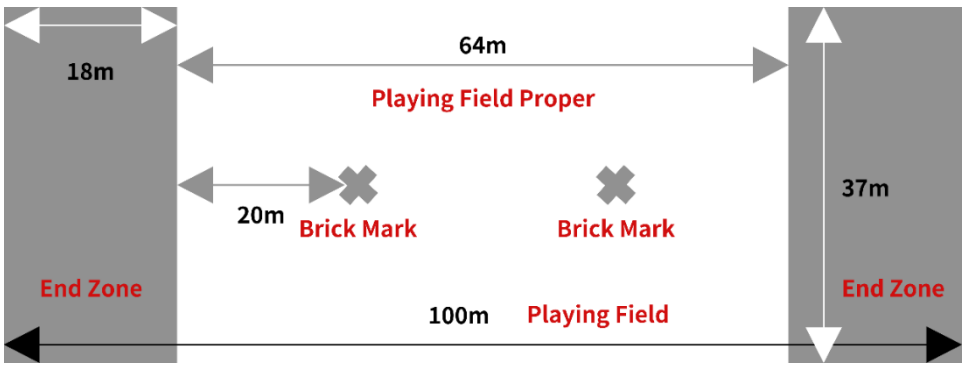


Fig. 2. Ultimate Frisbee Playing Field

First, a comprehensive review and synthesis of literature related to athlete selection in UF was conducted to identify potential evaluation indicators. Subsequently, an anonymous expert consensus technique was employed to gather opinions from coaches and referees with over four years of experience in UF and participation in more than five collegiate-level competitions. All invited experts were required to hold official coaching or refereeing certification in UF to ensure their deep understanding of the sport and professional judgment capabilities.

In an undisturbed setting, expert interviews were conducted to collect evaluations on various athlete selection indicators. Upon completion of all interviews, expert opinions were synthesized, feedback was provided, and revisions were made to reach consensus on the key evaluation criteria for UF athlete selection. This iterative process not only minimizes the influence of individual bias but also enhances the scientific rigor and rationality of the selection indicators through multiple rounds of feedback and refinement.

Step 1.1: Formulate Research Questions and Objectives

The primary research question and objective of this study focus on the in-depth exploration of athlete selection criteria in UF.

Step 1.2: Literature Review and Generation of Interview Outlines

Interview Outline

I. Respondent Background Information

How long have you been involved in UF?

Do you hold any certifications or licenses related to UF?

How many collegiate-level UF competitions have you participated in?

Follow-up: Have you participated in any national or international tournaments?

II. Athlete Selection in UF

In your opinion, what are the primary criteria that should be considered when selecting UF athletes?

Follow-up: Why do you consider these criteria particularly important?

Based on your experience, do you think the current selection standards need improvement? If so, please elaborate.

During the selection process, which do you consider more important—technical skills or physical fitness? Why?

As a coach, which athlete attributes do you value most?

Follow-up: How do these attributes influence performance during competition?

Beyond technical and physical abilities, how significant is psychological resilience in the selection process? Why?

Follow-up: Do you believe an athlete's moral values influence selection decisions?

How important is teamwork in UF? Please provide examples.

Follow-up: Do you think communication skills affect athlete selection?

Have you ever been involved in selecting UF athletes? If so, please share your selection process and experience.

How should experience and potential be balanced in athlete selection? Which aspect should be prioritized?

During selection, how do you assess and measure an athlete's potential?

What common errors or biases do you think may affect the fairness of selection? How can they be avoided?

III. Future Perspectives and Recommendations

What suggestions do you have for the future development of UF selection standards?

How can we more effectively cultivate and select outstanding UF athletes?

Based on your experience, what methods or tools can help improve the accuracy and scientific validity of athlete selection?

Step 1.3: Identify Participating Members

All 10 experts possess over four years of coaching experience and hold official certification. According to literature on the Delphi method, a panel of 8 to 12 experts is considered sufficient to reach high-quality consensus when the participants possess deep domain expertise [36]. This ensures the methodological validity of our indicator selection process. A summary of the participants is presented in Table 1.

Table 1. Participants in the Modified Delphi Method

Expert ID	Certification Held	Years of UF Experience	Number of Collegiate-Level Competitions
A	Coach Certificate	11	36
B	Referee Certificate	7	10
C	Coach & Referee Certificate	8	22
D	Coach & Referee Certificate	11	28
E	Coach Certificate	5	8
F	Coach Certificate	6	10
G	Coach Certificate	5	10
H	Coach Certificate	6	8
I	Referee Certificate	6	11
J	Referee Certificate	8	20

Step 1.4: Conduct Interviews

Expert A: In UF, I believe team identification is crucial for players. During matches, short-distance sprints are essential for both offense and defense, so explosive power (EP) is a key attribute. We often face adverse situations, and the ability to withstand pressure and continue scoring becomes a decisive factor.

Expert B: To be a good player, self-management is especially important. This includes perseverance on the field, stress resilience (SR), and maintaining focus and motivation during daily training.

Expert C: Team Spirit (TS) is vital in UF—not only in tactical coordination (Coord.) but also in fostering overall cohesion. Muscular Endurance (ME) is a core capability, as players must sustain high-intensity movement throughout the game. Coord. helps ensure accurate catching and throwing during rapid motion. Maintaining a positive attitude in tense situations boosts team morale. Additionally, short passing is a fundamental skill that enables quick offensive transitions and rhythm.

Expert D: Interception ability is one of the keys to winning in UF. Successfully intercepting the disc can create immediate counterattack opportunities and shift the momentum of the game. Short passing is indispensable for stable offensive progression. Mastering the upside-down throw allows for unexpected passes or scores from unique angles, especially against zone defenses. EP is necessary for quick starts and short sprints to gain advantageous positions. ME supports consistent performance throughout high-intensity matches.

Expert E: Willpower is synonymous with success in UF. Whether facing adversity or enduring long matches, players must maintain a determined mindset. Backhand and forehand throws are foundational skills; mastering them enhances offensive threat. The V-cut running technique, shaped like the letter "V," helps players break free from defenders and create passing opportunities. Communication skills are also critical, especially since players must self-regulate fouls and violations without referees.

Expert F: V-cut movement is a fundamental skill that enables greater tactical flexibility and offensive options. On the field, moral integrity is highly valued—not only as a

respect for the spirit of the game but also as a foundation for mutual trust. Forehand throwing (FT) is indispensable; without it, many game situations cannot be properly executed. In tight matches, strong SR helps maintain composure, and a sense of responsibility ensures full commitment, giving teammates confidence when you're on the field.

Expert G: TS is the foundation of victory in UF. Every coordinated play requires trust and synergy. Layout ability (diving catches) can be unexpectedly impactful. While not essential for every player, those who possess it can energize the team. Maintaining aggressive offense ensures readiness to catch every disc—embodying the "no disc drops, never give up" mentality. ME is vital for sustained performance in high-intensity games. Proficient forehand technique helps break through defenses and improves offensive fluidity and efficiency.

Expert H: Moral integrity is indispensable in UF, especially given the frequent disputes over fouls and violations. TS is the core of success; every throw and cut relies on trust and cooperation. Stable and accurate long throws create more scoring opportunities during offense. Good self-management—including control over physical condition, mindset, and technique—ensures optimal performance throughout the match. As for height, while not the sole determinant of success, it does offer advantages in aerial contests.

Expert I: ME and willpower are foundational for maintaining consistent performance throughout an UF match, which demands continuous running and rapid state transitions. Good Coord. enables precise execution of catching and throwing during high-speed movement, enhancing technical performance. Strong TS and communication skills ensure players can quickly understand each other's intentions, leading to effective collaboration during the game.

Expert J: Layout ability, while not essential, can change the outcome of critical plays and increase the margin of error for teammates' throws. However, it often requires strong EP. Excellent Coord. allows for precise actions during high-speed movement, especially in catching, throwing, and directional changes such as V-cut runs. Regarding height, as in most sports, having a height advantage benefits stride length and aerial contests.

Step 1.5: Compilation of Expert Interview Materials and Literature

Keywords extracted from expert interviews were compiled and merged with frequency statistics from the literature to identify key factors influencing athlete selection in UF. A summary of these factors is presented in Table 2.

Step 1.6: Determine Evaluation Criteria

Based on Table 2, selection indicators mentioned at least four times across both literature and expert interviews were identified as the core criteria for screening UF athletes. To determine expert consensus, we employed a 5-point Likert scale (1 = extremely unimportant to 5 = extremely important) and the interquartile range (IQR) method [37]. An item was deemed to have reached consensus but was removed from the evaluation framework if its IQR was ≤ 0.50 and its average importance score was below 4.00. These ten evaluation indicators—ME, height, EP, Coord., SR, positivity, willpower, forehand, V-cut transition speed (V-Cut T. S.), and TS—were selected for use in the second-stage Grey Relational Analysis (GRA).

Table 2. Literature and Expert Evaluation of Athlete Selection Factors in Ultimate

Frisbee

Dimension	Indicator	Literature Reference	Expert ID(s)	Importance	Quartile Deviation	Deletion or Not
Physical Attributes	ME	[38-39]	C, D, G, I	4.33	0.74	Did not reach a consensus
	Height	[38-40]	H, J	4.36	0.78	Did not reach a consensus
	EP	[38-40]	A, D, J	4.27	0.73	Did not reach a consensus
	Flexibility	[38-39]	—	3.63	0.38	Delete
	Coord.	[38-39]	C, I, J	4.29	0.67	Did not reach a consensus
Psychological Attributes	SR	[41]	A, B, F	4.26	0.65	Did not reach a consensus
	Self-Confidence	[41]	H	3.32	0.33	Delete
	Positivity	[41]	B, C, G	4.16	0.62	Did not reach a consensus
	Willpower	[41]	B, E, I	4.28	0.53	Did not reach a consensus
	Concentration	[41]	B	3.19	0.32	Delete
Throwing Techniques	Forehand	—	A, E, F, G	4.48	0.69	Did not reach a consensus
	Backhand	—	E	2.86	0.36	Delete
	Hammer Throw	—	D	3.19	0.38	Delete
	Long Throw	—	H	3.32	0.35	Delete
	Short Pass	—	C, D	3.52	0.41	Delete
Defense / Movement Ability	10-Meter Sprint	[40-41]	A	3.62	0.43	Delete
	V-Cut T. S.	[40]	E, F, J	4.21	0.63	Did not reach a consensus
	Interception Ability	—	D	3.67	0.41	Delete
	Layout Ability	—	G, J	4.28	0.43	Delete
	T-Test Agility	—	—	2.66	0.26	Delete
Ethics and Personal Traits	TS	[41]	A, C, H, G, I	4.57	0.78	Did not reach a consensus
	Sense of Responsibility	[41-42]	F	3.81	0.43	Delete
	Moral Integrity	[41, 43]	H, F	3.55	0.42	Delete
	Communication Skills	—	E, I	3.81	0.39	Delete
	Self-Management	[41]	B	3.82	0.36	Delete

Stage 2: Grey Relational Analysis (GRA)

Based on literature and expert input, ten key evaluation indicators for UF athlete selection were identified. In this stage, Grey Relational Analysis (GRA) was employed to objectively calculate the grey relational degree for each athlete, evaluating 20 UF players

from the National Taiwan University of Sport. The grey relational degrees were then used to construct a selection matrix for athlete evaluation. The procedure is outlined as follows:

Step 2.1: Converting Data into Raw Sequences

The expert opinion sequences were averaged using the following formula:

$$X_0 = (1 + 2 + \cdots + N) / N \quad (1)$$

Athlete data for the ten selection criteria—ME, height, EP, Coord., SR, positivity, willpower, FT, V-Cut T. S., and TS—were averaged and compiled. A summary of the raw data is presented in Table 3.

Table 3. Conversion of Data into Raw Sequences

UF Players	ME	Hight	EP	Coord.	SR	Positivity	Willpower	Forehand	V-Cut T. S.	TS
1	7.333	7.000	7.666	7.666	6.666	8.333	8.666	9.333	9.333	7.666
2	6.336	9.000	6.333	5.333	5.666	7.333	7.000	7.000	6.666	7.000
3	6.000	6.000	5.666	4.666	5.000	7.333	7.666	8.000	6.666	8.000
4	7.666	8.000	8.000	7.333	6.666	7.666	7.666	8.333	8.666	7.000
5	4.333	6.000	5.000	5.333	6.000	4.666	5.000	4.333	4.333	7.000
6	4.666	8.000	5.666	5.666	8.000	6.000	6.333	6.666	5.666	7.333
7	5.333	7.666	5.333	5.666	8.333	8.333	7.666	6.666	8.000	7.000
8	6.666	7.000	7.333	7.000	6.666	7.666	7.333	7.333	8.666	7.666
9	6.666	7.666	8.000	7.666	7.333	7.000	7.666	8.333	8.666	7.000
10	6.666	6.666	7.666	7.333	7.000	7.333	6.666	8.333	8.000	7.333
11	6.000	5.000	6.333	6.666	5.000	6.666	6.000	7.000	6.333	6.333
12	7.333	7.000	8.000	7.333	7.000	7.666	7.333	8.000	8.666	7.000
13	7.000	6.000	7.666	7.333	6.333	6.666	6.666	7.333	7.666	7.000
14	6.666	7.000	7.000	7.000	6.666	8.000	8.000	7.333	7.000	8.000
15	6.000	8.000	5.666	7.333	5.666	6.333	6.666	7.666	6.333	5.666
16	7.666	7.000	7.666	6.000	7.333	6.666	7.666	6.000	5.666	6.666
17	4.333	6.333	4.666	4.333	4.000	4.000	4.000	4.000	3.666	6.666
18	4.666	6.333	5.333	6.000	5.666	5.666	5.333	7.333	6.333	4.666
19	6.333	7.000	6.666	6.666	5.333	7.000	7.000	7.666	7.666	8.000
20	6.333	7.000	6.333	5.666	4.666	7.000	6.000	5.333	6.000	6.000

Step 2.2: Normalizing the Data

The ten evaluation criteria for UF athlete selection were normalized using Equations (2) and (3). The data normalization process is divided into three categories:

Benefit Indicators – where higher values are preferable:

$$\gamma_i(j) = \frac{X_i(j) - \min[X_i(j)]}{\max[X_i(j) - \min[X_i(j)]} \quad (2)$$

Where $\max[X_i(j)]$ represents the maximum value of a given criterion.

Cost Indicators – where lower values are preferable:

$$\gamma_i(j) = \frac{\max[X_i(j)] - X_i(j)}{\max[X_i(j)] - \min[X_i(j)]} \tag{3}$$

Where $\min[X_i(j)]$ represents the minimum value of a given criterion.

Target Indicators – where a specific target value lies between the maximum and minimum:

$$\gamma_i(j) = \frac{\left|X_i(j) - X_{ob}(j)\right|}{\max[X_i(j)] - X_{ob}(j)} \tag{4}$$

In this case, $\max[X_i(j)]$ and $\min[X_i(j)]$ are defined as in Equations (2) and (3), and $X_{ob}(j)$ denotes the target value for the j^{th} criterion.

The raw data for the twenty UF athletes were normalized based on the ten selection criteria. The reference sequence for these criteria was defined as: X_0 = (7.666, 9.000, 8.000, 7.666, 8.333, 8.333, 8.666, 9.333, 9.333, 8.000). Normalization was performed using Equation (2), and the results are presented in Table 4.

Table 4. Data Normalization Results

UF Players	ME	Hight	EP	Coord.	SR	Positivity	Willpower	Forehand	V-Cut T. S.	TS
1	0.900	0.500	0.900	1.000	0.615	1.000	1.000	1.000	1.000	0.900
2	0.600	1.000	0.500	0.300	0.384	0.769	0.643	0.563	0.529	0.700
3	0.500	0.250	0.300	0.100	0.231	0.769	0.786	0.750	0.529	1.000
4	1.000	0.750	1.000	0.900	0.615	0.846	0.786	0.812	0.882	0.700
5	0.000	0.250	0.100	0.300	0.462	0.154	0.214	0.062	0.118	0.700
6	0.100	0.750	0.300	0.400	0.923	0.462	0.500	0.500	0.353	0.800
7	0.299	0.667	0.200	0.400	1.000	1.000	0.786	0.500	0.765	0.700
8	0.700	0.500	0.800	0.800	0.615	0.846	0.714	0.625	0.882	0.900
9	0.700	0.667	1.000	1.000	0.769	0.692	0.786	0.812	0.882	0.700
10	0.700	0.417	0.900	0.900	0.692	0.769	0.571	0.812	0.765	0.800
11	0.500	0.000	0.500	0.700	0.231	0.615	0.429	0.563	0.471	0.500
12	0.900	0.500	1.000	0.900	0.692	0.846	0.714	0.750	0.882	0.700
13	0.800	0.250	0.900	0.900	0.538	0.615	0.571	0.625	0.706	0.700
14	0.700	0.500	0.700	0.800	0.615	0.923	0.857	0.625	0.588	1.000
15	0.500	0.750	0.300	0.900	0.384	0.538	0.571	0.687	0.471	0.300
16	1.000	0.500	0.900	0.500	0.769	0.615	0.786	0.375	0.353	0.600
17	0.000	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.600
18	0.100	0.333	0.200	0.500	0.384	0.384	0.286	0.625	0.471	0.000
19	0.600	0.500	0.600	0.700	0.308	0.692	0.643	0.687	0.706	1.000
20	0.600	0.500	0.500	0.400	0.154	0.692	0.429	0.250	0.412	0.400

Step 2.3: Calculating Difference Sequence

Calculate the absolute difference between the reference sequence X_0 and the comparative sequence X_i for the k^{th} criterion,

$$\Delta_{oj}(j) = \left| X_0(j) - X_i(j) \right| \tag{5}$$

$i = 1, 2, \ldots, N; j = 1, 2, \ldots, K$

Using Equation (5), the difference sequences between the twenty UF athletes and the reference sequence were calculated. The results are presented in Table 5.

Table 5. Difference Sequences Between Reference and Comparative Series $\Delta_{0j}(j)$

UF Players	ME	Hight	EP	Coord	SR	Positivity	Will-power	Forehanc	V-Cut T. S.	TS
1	0.100	0.500	0.100	0.000	0.385	0.000	0.000	0.000	0.000	0.100
2	0.400	0.000	0.500	0.700	0.616	0.231	0.357	0.437	0.471	0.300
3	0.500	0.750	0.700	0.900	0.769	0.231	0.214	0.250	0.471	0.000
4	0.000	0.250	0.000	0.100	0.385	0.154	0.214	0.188	0.118	0.300
5	1.000	0.750	0.900	0.700	0.538	0.846	0.786	0.938	0.882	0.300
6	0.900	0.250	0.700	0.600	0.077	0.538	0.500	0.500	0.647	0.200
7	0.701	0.334	0.800	0.600	0.000	0.000	0.214	0.500	0.235	0.300
8	0.300	0.500	0.200	0.200	0.385	0.154	0.286	0.375	0.118	0.100
9	0.300	0.334	0.000	0.000	0.231	0.308	0.214	0.188	0.118	0.300
10	0.300	0.584	0.100	0.100	0.308	0.231	0.429	0.188	0.235	0.200
11	0.500	1.000	0.500	0.300	0.769	0.385	0.571	0.437	0.529	0.500
12	0.100	0.500	0.000	0.100	0.308	0.154	0.286	0.250	0.118	0.300
13	0.200	0.750	0.100	0.100	0.462	0.385	0.429	0.375	0.294	0.300
14	0.300	0.500	0.300	0.200	0.385	0.077	0.143	0.375	0.412	0.000
15	0.500	0.250	0.700	0.100	0.616	0.462	0.429	0.313	0.529	0.700
16	0.000	0.500	0.100	0.500	0.231	0.385	0.214	0.625	0.647	0.400
17	1.000	0.667	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.400
18	0.900	0.667	0.800	0.500	0.616	0.616	0.714	0.375	0.529	1.000
19	0.400	0.500	0.400	0.300	0.692	0.308	0.357	0.313	0.294	0.000
20	0.400	0.500	0.500	0.600	0.846	0.308	0.571	0.750	0.588	0.600

Step 2.4: Calculating the Grey Correlation Coefficient

Calculate the relational coefficient between the reference sequence X_0 and the comparative sequence X_i at j point,

$$\gamma_{0i}(j) = \frac{\Delta\min + \Delta\max}{\Delta_{0j}(j) + \Delta\max} \tag{6}$$

Where: $\gamma_{0i}(j)$ represents the absolute difference between the reference sequence X_0 and the comparative sequence X_i at point j; $\Delta\max = \max_i \min_j \Delta_{0j}(j)$; $\Delta\min = \min_i \min_j \Delta_{0j}(j)$

Using Equation (6), the grey relational coefficients $\gamma_{0i}(j)$ for each athlete were calculated. The results are presented in Table 6.

Table 6. Calculation of Grey Relational Coefficients

UF Players	ME	Hight	EP	Coord.	SR	Positivity	Willpower	Forehand	V-Cut T. S.	TS
1	0.909	0.667	0.909	1.000	0.722	1.000	1.000	1.000	1.000	0.909
2	0.714	1.000	0.667	0.588	0.619	0.812	0.737	0.696	0.680	0.769
3	0.667	0.571	0.588	0.526	0.565	0.812	0.824	0.800	0.680	1.000
4	1.000	0.800	1.000	0.909	0.722	0.867	0.824	0.842	0.895	0.769
5	0.500	0.571	0.526	0.588	0.650	0.542	0.560	0.516	0.531	0.769
6	0.526	0.800	0.588	0.625	0.929	0.650	0.667	0.667	0.607	0.833
7	0.588	0.750	0.556	0.625	1.000	1.000	0.824	0.667	0.810	0.769
8	0.769	0.667	0.833	0.833	0.722	0.867	0.778	0.727	0.895	0.909
9	0.769	0.750	1.000	1.000	0.812	0.765	0.824	0.842	0.895	0.769
10	0.769	0.632	0.909	0.909	0.765	0.812	0.700	0.842	0.810	0.833
11	0.667	0.500	0.667	0.769	0.565	0.722	0.636	0.696	0.654	0.667
12	0.909	0.667	1.000	0.909	0.765	0.867	0.778	0.800	0.895	0.769
13	0.833	0.571	0.909	0.909	0.684	0.722	0.700	0.727	0.773	0.769
14	0.769	0.667	0.769	0.833	0.722	0.929	0.875	0.727	0.708	1.000
15	0.667	0.800	0.588	0.909	0.619	0.684	0.700	0.762	0.654	0.588
16	1.000	0.667	0.909	0.667	0.812	0.722	0.824	0.615	0.607	0.714
17	0.500	0.600	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.714
18	0.526	0.600	0.556	0.667	0.619	0.619	0.583	0.727	0.654	0.500
19	0.714	0.667	0.714	0.769	0.591	0.765	0.737	0.762	0.773	1.000
20	0.714	0.667	0.667	0.625	0.542	0.765	0.636	0.571	0.630	0.625

Step 2.5: Calculating Gray Relational Degree

$$\Gamma_{0i} = \sum_{j=1}^{K} w_j \gamma_{0i}(j) \quad (7)$$

Where w_j represents the weight assigned to the j^{th} evaluation criterion. This study applied an equal weighting scheme because the experts identified these 10 indicators as equally critical core components during the MDM rounds. According to Graefe [44], when indicators are considered of similar importance by domain experts, an equal weighting approach acts as a robust strategy to minimize the risk of statistical overfitting and enhance model stability compared to more complex weighting methods. Research suggests that when indicators are of similar importance, an equal weighting approach is a robust strategy to minimize the risk of statistical overfitting and enhance model stability [44].

Using Equation (7), the grey relational grade Γ_i for each athlete was calculated.

The results are presented in Table 7. Subsequently, the twenty UF athletes were ranked based on their grey relational grades, with the final ranking shown in the rightmost column of Table 7.

Table 7. Grey Relational Grades and Ranking Results of 20 Athletes

UF Players	ME	Hight	EP	Coord.	SR	Positivity	Willpower	Forehand	V-Cut T. S.	TS	Γ_{0i}
1	0.909	0.667	0.909	1.000	0.722	1.000	1.000	1.000	1.000	0.909	0.9116
2	0.714	1.000	0.667	0.588	0.619	0.812	0.737	0.696	0.680	0.769	0.7283
3	0.667	0.571	0.588	0.526	0.565	0.812	0.824	0.800	0.680	1.000	0.7034
4	1.000	0.800	1.000	0.909	0.722	0.867	0.824	0.842	0.895	0.769	0.8627
5	0.500	0.571	0.526	0.588	0.650	0.542	0.560	0.516	0.531	0.769	0.5754
6	0.526	0.800	0.588	0.625	0.929	0.650	0.667	0.667	0.607	0.833	0.6892
7	0.588	0.750	0.556	0.625	1.000	1.000	0.824	0.667	0.810	0.769	0.7587
8	0.769	0.667	0.833	0.833	0.722	0.867	0.778	0.727	0.895	0.909	0.8000
9	0.769	0.750	1.000	1.000	0.812	0.765	0.824	0.842	0.895	0.769	0.8426
10	0.769	0.632	0.909	0.909	0.765	0.812	0.700	0.842	0.810	0.833	0.7981
11	0.667	0.500	0.667	0.769	0.565	0.722	0.636	0.696	0.654	0.667	0.6543
12	0.909	0.667	1.000	0.909	0.765	0.867	0.778	0.800	0.895	0.769	0.8358
13	0.833	0.571	0.909	0.909	0.684	0.722	0.700	0.727	0.773	0.769	0.7599
14	0.769	0.667	0.769	0.833	0.722	0.929	0.875	0.727	0.708	1.000	0.8000
15	0.667	0.800	0.588	0.909	0.619	0.684	0.700	0.762	0.654	0.588	0.6971
16	1.000	0.667	0.909	0.667	0.812	0.722	0.824	0.615	0.607	0.714	0.7537
17	0.500	0.600	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.714	0.5314
18	0.526	0.600	0.556	0.667	0.619	0.619	0.583	0.727	0.654	0.500	0.6051
19	0.714	0.667	0.714	0.769	0.591	0.765	0.737	0.762	0.773	1.000	0.7491
20	0.714	0.667	0.667	0.625	0.542	0.765	0.636	0.571	0.630	0.625	0.6442

Step 2.6：Finding the Top Seven UF Players

Based on the grey relational grade rankings in Table 7, the seven optimal starting UF athletes are players numbered 1, 4, 9, 12, 14, 8, and 10.

Step 2.7：Building a Positioning Matrix for Frisbee Players

This study proposes an athlete selection matrix for UF, integrating the comprehensive evaluation data of 20 athletes derived from Grey Relational Analysis (GRA). The matrix is constructed with the X-axis representing physical attributes and the Y-axis representing grey relational grades. Based on these two dimensions, athletes are categorized into four quadrants: Elite, Outstanding, Advanced, and Alternate, as illustrated in Figure 3. The threshold value of 0.7 for the four-quadrant matrix was determined based on the median values and the statistical distribution of the sample data. This norm-referenced approach is widely used in sports science to effectively differentiate between "high-performing" and "developing" cohorts within a specific population [45]. However, it is important to note that this threshold is specific to the current sample; therefore, practitioners should recalculate and adjust this value based on their own data distributions to ensure the model's contextual accuracy. The definitions and descriptions of each category are detailed below [46]:

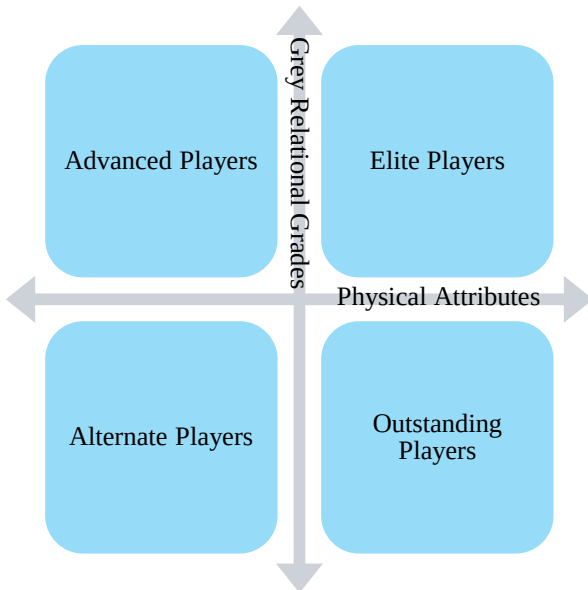


Fig. 3. Selection Matrix for Ultimate Frisbee Contestants

(1) Elite Players

Elite players are the core members of the team, possessing top-tier technical skills, physical fitness, and tactical intelligence. They consistently deliver exceptional performance under pressure and often make decisive contributions during critical moments. These athletes exhibit high physical attribute scores and grey relational grades. Their technical proficiency enables execution of complex maneuvers; their physical capabilities support sustained excellence in high-intensity matches; and their tactical understanding allows for adaptive decision-making and team leadership. Typically, elite players have extensive international experience, having participated in multiple top-level competitions and earned accolades. They are pivotal to team success.

(2) Outstanding Players

Outstanding players demonstrate high potential, though they may not yet have fully realized it. They possess strong technical and physical capabilities and are likely to become future stars. With further competitive experience and tactical training, they can reach elite status. These athletes show moderate grey relational grades and upper-intermediate physical scores. Their technical skills are well-developed, enabling them to handle diverse game scenarios; their physical fitness supports demanding match conditions; and their tactical understanding allows them to execute complex strategies. They have participated in several national-level competitions and possess solid match experience. With continued development, they can evolve into core team members.

(3) Advanced Players

Advanced players exhibit stable technical performance and moderate physical fitness, supported by extensive match experience. They are reliable contributors who provide consistent performance and serve as the backbone of the team. These athletes have moderate physical scores and relatively high grey relational grades. Their technical execution is dependable, allowing them to fulfill tactical roles effectively. While they may not sustain prolonged high-intensity play, they possess sound tactical awareness and on-field decision-making. Having competed in numerous national tournaments, their steady performance ensures competitive stability for the team.

(4) Alternate Players

Alternate players are typically newer team members or those whose technical and physical capabilities have not yet met competitive standards. They require additional training and match experience to elevate their performance level and often contribute during practice sessions or friendly matches. These athletes have lower physical scores and grey relational grades. They possess basic throwing and catching skills, with room for technical improvement; their physical endurance is foundational but needs enhancement to meet match demands. Their tactical understanding is preliminary, with limited application in competitive settings. Most have participated in school-level or community tournaments and require further development to unlock their potential.

This study applies two key indicators—physical attributes and grey relational grade—to conduct a comprehensive performance analysis of the athletes. The grey relational grade reflects the overall evaluation score, while physical attributes represent the most prominent dimension among the five evaluated domains. Based on the analytical results, athletes are classified into four performance categories: Elite, Outstanding, Advanced, and Alternate, as illustrated in Figure 4.

This study conducted an in-depth analysis of participants' overall performance using two key indicators: physical attributes and grey relational grade. The grey relational grade represents the athlete’s comprehensive evaluation score, reflecting their overall performance across multiple criteria. Physical attributes were selected as the primary analytical dimension due to their prominence among the five evaluated domains. Based on the analytical results, athletes were classified into four performance categories: Elite, Outstanding, Advanced, and Alternate, as illustrated in Figure 4. The definitions and descriptions of each category are provided below [47]:

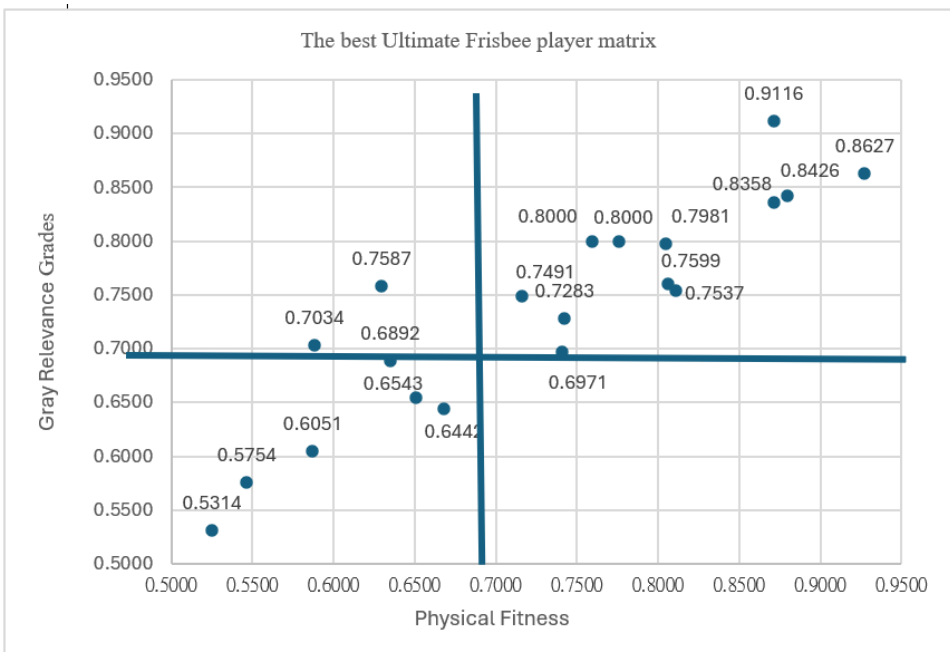


Fig. 4. Ultimate Frisbee player matrix

(1) Elite Players

Located in the upper-right quadrant, elite players exhibit both high physical attributes (approximately 0.8–0.9) and high grey relational grades (above 0.8), indicating outstanding performance in both physical fitness and overall evaluation. These athletes are considered leaders within the cohort. The elite quadrant includes 11 athletes (IDs: 1, 2, 4, 8, 9, 10, 12, 13, 14, 16, 19). Among them, athlete No. 1 achieved the highest grey relational grade of 0.9113 and is recognized as the most outstanding member of a national university UF team—serving as the team's cornerstone. Athlete No. 2, with the lowest score in this group (0.7283), possesses strong physical capabilities and requires further training and match experience to reach full potential. Notably, the university's regular starting lineup includes seven of the top elite players (IDs: 1, 4, 8, 9, 10, 12, 18), who play critical roles in game control and scoring, making them indispensable core members of the team.

(2) Outstanding Players

Positioned in the lower-right quadrant, outstanding players demonstrate relatively high physical attributes (around 0.8) but slightly lower grey relational grades (below 0.7). These athletes outperform most peers in terms of physical fitness, yet still have room for improvement in overall performance metrics. This quadrant includes one athlete (ID: 15), who possesses excellent physical traits and can effectively collaborate with elite players during matches. With enhanced team integration and tactical development, this athlete has the potential to transition into the elite category and contribute more significantly to team success.

(3) Advanced Players

Located in the upper-left quadrant, advanced players show strong performance in grey relational grade (above 0.7) but relatively lower physical attributes (below 0.7). This suggests that these athletes excel in specialized skills or specific domains but require improvement in physical conditioning. The advanced quadrant includes two athletes (IDs: 3, 7), both of whom have extensive match experience and strong team awareness. Although their physical fitness is slightly below that of elite players, their consistent performance and tactical reliability make them valuable contributors to team stability and overall competitiveness.

(4) Alternate Players

Situated in the lower-left quadrant, alternate players score below 0.7 in both physical attributes and grey relational grade (approximately 0.53–0.6), indicating greater room for improvement across all evaluation dimensions. This group includes six athletes (IDs: 5, 6, 11, 17, 18, 20). These players require targeted training to enhance their competitive capabilities, particularly in disc throwing techniques, rule comprehension, and team coordination. With focused development, they can improve their performance and better integrate into the team structure.

Through this four-quadrant analysis, the study effectively identifies the strengths and weaknesses of individual athletes, providing a practical reference for future training strategies and resource allocation. By categorizing athletes based on their performance in physical attributes and grey relational grade, this framework highlights the characteristics and developmental potential of each group. Elite players demonstrate exceptional physical and overall performance, serving as the team's core force; outstanding players possess physical advantages but require further enhancement in comprehensive ability; advanced players contribute stability through technical consistency and experience; and alternates, while currently weaker across indicators, show potential for growth. For instance, athlete ID 15 exhibits high physical traits but a lower Grey Relational Grade due to sub-optimal scores in "Team Spirit" and "Spirit of the Game" indicators. This highlight demonstrates the model's ability to prioritize holistic athlete quality over pure physical dominance. This analysis offers a clear foundation for tiered athlete management and targeted training strategies, enabling more effective resource deployment and elevating overall team performance.

To verify the practical validity of the proposed model, the 7 identified starting players (IDs 1, 4, 9, 12, 14, 8, 10) were compared with the actual coaching decisions during the 2024–2025 competition season. Records indicate that 6 of these 7 athletes (85.7%) were consistently selected for the starting lineup in major tournaments. This high level of congruence suggests that the multi-criteria framework effectively captures the tacit knowledge and empirical judgment of professional coaches, while providing a more objective, data-driven foundation for talent selection.

4. CONCLUSION AND RECOMMENDATIONS

Based on the analytical results of this study, the comprehensive performance of UF athletes was successfully classified into four distinct categories: Elite, Outstanding, Advanced, and Alternate. The findings reveal that elite players exhibit exceptional performance in both physical attributes and grey relational grade, making them suitable as core members of the team. Outstanding players demonstrate strong physical foundations but still have room for improvement in overall evaluation metrics. Advanced players possess strengths in specific skills or performance areas, though their physical conditioning requires enhancement. Alternate players show relatively lower scores in both physical and comprehensive indicators, and thus require targeted training to improve their competitive capabilities.

This clustering-based analytical approach not only facilitates precise identification of individual strengths and weaknesses but also provides a scientific foundation for future athlete selection, training programs, and resource allocation—ultimately enhancing the overall competitiveness of the team. This study contributes to the selection and training of UF athletes in the following three key aspects:

(1) Establishment of a Scientific Selection Evaluation Framework

The proposed four-type athlete classification model integrates physical attributes and grey relational grade indicators to construct a systematic selection framework. This framework enables accurate identification of individual strengths and weaknesses in both fitness and skill dimensions, thereby enhancing the objectivity and precision of the selection process. Moreover, it holds potential for application in other team sports.

(2) Application of Clustering Methods in Athlete Training

The clustering results offer targeted training recommendations: elite players should undergo high-intensity training to maintain their leading status; outstanding players require enhancement of comprehensive capabilities; advanced players should focus on improving physical conditioning; and alternate players need foundational training and skill development. This classification approach supports rational resource allocation, improves training efficiency, and helps the team maximize its potential. Specifically, we now provide tailored training interventions for each quadrant: for instance, athletes in the "High Potential" quadrant (high relational grade but lower physical scores) are recommended for targeted explosive power conditioning, while those in the "Technical Development" quadrant should focus on V-cut agility and throwing precision.

(3) Optimization of Resource Allocation and Team Development

Through athlete clustering analysis, team resources can be allocated more effectively, providing objective guidance for core player development. Based on the characteristics of each athlete category, team managers can allocate training resources more precisely prioritizing elite and outstanding players to boost overall competitiveness, while offering targeted support to advanced and alternate players. This resource distribution strategy contributes to structural optimization and balanced development of team strength.

This study has several limitations. First, the sample was limited to UF athletes from a single national university, with a relatively small sample size, which may affect the external validity of the findings. Consequently, the selection threshold (0.7) derived from this

study should be viewed as a baseline; we recommend that future users and coaches adapt this threshold according to the performance level and data distribution of their respective teams. Future research should expand the sample scope to include athletes from diverse backgrounds to validate the generalizability of the results.

Additionally, the ten selection criteria used in this study were primarily based on expert judgment. While they hold practical value, future studies may consider incorporating data-driven indicators to enhance the comprehensiveness and precision of the evaluation. Although GRA effectively assessed athlete performance, it may overlook interactions among indicators. Furthermore, while the equal weighting scheme applied in this study ensures model stability and minimizes statistical overfitting, it is acknowledged as a limitation that such a scheme might not fully capture 'dynamic importance shifts' between criteria in high-intensity competitive contexts, where certain traits like explosive power may temporarily carry greater strategic weight. Therefore, it is recommended that future research integrate other multivariate analytical methods—such as Principal Component Analysis (PCA) or Analytic Hierarchy Process (AHP)—to further optimize the selection model and improve its predictive validity.

Based on the findings of this study, future research may explore the following directions: Enhancing indicator objectivity and comprehensiveness through big data analytics, identifying representative key indicators from large-scale athlete datasets. Incorporating multivariate analytical methods to address the limitations of GRA in capturing indicator interactions, thereby improving the accuracy and robustness of the model. Adopting longitudinal data tracking to observe the dynamic development of athlete performance over time, enabling more precise selection recommendations. Applying the proposed selection model to other sports disciplines to evaluate its applicability and generalizability, offering a potential avenue for cross-sport validation. Through these explorations, it is expected that the athlete selection system can be further refined, making the selection process more scientific and accurate, and providing a solid foundation for team development and athlete cultivation.

REFERENCES

1. G. Griggs, “The origins and development of ultimate frisbee,” The Sport Journal, Vol. 12, 2009.
2. G. Griggs, “‘This must be the only sport in the world where most of the players don't know the rules’: operationalizing self-refereeing and the spirit of the game in UK ultimate frisbee,” Sport in Society, Vol. 14, 2011, pp. 97-110.
3. World Flying Disc Federation, “WFDF,” 2024. Available: https://wfdf.sport/
4. K. Johnston, N. Wattie, J. Schorer, & J. Baker, “Talent identification in sport: A systematic review,” Sports Medicine, Vol. 48, No. 1, 2018, 97–109. https://doi.org/10.1007/s40279-017-0803-2
5. Ö. Kaynar, “Investigation of talent selection methods in different sports branches,” Journal of Education and Training Studies, Vol. 6, 2019, pp. 44-48.
6. L. E. Suryadia, “Identification of sport talents with the sport search methods,” Journal of Physics: Conference Series, Vol. 1539, 2020, 012043.

7. S. Muniroglu and E. Subak, “An overview of the important points of talent selection in sports,” Research & Investigations in Sports Medicine, Vol. 3, 2018, pp. 1-4.
8. J. Baker, J. Schorer, and N. Wattie, “Compromising talent: issues in identifying and selecting talent in sport,” Quest, Vol. 70, 2018, pp. 48-63.
9. S. Barraclough, K. Till, A. Kerr, and S. Emmonds, “Methodological approaches to talent identification in team sports: a narrative review,” Sports, Vol. 10, 2022, pp. 81.
10. B. Ko, “Sports talent identification and selection in Korea,” International Journal of Applied Sports Sciences, Vol. 26, 2014, pp. 99-109.
11. M. Bar-Eli, R. Lidor, F. Lath, and J. Schorer, “The feudal glove of talent-selection decisions in sport: strengthening the link between subjective and objective assessments,” Asian Journal of Sport and Exercise Psychology, Vol. 4, 2024, pp. 1-6.
12. J. Deng, “Control problems of grey system,” Systems and Control Letters, Vol. 1, 1982, pp. 1-24.
13. J. D. Connor, D. Berkelmans, and K. Doma, “Examining the talent selection determinants of Ultimate Frisbee players selected into a national youth team,” International Journal of Sports Physiology and Performance, Vol. 18, No. 11, 2023, 1263–1268. https://doi.org/10.1123/ijspp.2022-0309
14. X. Wang, Z. Wang, and D. Zhu, “Grey relational degree-based universities football teaching development trend study,” The Open Automation and Control Systems Journal, Vol. 7, 2015, pp. 1589-1592.
15. X. Zhu and L. Wang, “A study on the grey relation analysis between the overall performance and individual event scores of international elite trampolinists,” Frontiers in Sports and Active Living, Vol. 6, 2024, Article ID 1373481.
16. D. Chen, X. Ma, and J. Dong, “Technical diagnosis on elite female discus athletes based on grey relational analysis,” Computational Intelligence and Neuroscience, Vol. 2022, 2022, Article ID 8504369.
17. L. Wang, “Construction of evaluation model of tennis skills and tactic level and application of grey relational algorithm,” Journal of Sensors, Vol. 2022, 2022, Article ID 9446175.
18. C. C. Chuang, T. T. Chen, and C. C. Chen, “Application of grey theory in the construction of impact criteria and prediction model of players’ salary structure,” Mathematical Problems in Engineering, Vol. 2018, 2018, Article ID 7365615.
19. S. Pradhan, “Ranking regular seasons in the NBA’s modern era using grey relational analysis,” International Journal of Sport Finance, Vol. 12, 2017, pp. 31-40.
20. C. Oral, “Financial performance evaluation of sport clubs traded in Borsa Istanbul by using grey relational analysis,” International Journal of Economics and Finance, Vol. 8, 2016, pp. 293-299.
21. T. S. Lan, Y. C. Kuei, Y. H. Lan, and X. J. Dai, “Grey relational analysis of network model for live broadcast platform in e-sports market,” The International Journal of Organizational Innovation, Vol. 13, 2021, pp. 25-36.
22. X. Sun, L. Su, B. Zhou, T. Bu, and Y. Zhang, “Systematic evaluation of integration between China’s digital economy and sports industry: two-stage grey relational analysis and vector autoregressive model,” PLOS ONE, Vol. 19, 2024, e0303572.
23. H. Yan, H. Li, and L. Zhang, “Key influencing factors of rural public service resilience in China: a grey correlation analysis approach,” Environment, Development and Sustainability, 2025.

24. O. Ecemis, F. Akcan, and U. Abakay, "Analysis of the performance of football teams via the entropy-gray relational analysis method: Turkish super league model," Spormetre The Journal of Physical Education and Sport Sciences, Vol. 19, 2021, pp. 51-59.
25. A. Graefe and D. Armstrong, "Predicting baseball game outcomes using a modified delphi method and grey relational analysis," Journal of Quantitative Analysis in Sports, Vol. 7, 2011, Article 5.
26. N. Dalkey, "An experimental study of group opinion: the Delphi method," Futures, Vol. 1, 1969, pp. 408-426.
27. J. W. Murray and J. O. Hammons, "Delphi: a versatile methodology for conducting qualitative research," The Review of Higher Education, Vol. 18, 1995, pp. 423-436.
28. A. Quartiroli, "The Delphi technique in sport, exercise, and performance psychology: extensive scoping review, insights, and recommendations for scholars," Sport, Exercise, and Performance Psychology, Vol. 14, 2025, pp. 57-77.
29. C. A. Costa, "The status and future of sport management: a Delphi study," Journal of Sport Management, Vol. 19, 2005, pp. 117-142.
30. Z. Sadeqi-Arani and E. A. Ghahfarokhi, "Sports business resilience in the COVID-19 crisis: the delphi qualitative approach," Iranian Journal of Management Studies, Vol. 15, 2022, pp. 69-84.
31. O. Kuvaldina, A. Sarkauskiene, and O. Rybak, "Top 10 needs of Ukraine's Olympic sports in hostile conditions: a Delphi study," BMJ Open Sport & Exercise Medicine, Vol. 10, 2024, e001653.
32. S. Parent, et al., "Identifying future research priorities in the field of interpersonal violence (IV) towards athletes in sport: a Delphi study," British Journal of Sports Medicine, Vol. 58, 2024, pp. 1345-1352.
33. R. Hashemi Mad, J. Adabi Firouzjah, R. Saboonchi, and H. Alimohammadi, "Identification of public relations components of physical education managers of islamic azad universities based on fuzzy delphi method," Communication Management in Sport Media, Vol. 9, 2022, pp. 98-114.
34. R. J. Keegan, et al., "Defining physical literacy for application in Australia: a modified Delphi method," in Routledge Handbook of Physical Literacy, Routledge, 2019, pp. 104-118.
35. D. T. N. Quyen, "Developing university governance indicators and their weighting system using a modified Delphi method," Procedia - Social and Behavioral Sciences, Vol. 141, 2014, pp. 828-833.
36. C. C. Hsu, and B. A. Sandford, "The Delphi technique: Making sense of consensus," Practical Assessment, Research, and Evaluation, Vol. 12, No. 1, 2007, Article 10.
37. V. Faherty, "Continuing Social Work Education: Results of a Delphi Survey," Journal of Education for Social Work, Vol. 15, No.1, 1979, pp. 12-19.
38. J. Portillo, A. Bravo-Sánchez, P. Abián, A. Dorado-Suárez, and J. Abián-Vicén, "Influence of secondary school students' physical fitness on sports performance during an ultimate frisbee competition," International Journal of Environmental Research and Public Health, Vol. 19, 2022, pp. 3997.
39. T. A. Murray, "Ranking ultimate teams using a bayesian score-augmented win-loss model," Journal of Quantitative Analysis in Sports, Vol. 13, 2017.
40. J. D. Connor, D. Berkelmans, and K. Doma, "Examining the talent selection determinants of ultimate frisbee players selected into a national youth team," International Journal of Sports Physiology and Performance, Vol. 18, 2023, pp. 1263-1268.

41. N. K. Abu Talip, D. M. M. D. Moksan, and K. Chou, "Borneo ultimate frisbee team: agility and speed in relation with playing position," Jurnal Borneo-Kalimantan, Vol. 5, 2019, pp. 9.
42. M. Humara, "Personnel selection in athletic programs," Athletic Insight: The Sport Journal, Vol. 2, 2000.
43. J. P. Amoroso, J. Valente-dos-Santos, G. E. Furtado, R. Rebelo-Gonçalves, R. Antunes, and L. Calmeiro, "Ultimate frisbee players: characteristics according to their competitive level and spirit of the game," Sports, Vol. 10, 2022, pp. 197.
44. A. Graefe, "Improving forecasts using equally weighted combinations," Journal of Business Research, Vol. 68, No. 8, 2015, pp. 1792-1799.
45. S. J. Robertson, A. F. Burnett, and J. Cochrane, "Tests used for multidimensional selection in youth tennis: Are they reliable, valid, and able to discriminate level?" Journal of Sports Sciences, Vol. 32, No. 14, 2014, pp. 1311-1318.
46. W. S. Chiu, S. Y. Lee, P. C. Shen, T. T. Chen, and C. C. Chen, "Using Delphi technique to construct the elements of the adolescent baseball pitchers selection," Journal of Sport and Recreation Management, Vol. 18, 2021, pp. 44-55.
47. K. L. Huang, "Constructing an athlete selection analysis matrix for ultimate frisbee," Master's thesis, National Taiwan University of Sport, 2025.



Wu-Shiun Tao (陶武訓) is an Associate Professor at Department of Ball Sport, National Taiwan University of Sport, Taichung, Taiwan. He holds a Ph.D from Chinese Culture University. His research interests include sport management, sport science, and sport marketing**.**



Chin-Wei Fan (黃楷霖) received the B.S. and M.S. degrees in Department of Recreational Sport from National Taiwan University of Sport, Taiwan. His research interests include ultimate frisbee, leisure sports, and decision science.



Che-Wei Chang (張哲維) is a professor of Department of Recreational Sport, National Taiwan University of Sport. He specializes in semiconductor quality engineering, robust systems designs, software quality engineering, software evaluation, system evaluation, and grey systems. His paper appeared in International Journal of Advanced Manufacturing Technology, International Journal of Manufacturing Technology and Management, Information and Software Technology, Robotics and Computer Integrated Manufacturing, Production Planning & Control, Computers & Industrial Engineering, Expert Systems with Applications, Information Sciences, Journal of Internet Technology, Applied Sciences, Mathematics, Sustainability, Knowledge Management Research & Practice and others.