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ORIGINAL ARTICLE

A Fuzzy Logic Model for Talent Identification and Selection Indonesian Junior Rowing Athletes

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ABSTRACT

Background. Investigations in talent identification are mostly based on determining effective parameters, more specifically the determination of norms for Indonesian junior rowing athletes. **Objectives.** This research aimed to design a smart model in talent identification and selection for rowing athletes based on the weighting of priority criteria generated from the analytic hierarchy process (AHP) of anthropometric, biomotor, psychological, physiological, and technical variables of fuzzy logic. **Methods.** The method was mixed methods research (MMR), it involves the use of both quantitative and qualitative methods in a study. Furthermore, it selected important criteria through a hierarchical analytical process of anthropometric, biomotor, psychological, physiological, and technical variables. The norms of elite rowing junior athletes aged 16-18 years were used as a comparative index. Furthermore, the smart model is designed based on fuzzy logic using MATLAB software. **Results.** The athletes were categorized into unmatched, semi-matched, matched, brilliant, and rare groups. The fuzzy testing of all talent identification and selection criteria for rowing athletes shows that Indonesian rowing male athletes must be in the "brilliant" classification or equal to 88.5% supported by anthropometric criteria, 10.6% supported by physiological criteria, and 89.4% supported by biomotor criteria. **Conclusion.** Leg height and length, muscle power and leg strength, self-confidence and motivation, specific endurance, catch, drive, and recovery parameters were demonstrated as the main criteria and weighted by the analytic hierarchy process. This smart model analyzes these variables on the norms of elite rowing junior athletes and makes specific results from player talent. Therefore, It is a reliable and useful method for decision-making in talent identification and the selection of rowing athletes at a young age.
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KEYWORDS: ***Rowing, Talent Identification, Fuzzy Logic, Analytic Hierarchy Process.***

INTRODUCTION

Talent identification (TI) is a scientific, measurable, and systematic method of determining an athlete's talents to maximize their potential (1). Talent identification programs are an integral part of the selection process for elite-level athletes (2). In recent years, these programs have grown in popularity and are seen as critical avenues for maximizing athletes' potential to

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achieve success. This is essential as pressure on nations to excel in international sports competitions (3–5). It is common for developed countries to invest millions of dollars in talent development. Also, it has been suggested that effective talent identification programs have the potential to detect talent early, which can act as a vital component of increasing a nation's chances of sporting success (6) . According to (7) these programs can identify outstanding athletes from an early age, thereby concentrating funding and training opportunities on individuals with the greatest potential for success. However, there are still discrepancies between what is proposed and observed in research and practice (8).

Identifying talented athletes in sports is diverse and complex (9). Only one-third of worldwide junior athletes reemerged as seniors, according to the results. This confirms the difficulty of predicting later success based on early talent identification and selection (9). Talent in sports is identified by characteristics that are at least partially determined, influenced by various environmental conditions, and difficult to obtain accurately (10). Moreover, talent in adolescents is recognized in the interaction of innate abilities, demonstrating adult play patterns at an early age and highly sport-specific skills (11).

Researchers are constantly trying to find effective methods to identify the best human resources for the future. This field is widely practiced by people all over the world, and there is fierce competition for success despite limited financial resources. An organization or team that has the desire to remain competitive must recruit and develop human resources before they are taken over by other competitors (2). The challenge is to develop specific test designs that are valid and reliable to determine the current abilities of young athletes in a particular sport, accelerate their development and provide good predictive value for future performance or success (12). Many sports organizations in several countries use talent identification programs, for which there appears to be no clear and consistent variable predicting future success (13–15). This is because the determinants of success in talent identification cannot be found on a single parameter (16). The talent identification process should be carried out in a comprehensive and multidisciplinary manner. Research that has been conducted on anthropometrics on adult male and female rowers today places a lot of emphasis on body mass variables (17, 18) and body size (19) in predicting rowing performance at the international level. Several studies have observed (18, 20) that rowers in open numbers have characteristics of tall stature, heavy body weight, and leanness with a high percentage of muscle that contract slowly (providing endurance rather than strength). Similarly, research on junior athletes suggests that the profile of junior rowers has dimensions of length, height, and weight; their body size is larger than that of the general population of the same age group (21).

In recent years, talent identification research was determined by following the norm measurements of elite players and comparing the results with elites (8). However, coaches struggle with talent identification problems, especially rowing, considering there are too many factors to consider based on the sport's features. A systematic weighting procedure is necessary because the trainer's approach is insufficient, and it is unavoidable that misjudgment is necessary. This is because performance indicators should be determined and analyzed systematically (22).

An Analytic Hierarchy Process (AHP) has been carried out in volleyball concerning talent identification and selection. Meanwhile, intelligent models analyze variables that are compared against elite norms and make specific results from player talent (23). Applying a model based on artificial intelligence algorithms for the processing ability of extremely huge data volumes and the appropriate interpretive capacity can result in a valid method for identifying sports talent (23). Moreover, the scientific selection of badminton players with a literature review and the AHP method was used by many coaches in Taiwan (24).

Nisel (25) presented all research using AHP for exercise-related problems. Meanwhile, Noori and Sadeghi (23) stated that providing appropriate tools and a scientific approach in volleyball talent identification can lead to the rapid detection of sports talent for championships. Lorains, Ball, and MacMahon (26) suggested that decision-making is a key aspect of expert performance in several game sports. According to Budak, Kara, and İç (27), the issue of sports club team formation has become one of the most significant obstacles to being economically and athletically competent.

The use of fuzzy logic becomes important as a decision-making system regarding unclear

criteria. Due to the significant degree of subjectivity in talent identification, the fuzzy logic position seeks to limit the chance for error. Fuzzy logic offers an objective, transparent, and authentic decision-making system. Currently, artificial intelligence, such as fuzzy logic, is possibly used for decision-making processes in talent identification and selection in the rowing sport. Based on the aforementioned issues, this research evaluated the process of assembling criteria, employing the AHP method in priority weighting, and building a decision-making system for rowing athletes by using fuzzy logic in talent identification.

MATERIALS AND METHODS

Participants. Participants in this study were 10 Indonesian national team, junior rowing athletes (age 17 ± 1 year, height 185.5 ± 6.5 years). We assess 10 junior national team athletes using predetermined indicators. Talent indicators have been determined through the AHP process based on previous research (28), Data from this study (28) formulate theories related to indicators and sub-indicators for rowing athletes' talent identification.

Research procedure. Mamdani fuzzy logic modeling is used for decision-making in talent identification of rowing athletes using the toolbox in Matlab software version 2013a from Mathwork Inc. The steps are as follows:

The software contains instruments for designing Mamdani fuzzy logic models. It has five tools often used in designing the desired design. This section describes the steps in the design process for talent identification and selection of rowing athletes.

a. Determining input and output variables in the FIS editor.
b. Forming a fuzzy set.
c. Establishing a membership function.
d. Forming the rule line.
e. Defuzzification process.

RESULTS

Table 1 The operation of the sub-criteria input variables in fuzzy logic modeling includes the sub-criteria in the anthropometric (ANT), physiological (FIS), and biomotor (BIO) variables. The criteria in the selected sub-criteria refer to the results of the AHP (30). Furthermore, two sub-criteria are taken, with the highest priority value from each criterion, as summarized in Table 1.

Table 1. Talent Identification (TI) Sub Criteria

Indicator	Sub Indicator
ANT	Height
	Leg Length
FIS	Aerobic Power
	Aerobics
BIO	Muscle Power
	Squat

The range of the parameters is determined from secondary data, and the number refers to the normative criteria for rowing junior elite athletes. Meanwhile, the output variable range is 0 to 100, which is classified as Unmatched (<10), Semimatched (= 30), Matched (= 50), Brilliant (=70), and Rare (> 90) (Figure 1).

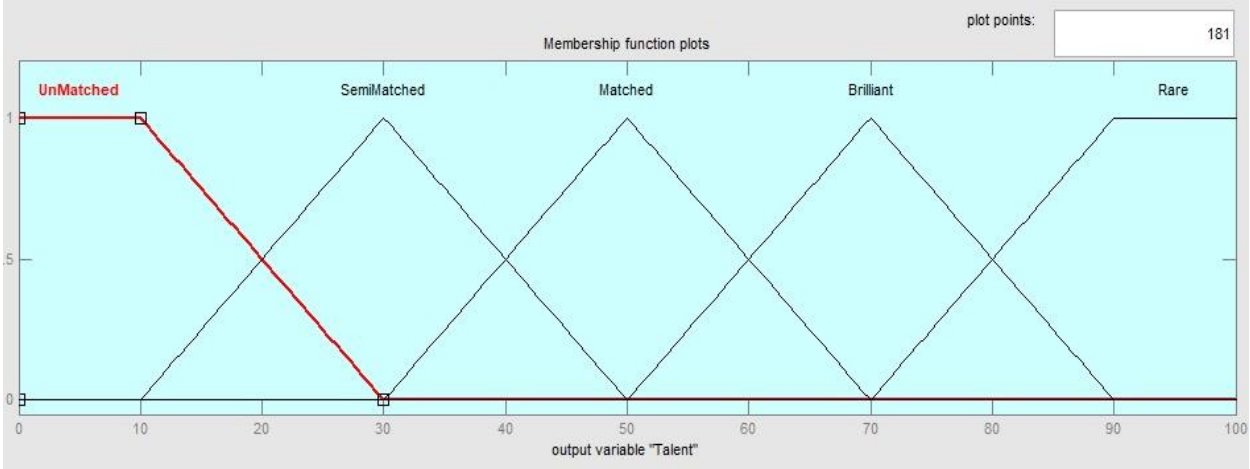


Figure 1. Fuzzy Output Variable Talent

The decision-making step using fuzzy logic is carried out by making operations from the sub-criteria of each input variable. After collecting fuzzy data from the operation, then the input variables for each talent identification and selection indicator are conducted. Furthermore, the results of testing the fuzzy logic design for rowing athletes are as follows:

Testing on Anthropometric Sub Criteria. Anthropometric criteria consisted of height and leg length. The membership function (MFs) can be seen in the fuzzy image display consisting of MFs for height and leg length. The height ranges from 143.3 to 209.3, while MFs of leg length range from 77.6 to 98.6. Further testing is carried out by entering numbers from the actual rowing athlete data (n =10) in the input column of the rule viewer.

From the data entered in the rule viewer, when the athlete's height is 187 cm and the leg length is 102 cm, the talent criteria value is 83.2% or equivalent to "rare". Based on Figure 2, the value of the leg length is recorded as 98.6, meaning that the range in the fuzzy design for the highest level is 98.6. Furthermore, when the data on the athlete is greater than the number in the range, the fuzzy system considers the number to be in the "excellent" criteria. The data in Table 2 is calculated using the fuzzy system.

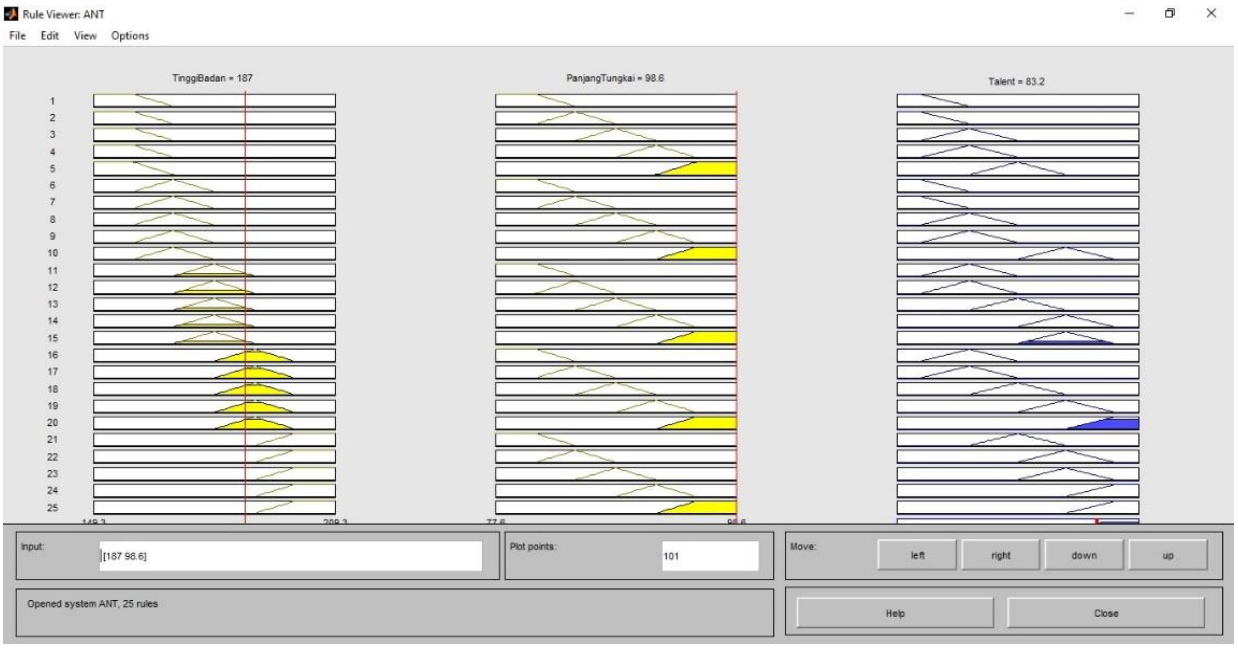


Figure 2. Anthropometric Rule Viewer

Table 2. Recapitulation of Anthropometric Results using Fuzzy Logic

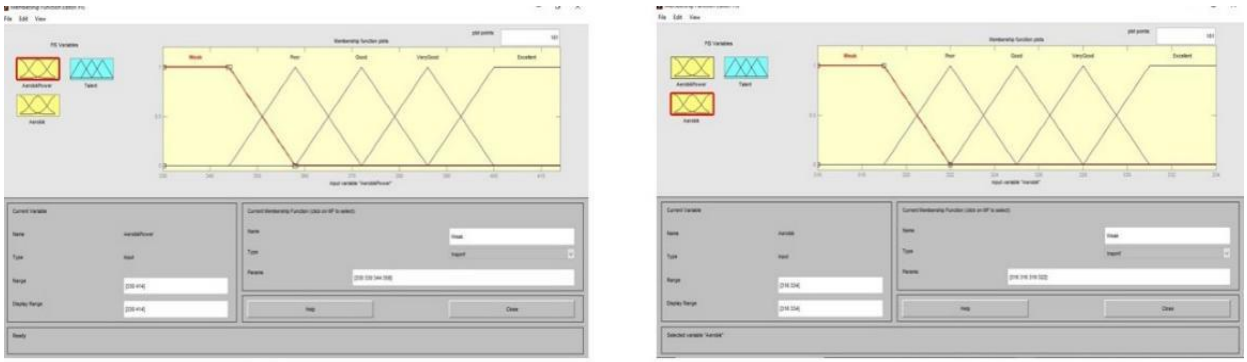
Subject	ANT		Decision (%)	Final Decision
	Height (cm)	Leg Length (cm)		
1	187	102	83.2	**Rare**
2	192	120	88.5	**Rare**
3	184	103	77.1	**Rare**
4	179	100	70	**Rare**
5	182	103	73.8	**Rare**
6	181	103	72.4	**Rare**
7	174	97	70	**Rare**
8	192	120	88.5	**Rare**
9	184	110	77.1	**Rare**
10	181	110	72.4	**Rare**

The results of Table 3 in the decision column (%) help the coach to determine the level in making decisions of each athlete on the anthropometric sub-criteria. Meanwhile, the final decision column is the level of making decisions based on linguistic values, assisting the coach to be more confident in making decisions.

Testing for Physiological Sub Criteria. The sub-criteria for physiology include testing for aerobic power using a fuzzy method, and 10 rowing athletes have been subjected to measurements. Fuzzy design testing on physiological criteria obtained membership functions consisting of an aerobic power range of 330 to 414 [figure 3 (a)] and aerobics ranging from 316 to 334 [figure 3 (b)].

Table 3. Recapitulation of Physiological Results using Fuzzy Logic

Subject	FIS		Decision (%)	Final Decision
	Aerobic Power (watt)	Aerobic (watt)		
1	340	266	10.6	**SemiMatched**
2	329	247	10.6	**SemiMatched**
3	330	252	10.6	**SemiMatched**
4	337	243	10.6	**SemiMatched**
5	249	195	10.6	**SemiMatched**
6	309.4	223.7	10.6	**SemiMatched**
7	279.4	218	10.6	**SemiMatched**
8	282.5	228.3	10.6	**SemiMatched**
9	288.9	267.3	10.6	**SemiMatched**
10	311.1	230.1	10.6	**SemiMatched**



(a) (b)

Figure 3. (a) MFs Aerobic power, (b) MFs Aerobic

Based on Figures 3 (a) and (b), the classification of fuzzy sets in each MFs has linguistic values of Weak (W), Poor (P), Good (G), Very good (VG), and Excellent (EX). The results of the decision level in numerical values can be reviewed using the rule viewer in Figure 4.

From the data entered in the rule viewer, when the athlete's aerobic power is 340 watts and aerobics is 316, the numerical value of the talent is 10.6% or equivalent to the "semi-matched" criteria. As explained in the anthropometric test, the aerobic sub-criteria referring to Figure 4 is recorded as 316. Therefore, the range in the fuzzy design for the lowest level based on Figure 4 on aerobics is 316. The fuzzy system assumes the number is in the "weak" criteria when the data on the athlete is smaller than the minimum range. Table 3 is the calculation result of the aerobic power and sub-criteria using a fuzzy system.

Information related to the calculation of physiological criteria using fuzzy logic is presented in Table 3. Talent identification and

selection conducted on 10 prospective rowing athletes based on physiological criteria shows the same numerical value of 10.6% for decision-making in the semi-matched criteria.

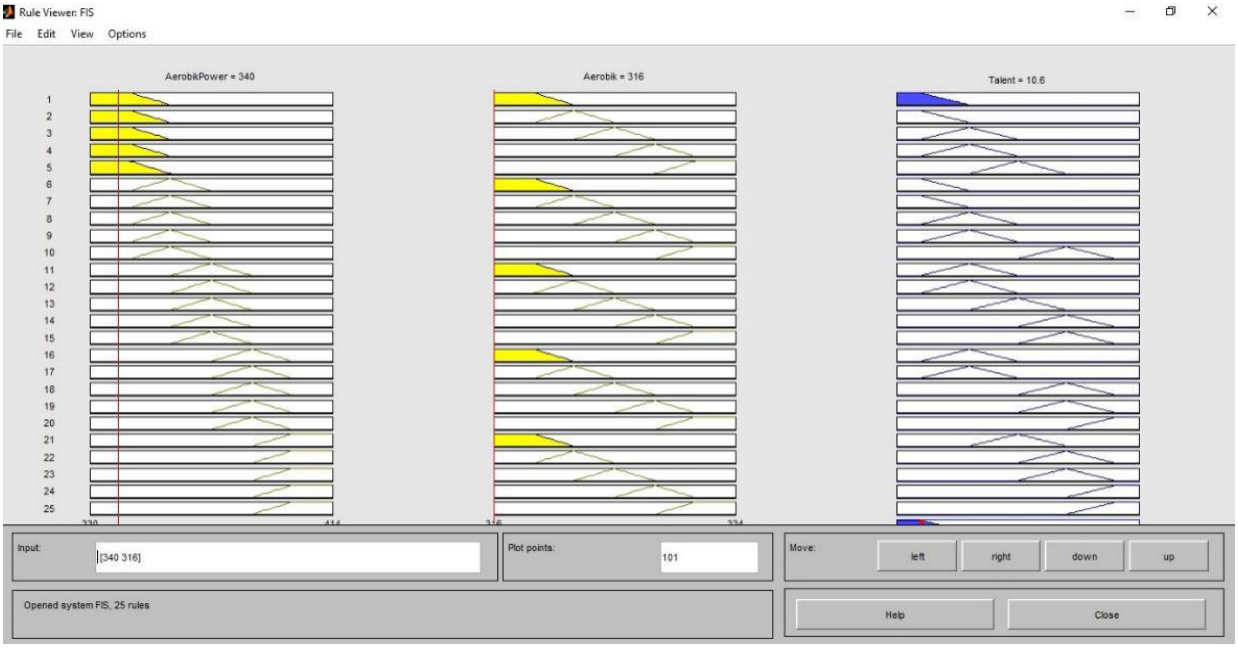
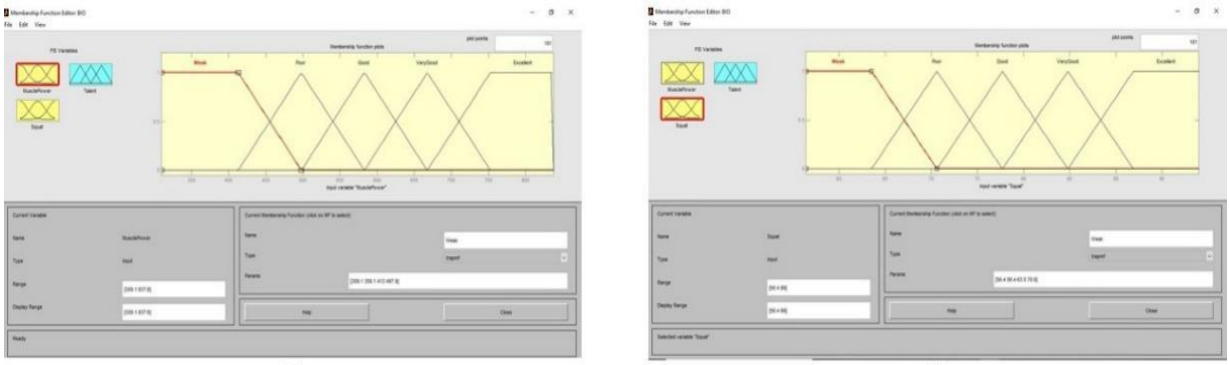


Figure 4. Physiology Rule Viewer

Testing of Biomotor Sub Criteria. Muscle power and squat are sub-criteria of biomotor in talent identification and selection of rowing athletes. Fuzzy testing is performed by comparing the range and actual value in the system. MFs on biomotor criteria, which include muscle power sub-criteria, are in positions 309.1 to 837.6 [Figure 5 (a)], and squats are in the range of 56.4 to 99 [Figure 5 (b)].



(a) (b)

Figure 5 .(a) MFs Muscle Power, (b) MFs Squat

The number of rules on biomotor indicators is similar to anthropometric and physiological criteria, which is 25 rule bases. This rule base will set the graph changes based on the numbers entered in the input field.

Figure 6 showed the fuzzy testing on anthropometric and physiological criteria. The athletes with muscle power 570 and squat 99 produce a talent value of 70%. Therefore, the athlete based on biomotor belongs to the brilliant criteria. Table 4 presents information on calculating biomotor indicators using fuzzy.

The data from fuzzy calculations for ten rowing athletes showed that one athlete had a talent rate of 89% or the linguistic value was in the rare classification. This implies that athletes with such large biomotor were rare candidates.

Figure 6. Rule Viewer Bimorotika

Table 4. Recapitulation of Biomotor Results using Fuzzy Logic

Subject	BIO		Decision (%)	Final Decision
	Muscle Power (watt)	Squat (Watt)		
1	570	100	50	**Brilliant**
2	710	105	89.4	**Rare**
3	620	105	50	**Brilliant**
4	570	90	50	**Brilliant**
5	627	150	53.5	**Brilliant**
6	558	110	50	**Brilliant**
7	513.6	90	50	**Brilliant**
8	567.9	110	50	**Brilliant**
9	612.1	119	50	**Brilliant**
10	612.1	116	50	**Brilliant**

Fuzzy Logic Test Results against Rowing Athlete Talent Identification (TI) Criteria. Subsequent fuzzy testing is conducted on all talent identification and selection criteria. Recapitulation of actual athlete data from all criteria and sub-criteria for talent identification can be seen in Table 5. Talent identification and selection of junior rowing athletes aged 17 from three criteria was also reported. Based on the data, there are different units in each sub-criteria. The use of fuzzy logic determines the percentage of each subject to talent identification and selection.

Table 5 shows talent identification and selection of Rowing junior athletes aged 15 years from three main indicators. According to the data, there are different units in each sub-indicator. The use of fuzzy logic in this step determines the percentage of each subject to talent identification and selection. Furthermore, the calculation steps in the fuzzy system for all indicators are as follows.

Table 5. Recapitulation of Indonesia Rowing Junior Athlete Talent Identification (TI)

Subject	ANT		FIS		BIO	
	Height (cm)	Leg Length (cm)	Aerobic Power (watt)	Aerobic (watt)	Muscle Power (watt)	Squat (Rep)
1	187	102	340	266	570	100
2	192	120	329	247	710	105
3	184	103	330	252	620	105
4	179	100	337	243	570	90
5	182	103	249	195	627	150
6	181	103	309.4	223.7	558	110
7	174	97	279.4	218	513.6	90
8	192	120	282.5	228.3	567.9	110
9	184	110	288.9	267.3	612.1	119
10	181	110	311.1	230.1	612.1	116

FIS editor input and output variables. FIS editor on fuzzy made 1 FIS editor with three and one variable input (Figure 7) and output (Figure 8).

The input variables include anthropometric, physiological, and biomotor indicators, while the outputs are talent, as indicated in Figures 7 and 8.

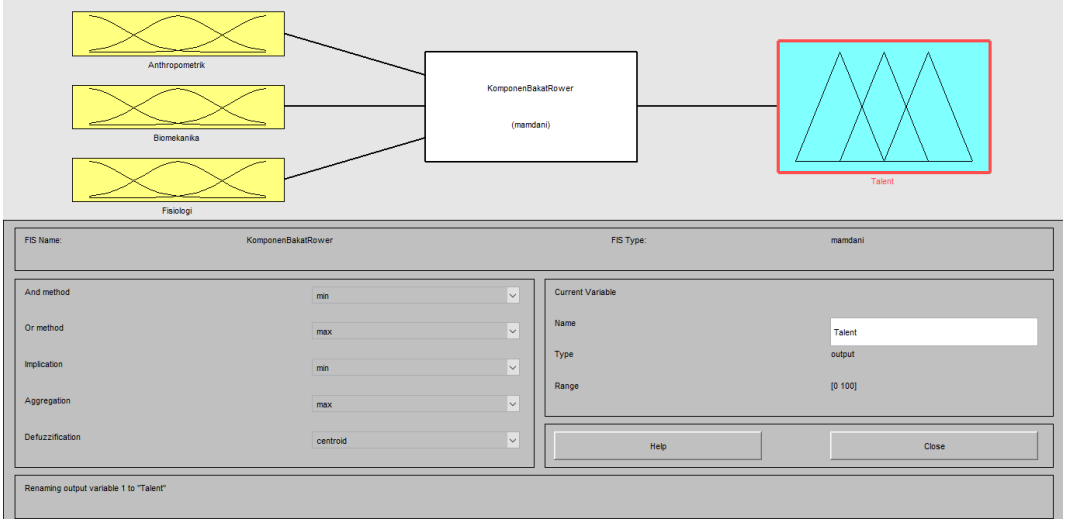


Figure 7. The MFs Talent Input Variable

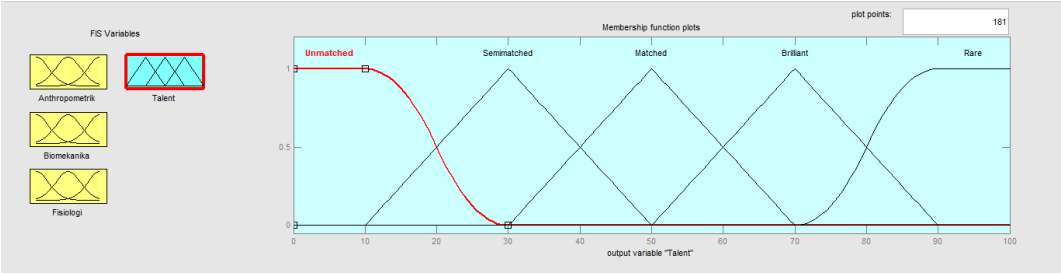


Figure 8. The MFs Talent Output Variable

Fuzzy sets. The fuzzy set arranged in this stage is divided into five sets, which are represented as follows:

a) Anthropometric variables (ANT):
b) {Unmatched (UM), Semimatched (SM), Matched (M), Brilliant (B), Rare (R)}
c) Physiological variables (FIS):
d) {Unmatched (UM), Semimatched (SM), Matched (M), Brilliant (B), Rare (R)}
e) Biomotor Variables (BIO):
f) {Unmatched (UM), Semimatched (SM), Matched (M), Brilliant (B), Rare (R)}

g) Talent variable (Talent):
h) {Unmatched (UM), Semimatched (SM), Matched (M), Brilliant (B), Rare (R)}

Membership Function. The parameters entered are the basis for the data referring to the results of the crips values for each sub-indicator. The linguistic attributes entered are appropriate to those contained in the fuzzy set for all talent identification indicators with each range in each variable, namely 0-100.

Table 6 shows the results of the output variables from the fuzzy logic decision-making model. Based on the data in Table 6, the criteria for a brilliant athlete are obtained with an identification and selection level of 66.7%. Fuzzy testing of all talent identification and selection criteria for rowing athletes showed that Indonesian rowing athletes must be in the "brilliant" classification or equal to 88.5% supported by anthropometric criteria, 10.6% supported by physiological criteria, and 89.4% supported by biomotor and morotic criteria. If translated according to the sub-criteria, height has a value of 192 cm, leg length 120 cm, 329 watts of aerobic power, 247 watts of aerobics, 710 watts of muscle power, and 105 watts of squats These characteristics can be used to identify and select talent, with the assumption that we can predict the physical growth and development of athletes.

Table 6. Output Fuzzy Logic Decision-Making Model for Rowing Athlete TI

Sample	Height (Cm)	Leg Length (cm)	Aerobic Power (watt)	Aerobic (watt)	Muscle Power (watt)	Squat (watt)	Output 0-100	Talent Identification Result
1	187	102	340	266	570	100	42,6	Matched
2	192	120	329	247	710	105	66,7	**Brilliant**
3	184	103	330	252	620	105	37,6	Matched
4	179	100	337	243	570	90	30,9	Matched
5	182	103	249	195	627	150	35,8	Matched
6	181	104	309,4	223,7	558	110	33,1	Matched
7	174	97	279,4	218	513,6	90	30,9	Matched
8	192	120	282,5	228,3	567,9	110	48	Matched
9	184	110	288,9	267,3	612,1	119	37,6	Matched
10	181	110	311,1	230,1	612,1	116	33,1	Matched

DISCUSSION

The talent identification and selection system is considered responsible for inadequate performance, a limited number of top players, and inconsistent wins (29, 30) Talent identification and selection recognize current players with the potential to become elite players or athletes. The criteria for talent identification and selection of athletes, including anthropometrics, physiology, bimorotics, technique, and psychology, have a high correlation for rowing athletes (20, 31–34). To produce competent athletes in a sport, a talent identification and selection test is needed. However, talented athletes cannot be solved with one effort. Talent identification and selection instruments should be specific and adapted to each sport.

Implementation of Fuzzy Logic in Rowing Athletes TI. The steps for designing the model have been described in this research as the implementation of fuzzy logic, which is a decision-making process for coaches in determining the talent level of an athlete. Tests using fuzzy logic have been carried out on three data, which include anthropometric, physiological, and biomotor criteria. However, testing using fuzzy logic on technical and psychological criteria was not carried out. This is because this research did not obtain the publication of comparative data that should be entered into the fuzzy system for technical and psychological criteria. Furthermore, the comparative data refers to the normative criteria for the finalist athletes of the junior rowing world championship.

Based on fuzzy anthropometric criteria testing, the height sub-criteria shows the number 192 cm. Furthermore, the leg length is 120 cm in the "rare" classification with a decision-making rate of 85.5%. According to the results, an Indonesian junior rowing male athlete should be in the range of 192 (±10) cm and 120 (±4) cm to reach the top level of competition. The aerobic power sub-criteria shows a figure of 340 watts and aerobics 266 watts. The second sub-criteria from the physiological criteria yields a "semi-matched" athlete classification with a decision-making rate of 10.6%. Therefore, to reach the top competition, an Indonesian junior rowing male athlete should have aerobic power and

aerobics exceeding 340 (±4) watts and 266 (±3) watts. Meanwhile, the bimorotic criteria include muscle power with the value of 710 watts and leg muscle strength (squat) of 105 watts based on fuzzy testing. This results in a "rare" athlete classification with a decision-making rate of 89.4%. In conclusion, an Indonesian junior rowing male athlete should have a muscle power of 710 (±84.9) watts and a leg muscle strength of 105 (±7.1) watts.

The use of fuzzy logic provides the level of decision-making of each sub-criteria for talent identification and selection of rowing athletes. It measures the level of decision-making on all criteria with comparative data on the fuzzy system. Referring to the results, fuzzy testing of all talent identification and selection criteria shows that male Indonesian rowing athletes should be in the "brilliant" classification. This is supported by anthropometric, physiological, and biomotor criteria of 88.5%, 10.6%, and 89.4%. According to the sub-criteria, height is 192 cm, leg length is 120 cm, aerobic power is 329 watts, aerobics is 247 watts, muscle power is 710 watts, and squat is 105 watts. These characteristics can be used to identify and select talent to predict the growth and physical development of athletes.

Fuzzy logic can be used in the decision-making system for talent identification and selection of rowing athletes. The method makes it easier for coaches in talent identification and selection to be clear, honest, specific, and efficient. It is quite systematic and effective in identifying and selecting athlete talent. However, for the completion of the fuzzy logic design, the input variables can be supplemented with additional input values.

CONCLUSION

The results and findings show that fuzzy logic minimizes the element of subjectivity in talent identification and selection as well as in determining priority variables. The test on junior rowing athletes proves that Fuzzy Logic provides transparent and objective decisions. This research analyzes a practical and useful design of a decision-making system to promote a coherent process of talent identification and selection of teachers, coaches, and others involved in promoting physical activity and rowing.

Furthermore, intelligent models encourage the birth of policy standards in talent identification and selection of rowing athletes. Analysis of decision-making systems has helped rowing coaches to determine the criteria for talented athletes. Therefore, coaches can be assisted in preparing training programs appropriate to each athlete's characteristics. The limitation of this study is that it only focuses on rowing sports and only assesses anthropometric, physiological, and biomotor factors. Testing using fuzzy logic on technical and psychological criteria was not carried out. This is because the publication of comparative data that must be inputted into the fuzzy system for technical and psychological criteria was not found by the researchers. The comparative data that the researcher uses refers to the criteria for the athletes' norms for the junior rowing world championship finalists. The researcher has included this statement in the research limitations.

APPLICABLE REMARKS

- The use of fuzzy logic in this study has shown a model as a tool for identification and selection in rowing sports.
- Fuzzy logic is very helpful in minimizing the element of subjectivity in talent identification and talent selection in rowing.

AUTHORS' CONTRIBUTIONS

Study Concept and Design: Dede Rohmat Nurjaya. *Acquisition of data:* Dede Rohmat Nurjaya. *Analysis and interpretation of data:* Dede Rohmat Nurjaya. *Drafting of the manuscript:* Agus Rusdiana. *Critical revision of the manuscript for important information*: Agus Rusdiana. *Statistical analysis:* Ade Gaffar Abdullah. *Administrative, technical, and material support:* Toho Cholik Mutohir. *Study supervision:* Amung Ma'mun.

CONFLICT OF INTEREST

This manuscript contains no material that could be considered a conflict of interest by the authors.

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