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# ADAPTIVE MULTICRITERIA MODEL FOR SUPPORTING DECISION-MAKING IN SPORTS SELECTION PROBLEMS

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*In the current environment of information technology development, intelligent data analysis, and decision support systems, there is a need to formalize and automate sports selection processes. Existing models of multi-criteria assessment of athletes are usually static in nature and focused only on analyzing the current level of preparedness, which limits their effectiveness in selecting young candidates for whom development potential is important. This paper proposes an adaptive multi-criteria decision support model that integrates the assessment of the current level of candidates' characteristics with formalized consideration of their development dynamics over time. A mathematical apparatus for forming an integral assessment of prospects has been developed, based on the hierarchical aggregation of normalized indicators and the application of the hierarchy analysis method to determine weight coefficients. For the first time, a generalized characteristic indicator has been introduced, which combines normalized indicator values and the rate of their change, allowing not only current results but also development prospects to be assessed. An experimental study on a sample of 24 candidates showed a heterogeneous structure of the distribution of integral assessments, which confirms the feasibility of using adaptive thresholds to classify candidates according to their level of prospects. The sensitivity of the model to changes in the a parameter, which allows adjusting the balance between current indicators and development dynamics, was analyzed. The results confirmed the stability of the model and the consistency of the overall ranking structure of candidates when changing weight parameters. The proposed model ensures transparency, reproducibility, and interpretability of the assessment, which makes it suitable for use in intelligent decision support systems for the selection of young athletes. The practical benefit of the model is that it allows coaches and sports selection specialists to effectively and objectively identify candidates with high development potential, taking into account both their current level of preparedness and the dynamics of their characteristics. The model can be integrated into intelligent decision support systems for planning the training process and strategically forming teams of young athletes.*

*Keywords: decision support system (DSS), multi-criteria assessment, integrated assessment of prospects, adaptive model, development dynamics, athletic selection, hierarchy analysis method.*

## Introduction

In modern sports, achieving high results increasingly depends not only on the level of training of athletes, but also on the effectiveness of management decisions, in particular the process of selecting players for the team. Traditional approaches to sports selection, based primarily on the expert experience and intuition of the coaching staff, have limitations related to the subjectivity of assessment, the complexity of taking into account a large number of indicators, and the inability to quickly process large amounts of information. This increases the risk of wrong decisions and can negatively affect the results of competitive activities.

Modern developments in information technology, artificial intelligence, and big data analytics are creating the conditions for a transition to a new level of sports selection. This is particularly relevant when selecting talented young people, as the number of candidates significantly exceeds the number of selections typical for professional teams or national teams. Under such conditions, traditional expert approaches are not effective enough due to their limited ability to process large amounts of heterogeneous information and the high level of subjectivity in assessment [1].

Intelligent sports selection information systems allow for the integration of data on athletes' physical, technical, tactical, and psychological training, as well as game statistics, providing comprehensive analysis within a single information environment. The use of such systems contributes to the formalization of the selection process, increased transparency and reproducibility of decision-making, and reduced human influence.

At the same time, an analysis of existing information solutions and sports selection models shows that most of them are focused on static assessment of the current level of athletes' preparedness and do not take into account the dynamics of changes in their characteristics over time. This significantly limits the capabilities of such systems in the tasks of long-term selection and forecasting the development prospects of young candidates.

In this regard, it is important to develop adaptive multi-criteria decision support models capable of integrating current values of indicators with formalized characteristics of their temporal evolution. The use of such models makes it possible to improve the soundness of management decisions, ensure the scalability of the selection process, and create a basis for the implementation of modern information systems for decision support in the field of sports management.

**Related works**

The modern development of information technologies, intelligent data analysis, and decision support systems creates the prerequisites for formalizing and automating sports selection processes. At the same time, analysis of scientific publications shows that most existing models of multi-criteria assessment of athletes are static in nature and focused on analyzing the current level of preparedness, without taking into account the dynamics of changes in characteristics over time. This is a significant limitation in the selection of young candidates, for whom development potential is crucial.

In a previous work by the authors [2], a structure for a decision support system for the preliminary selection of players was proposed, which included a subsystem for data analysis and a decision support process. The proposed structure created the basis for formalizing the selection process and integrating heterogeneous information flows within a single information environment.

At the same time, the effectiveness of such systems directly depends on the evaluation models and decision-making algorithms used, which are capable of correctly taking into account the multi-criteria nature of the selection task. The problem of selecting athletes in modern sports is considered a complex multi-criteria decision-making task that requires the integration of diverse indicators of physical, technical, tactical, and psychological preparedness. Classic approaches based solely on the expert intuition of the coaching staff are gradually being replaced by formalized models that increase the objectivity, reproducibility, and transparency of the selection process. One area of research is the use of multi-criteria analysis methods to evaluate and rank athletes based on their current performance indicators. Thus, in a study devoted to the evaluation of football players using the COMET method in combination with fuzzy inference systems, an approach to ranking players based on game statistics is proposed [3]. The advantage of this approach is its ability to model nonlinear dependencies between criteria and avoid the problem of ranking reversal. At the same time, the model is focused on evaluating professional players and is static in nature, as it is based on data from individual matches or seasons. The model does not take into account the temporal dynamics of athletes' characteristics, which limits its application for long-term selection and identification of promising young candidates.

Another class of works focuses on building hierarchical expert models for selecting athletes using the hierarchy analysis method and its fuzzy modifications. In particular, [4] proposes an intelligent model for selecting elite rowers, which combines a modified Delphi method, Fuzzy AHP, and data obtained using Internet of Things technologies. Within this model, a hierarchy of criteria has been formed, covering anthropometric indicators, reaction and professional characteristics, psychological factors, as well as sensory IoT data. The use of Fuzzy AHP allows taking into account the uncertainty of expert judgments and determining the weights of the criteria. However, despite the use of modern data collection technologies, athletes are evaluated at a fixed point in time, and the dynamics of changes in indicators and development potential are not formally taken into account.

A similar approach is used in studies where Fuzzy AHP and Fuzzy TOPSIS are applied to select football players. In such studies, a set of criteria is formed, their weights are determined using expert pairwise comparisons, and then the candidates are ranked [5]. These methods reduce the subjectivity of evaluation and ensure a formalized approach to player selection, particularly for national teams. At the same time, most of these models are focused on selecting the optimal team composition at the current moment and do not provide for the analysis of changes in characteristics over time.

Some studies combine multi-criteria methods with optimization models [6]. For example, after determining the weights of the criteria using the AHP method, an integer programming problem is formed to select the optimal team composition, taking into account positional restrictions. Such approaches are effective for forming a competitive team, but they are also based on static assessments of players and do not take into account the prospects for their individual development.

A number of studies have proposed methodologies for selecting football players based on multi-criteria analysis, where criteria are grouped according to physiological, functional, and technical-tactical characteristics [7]. These approaches provide a structured representation of athletes' characteristics and allow for an integrated assessment, but the development of indicators over time is considered only indirectly or ignored altogether.

Recent reviews also note a trend toward combining multi-criteria analysis methods with machine learning methods for assessing and predicting athletic performance [8]. Such approaches allow for the analysis of large amounts of data and the identification of hidden patterns, but often require large training samples and remain difficult to interpret for practical use by coaching staff.

The latest works, in particular the hybrid FAHP-FTOPSIS models, are aimed at increasing the objectivity of sports selection and reducing the influence of the human factor [9]. They confirm the effectiveness of the multi-criteria approach, but in most cases remain static and focused on assessing the current level of athletes' preparedness.

A systematic review [10] examines contemporary approaches to evaluating athletic performance based on multi-criteria decision-making methods. The authors classified the applied MADM methods (in particular, AHP, TOPSIS, VIKOR, ELECTRE, COMET, and their hybrids), analyzed the areas of their application in various sports and the types of tasks solved, in particular, ranking, selection, and classification of athletes. The paper emphasizes that the vast majority of existing models are focused on static assessment of current performance indicators and do not provide for formalized consideration of the temporal dynamics of athletes' characteristics within a multi-criteria model.

Thus, analysis of existing studies shows that the vast majority of sports selection models are aimed at static ranking of athletes or forming an optimal team composition based on current indicators [11, 12]. The issue of formalized consideration of the dynamics of development characteristics and assessment of the potential of young candidates remains insufficiently researched.

Given the limitations of the approaches considered in this review, it is advisable to formulate the task of developing an adaptive multi-criteria decision support model that takes into account the dynamics of indicators over time for sports selection.

## Purpose

Therefore, the aim of this study is to formalize and solve the problem of multi-criteria evaluation and ranking of alternatives in sports selection, taking into account the temporal dynamics of athletes' characteristics.

To achieve this goal, the following subtasks must be solved in the work:

– formalize the sports selection process as a multi-criteria decision-making task within the information decision support system;

– develop a model for representing alternatives that combines current indicator values with formalized characteristics of their development;

– propose an adaptive mechanism for aggregating criteria that allows changing the selection strategy depending on management goals.

## Formalization of the sports selection process

The process of selecting players by the coaching staff is a complex multi-criteria management process aimed at forming the optimal team composition in accordance with tactical, physical, and strategic requirements. To increase the objectivity and effectiveness of decision-making, it is advisable to formalize the description of the process, which allows structuring the selection stages, determining the input and output data, as well as the criteria for evaluating candidates. In order to formalize the sports selection process and justify the structure of the intellectual information system, the IDEF0 methodology was used in the work. Figure 1 shows a functional model of the player selection process, which defines the main information flows, control influences, and decision-making mechanisms.
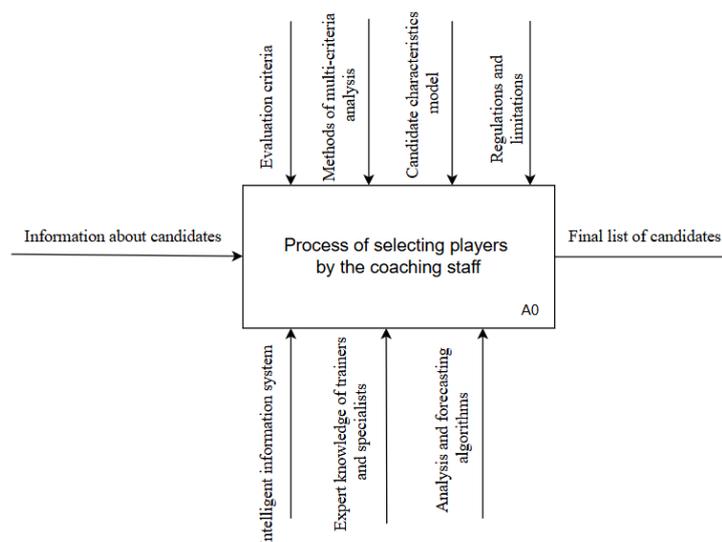


**Fig.1. A-0 Functional model of the selection process**

The input data consists of information about candidates, such as athletes' test results, training process observations, psychophysiological indicators, anthropometric data, development dynamics data, etc.

The output data is a list of players formed according to specified criteria.

The functional model of the selection process, presented in the form of an IDEF0 diagram, defines the structure and information flows of the process, but does not provide a quantitative assessment of candidates. Therefore, the next step is to build a mathematical model of multi-criteria player selection, which allows formalizing the evaluation criteria and implementing automated ranking.

The constructed IDEF0 diagram of the player selection process allows formalizing it at the functional level by defining the main stages of information processing, input and output data, as well as decision-making mechanisms. At the same time, in order to implement intelligent decision support, it is necessary to move from a functional description of the process to its formalization in the form of a mathematical model that provides quantitative assessment of candidates and the possibility of automated analysis.

### Mathematical model of the player selection process

The mathematical model of selection is based on a multi-criteria approach, which allows integrating diverse indicators of physical, technical, tactical, and psychological training of players into a single evaluation system. The process of player selection by the coaching staff is formalized as a multi-criteria selection task from a set of candidates.

Let $G = \{g_1, g_2, \ldots, g_n\}$ – be the set of candidate players..

Each player $g_i$ is described by a vector of characteristics of the form 1:

$$X = (x_{i1}, x_{i2}, \ldots, x_{im}), \tag{1}$$

where $x_{ij}$ – value of the j- th criterion for the i- th player.

The mathematical model of selection is based on a multi-criteria approach, which allows integrating heterogeneous indicators of candidates' preparedness into a single formalized assessment system. A distinctive feature of the proposed approach is its focus not only on the current level of characteristics, but also on their potential for development, which is fundamentally important for the task of selecting young people.

Within this model, each candidate is described by a vector of characteristics grouped into several main areas reflecting different aspects of preparedness. The indicators may vary in nature, measurement scale, and degree of variability, so at the initial stage, they are normalized using formula 2. This ensures data accuracy and prevents individual indicators from having an increased impact due to their numerical scale.

$$\widetilde{x_{ij}} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad , \tag{2}$$

where $x_j^{min}, x_j^{max}$ – the minimum and maximum permissible values of the relevant characteristic, taking into account age norms and restrictions.

As a result, we obtain the value of the normalized estimate within the specified interval $\widetilde{x_{ij}} \in [0,1]$.

The multi-criteria approach involves building a hierarchical structure of criteria, within which individual indicators are combined into group assessments. In turn, group assessments are combined into an integrated indicator of a candidate's prospects.

Taking into account the dynamics of indicators plays a special role in the model. For the youth selection process, it is not only current results that are important, but also how quickly they are improving. Analyzing such changes instead of static assessment allows for a better assessment of potential and more informed selection decisions.

The result of the mathematical model is an integrated assessment, based on which candidates are ranked and recommendations for further work with them are formed. The proposed model provides a formalized, transparent, and reproducible selection process, reducing the influence of subjective factors and creating a basis for building an intelligent decision support system.

The main groups of criteria considered are:
– physical fitness;
– technical indicators;
– tactical indicators;
– psychological stability;
– game statistics.

Physical fitness characterizes the basic level of the candidate's functional capabilities and determines their ability to withstand training and competition loads. This group includes indicators that reflect the development of strength, speed, endurance, coordination, mobility, etc. For young people, physical fitness is considered not only from the perspective of their current level, but also taking into account age standards and dynamics of change, which allows for an assessment of their potential for further development.

Technical indicators reflect the level of mastery of basic and specialized motor skills necessary for effective performance in the relevant subject area. This group of criteria characterizes the quality of technical elements, the stability of skills, and the ability to apply them in changing conditions. For young candidates, technical indicators are an important indicator of learning ability and the speed of acquiring new skills.

Tactical indicators describe a candidate's ability to analyze situations, make decisions, and choose optimal actions in a dynamic environment. These include indicators that characterize spatial thinking, adaptability, understanding of interaction with other participants, and the effectiveness of implementing the chosen strategy. In the selection model, tactical indicators are considered an important component of the intellectual component of activity, which becomes particularly important in the stages of further development.

Psychological stability reflects the individual characteristics of the candidate related to the ability to maintain performance in stressful situations, control emotional state, and maintain motivation. This group of criteria includes indicators of concentration, self-regulation, anxiety level, and readiness to learn. For young people, the psychological component is one of the key factors for long-term prospects, as it determines the ability to adapt to growing demands.

Game statistics summarize the candidate's performance based on objectively recorded data. They allow assessing the effectiveness of physical, technical, and tactical capabilities in practical activities.

The use of such a hierarchical system of criteria provides a comprehensive representation of the candidate's characteristics and creates a basis for building a formalized model of multi-criteria assessment within the framework of intellectual information technology for decision support.

An important aspect of this work is that the selection is made for young people and, as already mentioned, the dynamics of development and projected prospects are important here. Therefore, in order to take into account the dynamics of development, a development rate indicator is introduced, which is calculated using formula 3:

$$d_{ij} = \frac{\widehat{x_{ij}}(t_2) - \widehat{x_{ij}}(t_1)}{t_2 - t_1} \quad , \tag{3}$$

where $t_1$ – initial observation point (first testing of the candidate);
$t_2$ – next observation point (retesting after a certain period).

Time t is not abstract, but corresponds to the actual stages of control in the youth selection system and can be measured in months or training cycles. Thus, $d_{ij}$ reflects the average rate of change of the j-th characteristic of the i-th candidate per unit of time.

Next, it is necessary to determine the generalized performance indicator, which is calculated using the formula 4:

$$z_{ij} = \alpha \widetilde{x_{ij}} + (1 - \alpha) d_{ij}, \tag{4}$$

where the $\alpha$ coefficient determines the balance between the current level of development and growth potential. It should be noted that this coefficient is a controllable parameter of the selection model. It can vary depending on the objectives of the system.

Let us consider this point in more detail.

If $\alpha \to 1$, this indicates the priority of current indicators and is relevant for short-term decisions.

If $\alpha \to 0$, then we can talk about the priority of development dynamics, i.e., this moment is key for selecting talented young people. The range $\alpha \in [0.4; 0.6]$ indicates a compromise strategy used for long-term training programs.

It should be noted that within the intellectual information system supporting the decision-making of the coaching staff when selecting players, the following options for determining the coefficient $\alpha$ are possible:

1. A value set by experts. That is, it is determined by methodological recommendations or the coaching staff (for example, the same for the entire age group).

2. Fixed value. For example, the coefficient $\alpha$ is taken to be equal to 0.5, which ensures equal weighting of the current level and development dynamics.

3. Adaptive determination, where $\alpha$ is automatically adjusted based on:
– the candidate's age;
– the of indicators in the group;
– historical data on the success of selected athletes.

In the context of intellectual information technology $z_{ij}$ is used as input into a multi-criteria model (AHP), allowing candidates to be compared at different stages of development and reducing the risk of selection based solely on current indicators.

The obtained generalized indicators of individual characteristics $z_{ij}$ are used to form group assessments corresponding to the main areas of the candidate's preparedness (formula 5):

$$Z_i^k = \sum_{j \in J_k} v_{ik} z_{ij}, \tag{5}$$

where $J_k$ − a set of characteristics belonging to the $k$- th group;

$v_{ik}$ – weight coefficients of characteristics within a group, their total value should not exceed 1. They can be set by experts, calculated automatically using the hierarchy analysis method, or adapted based on statistics of successfully selected candidates.

Next, it is necessary to calculate the candidate's integral assessment of prospects, which is used as a generalised quantitative indicator reflecting the candidate's overall level of compliance with the selection model requirements, taking into account heterogeneous characteristics. Unlike traditional approaches, where decisions are often made based on current results, the integral assessment in the proposed model takes into account the dynamics of characteristics development, which is critical for the selection of young people. The integrated assessment can be used for automated recommendation generation, for analysing scenarios of changes in criterion weights, and for adapting the model based on accumulated statistics. The integrated assessment of a candidate's prospects is used for the formalised generalisation of heterogeneous characteristics within a multi-criteria selection model and serves as the basis for ranking, classification, and decision support for further work with candidates, as well as reducing the influence of subjective factors. It is calculated using formula 6:

$$S_{ik} = \sum_{j \in J_k} \omega_{ik} Z_{ij}, \qquad\qquad (6)$$

where $\omega_{ik}$ – weighting coefficients determine the relative importance of individual aspects of assessment in the overall structure of the selection model. Their introduction is due to the fact that different groups of characteristics have an unequal impact on a candidate's prospects, especially in the selection of young people, where individual aspects (e.g., technical training or psychological stability) may have greater long-term importance than current competitive results.

To formally determine weighting coefficients, the work uses the analytic hierarchy process (AHP) method, which allows combining expert knowledge with a mathematically sound procedure for their coordination. The main idea of AHP is to decompose a complex decision-making task into a hierarchy of levels and then determine priorities by pairwise comparison of elements at each level.

Within the proposed model, groups of criteria are compared with each other in terms of their contribution to the overall selection goal. The result of processing the pairwise comparison matrices is a priority vector, which is interpreted as a vector of weight coefficients. An additional advantage of the AHP method is the ability to verify the consistency of expert assessments, which increases the reliability and validity of the weights obtained. Thus, the use of AHP ensures the transparency of the weighting procedure, reduces the subjectivity of decision-making, and creates a methodological basis for further aggregation of group assessments within the integrated selection model.

The integral assessment of a candidate's prospects $S_{ik}$ is a generalised quantitative indicator that reflects the degree to which a candidate meets the requirements of the selection model, taking into account heterogeneous characteristics and their dynamics of development. Since all component indicators are reduced to a normalised interval $[0 ; 1]$, the value of $S_{ik}$ also belongs to this interval, which simplifies its interpretation and comparison between candidates. High values of this indicator indicate a combination of a sufficient current level of preparedness and positive dynamics of development, which is a sign of the candidate's high potential. Low values may indicate an insufficient level of individual characteristics or a low rate of their development, which requires correction of the individual training programme.

If $S_i \geq \theta_1$, these are candidates with high potential, recommended for further selection or inclusion in targeted development programmes; $\theta_2 \leq S_i < \theta_1$ – candidates with average potential, for whom it is advisable to develop individual development programmes; $S_i < \theta_2$ – candidates who require additional training or reassessment at subsequent stages.

The threshold values $\theta_1$ and $\theta_2$ are used to divide the set of candidates into classes of promise and are an important element of the decision-making model. Their selection is dictated by the need to interpret the integral assessment not only as a ranking indicator, but also as a tool for forming practical recommendations for further work with candidates.

Within the proposed model, there are several approaches to determining threshold values, which allows the selection procedure to be adapted to specific conditions and objectives.

1. Statistical approach. In the most general case, threshold values can be determined based on the statistical characteristics of the sample of integral assessments. This approach allows for the automatic consideration of the characteristics of a specific sample and ensures the adaptability of the model to changes in the composition of candidates.

2. Normative and methodological approach. If there are methodological recommendations or regulatory requirements, threshold values can be set at a fixed level. This option is appropriate for unified selection procedures when it is necessary to ensure the comparability of results between different groups or time periods.

3. Adaptive approach. Within the intellectual information system, it is possible to adaptively determine threshold values based on the analysis of historical data. In particular, thresholds can be adjusted taking into account the success of candidates selected in previous cycles, changes in age norms or the goals of the current stage of training. The threshold values of the integral assessment are not fixed rigidly, since the model is focused on a comparative

analysis of candidates within a specific sample and takes into account the dynamics of the development of their characteristics. This approach ensures adaptability and increases the practical value of the decision support system.

**Limitations and features of the selection model, taking into account the pace of development**

The proposed multi-criteria selection model is focused on assessing the prospects of young candidates, which necessitates taking into account a number of limitations related to age-specific developmental characteristics and the nature of indicator dynamics. Unlike models used to assess established professionals or highly skilled athletes, the key to selecting young people is not so much their current level of characteristics as the rate at which they change over time.

Within the model, it is assumed that all candidates belong to the same age group, and comparisons are made only between subjects who are at similar stages of development. This allows for the correct interpretation of both the absolute values of normalised characteristics and indicators of the pace of development, avoiding distortions associated with different phases of biological or psychophysiological maturation.

Particular attention is paid to the restrictions imposed on the rate of development indicator. Since the value of $d_{ij}$ is determined based on the difference between normalised indicators at two observation points, it is important to ensure the stability and representativeness of these measurements. To this end, the time intervals between observation points must correspond to the actual control stages and be the same or comparable for all candidates. This approach prevents the overestimation of random short-term fluctuations and ensures that the stable development trend is correctly reflected.

In addition, the model assumes that the rate of development is used only within acceptable ranges of values determined on the basis of age standards and statistical characteristics of the sample. This avoids situations where extreme or abnormal values of dynamics significantly affect the overall assessment of a candidate's prospects.

The introduction of a balance coefficient between the current level of indicators and their growth rate is also considered as an element of model control that imposes additional restrictions on the interpretation of results. Changing this coefficient allows the model to be adapted to different selection objectives, but requires consistency with the age characteristics of the group and long-term development goals. Thus, the integral assessment of prospects is formed not as an absolute indicator of abilities, but as a relative characteristic of the candidate's potential within the given conditions and time constraints.

The proposed system of restrictions ensures the methodological correctness of using the development rate indicator in a multi-criteria model and increases the reliability of decisions made on the basis of an integrated assessment of the prospects of young candidates.

Unlike models focused on assessing current performance, the proposed mathematical model takes into account the dynamics of candidates' characteristics, which allows for the assessment of potential and is critical for the task of selecting young people.

**Experiments**

The purpose of experimental research is to verify the assessment of the impact of a multi-criteria model and mechanisms for determining weight coefficients on selection results using intelligent information technology for decision support.

The experimental studies were conducted on a sample of 24 candidates aged 15 to 17 (sport: volleyball), for whom data were available for the main groups of criteria: physical training, technical indicators, tactical indicators, psychological stability, and game statistics. For each candidate, a vector of primary indicators was formed, reflecting their individual characteristics.

The first stage of the experiment involved the formation of a model of the candidate's characteristics. Input indicators, which varied in nature and scale of measurement, were brought to a comparable form by normalisation. This made it possible to eliminate the influence of the numerical scales of individual indicators on the results of further aggregation.

In the second stage, a selection model based on a multi-criteria approach was developed. The weighting coefficients of the criteria groups and individual indicators were determined using the hierarchy analysis method. For this purpose, matrices of pairwise comparisons were formed, reflecting the relative importance of the criteria, taking into account the specifics of youth selection. The weights obtained were used to aggregate the normalised indicators into group and integral assessments.

Based on the mathematical model developed, an integral assessment of the prospects was calculated for each candidate. The values obtained were used to form a ranking of candidates, which served as the basis for selection decisions.

During the experiment, particular attention was paid to analysing the impact of individual groups of criteria on the final assessment. To this end, calculations were performed with different sets of weighting coefficients, which made it possible to study the sensitivity of the model to changes in the structure of criteria and confirm its flexibility.

Each candidate $g_i$ was described by a vector of characteristics of type 1. The initial values of the athletes' readiness indicators were formed on the basis of test results, observations and game statistics, which were interpreted by the coaching staff in the form of expert assessments. Given the different physical nature of the indicators and the

different units of measurement, the raw data were converted to a unified scale from 0 to 100 points, reflecting the relative level of manifestation of the relevant characteristic of the candidate, taking into account age characteristics and selection conditions (Table 1). The use of such a scale is common practice in decision support systems and allows for the integration of heterogeneous indicators within a multi-criteria model without losing the interpretability of the results. The procedure for obtaining initial assessments is not the subject of this study, as the main focus is on modelling the process of aggregating indicators and supporting decision-making in sports selection tasks.

Table 1

**Initial values of athletes' readiness indicators**

| Players | Physical fitness | Technical training | Tactical training | Psychological preparation | Game statistics |
|---|---|---|---|---|---|
| $g_1$ | 75 | 68,6 | 76,5 | 85,2 | 67,7 |
| $g_2$ | 67,7 | 85,8 | 77,7 | 65,3 | 75,4 |
| $g_3$ | 65,4 | 65,3 | 72,4 | 50,9 | 52,8 |
| $g_4$ | 76,4 | 69,9 | 81,1 | 66,9 | 64,9 |
| $g_5$ | 84,7 | 67,7 | 70,7 | 55,8 | 64,6 |
| $g_6$ | 71,1 | 58,5 | 73,8 | 64 | 67,1 |
| $g_7$ | 56 | 82,5 | 65,9 | 69,4 | 90,2 |
| $g_8$ | 57,8 | 72,1 | 50,4 | 56,7 | 72 |
| $g_9$ | 77,4 | 71,7 | 68,8 | 67 | 55,2 |
| $g_{10}$ | 62,8 | 65,4 | 80,6 | 73,4 | 52,4 |
| $g_{11}$ | 85,2 | 76,1 | 71,2 | 82,1 | 89,3 |
| $g_{12}$ | 79,3 | 61,6 | 66,9 | 73,3 | 79,8 |
| $g_{13}$ | 65,2 | 68,1 | 58,9 | 58 | 78,1 |
| $g_{14}$ | 83,6 | 69,3 | 80 | 73,6 | 63,5 |
| $g_{15}$ | 73,6 | 85,4 | 69,6 | 85,6 | 43,8 |
| $g_{16}$ | 78,2 | 70,9 | 67 | 70,9 | 50,1 |
| $g_{17}$ | 59,8 | 67,6 | 80,8 | 74,8 | 73,9 |
| $g_{18}$ | 65 | 79,2 | 73,3 | 64,7 | 75,1 |
| $g_{19}$ | 71 | 79,7 | 63 | 66,7 | 66,1 |
| $g_{20}$ | 55,4 | 73 | 72,6 | 70,1 | 67,7 |
| $g_{21}$ | 47,8 | 59,8 | 62,6 | 72 | 80,4 |
| $g_{22}$ | 74 | 88,9 | 71,7 | 72,6 | 69,3 |
| $g_{23}$ | 50,8 | 69,7 | 70,6 | 94,6 | 68,1 |
| $g_{24}$ | 85 | 79,7 | 66,3 | 87,4 | 86,5 |

Since different groups of criteria have different variability and sensitivity at the age of 15–17, at the first stage, all indicators were brought to a single form using formula 2. This made it possible to avoid the dominance of physical indicators over psychological ones, ensure the correct aggregation of heterogeneous data, and preserve the interpretability of the results.

As already mentioned, the dynamics of development and projected prospects are important in the selection of young people, so the rate of development indicator was calculated using formula 3. Calculations were then performed using formulas 4 and 5.

To calculate the integral assessment, the weights of the criteria groups corresponding to the typical AHP structure for youth selection were applied:
- physical fitness – 0.25;
- technical indicators – 0.25;
- tactical indicators – 0.2;
- psychological stability – 0.15;
- game statistics – 0.15.

The results of calculations of the integral assessment of a candidate's prospects using formula 6 are shown in Table 3.

Table 3

**Comprehensive assessment of candidates' prospects**

| $G_i$ | $g_1$ | $g_2$ | $g_3$ | $g_4$ | $g_5$ | $g_6$ | $g_7$ | $g_8$ | $g_9$ | $g_{10}$ | $g_{11}$ | $g_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $S_i$ | **74.135** | **75.020** | 62.710 | 72.565 | 70.300 | 66.825 | 71.745 | 61.860 | 69.365 | 67.040 | **80.275** | 71.570 |
| $G_i$ | $g_{13}$ | $g_{14}$ | $g_{15}$ | $g_{16}$ | $g_{17}$ | $g_{18}$ | $g_{19}$ | $g_{20}$ | $g_{21}$ | $g_{22}$ | $g_{23}$ | $g_{24}$ |
| $S_i$ | 65.520 | **74.790** | 73.080 | 68.825 | 70.315 | 71.680 | 70.195 | 67.290 | 62.280 | **76.350** | 68.650 | **80.520** |

**Within the framework of the experimental study, integral assessments of Si prospects were calculated for a sample of 24 candidates. Analysis of the obtained values showed that the distribution of Si is uneven and is characterised by the presence of a distinct group of candidates with high integral assessment values, as well as a more numerous group with an average level of prospects. Figure 2 shows a histogram of the distribution of integral assessments of the prospects of candidates Si for a sample of 24 people. Analysis of the empirical distribution shows that the values of Si are uneven and are grouped mainly in the range of average values, with a separately pronounced group of candidates with high indicators. Under such conditions, the use of a fixed threshold value does not allow for the correct reflection of the relative differences between candidates and may lead to the loss of information about the structure of the sample. In**

**order to form a group of promising candidates, an approach based on the analysis of the empirical distribution of integral assessments was applied.**
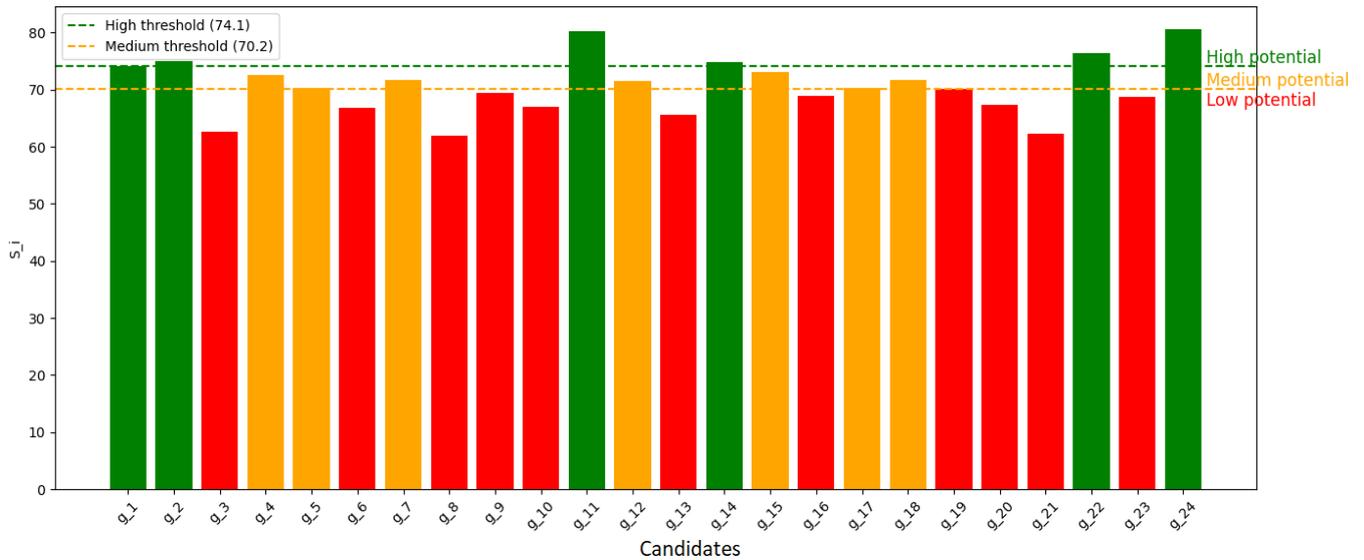


**Fig.2. Histogram of the distribution of integral assessments of candidates' prospects**

The upper threshold $\theta_1$ was determined as the value of the 75th percentile of the Si, istribution, which in this sample corresponds to the value $\theta_1 \approx 74.1$. The selected value ensures the selection of six candidates (Figure 3) who form the upper quartile of the sample and demonstrate consistently high values of the integral assessment for all groups of criteria. This number of promising candidates is sufficient for further targeted work with them and corresponds to the practical limitations of the experimental study. The lower threshold $\theta_2$ б was determined as the median value of the distribution of integral assessments, which for the sample under study is $\theta_2 \approx 70.2$. The use of the median allows us to separate candidates with an average level of promisingness from the group that, in terms of the set of indicators, is significantly inferior to the leaders of the sample. This choice of threshold is justified from the point of view of statistical stability, since the median is less sensitive to extreme values than the arithmetic mean.

The obtained threshold values allowed us to form three groups of candidates: a group with high potential $(S_i \geq \theta_1)$, a group with average prospects $(\theta_2 \leq S_i < \theta_1)$ and a development group $(S_i < \theta_2)$. An analysis of the composition of these groups showed that candidates in the top group are characterised not only by high current group scores, but also by a consistent level of development in all areas, confirming the appropriateness of the selected threshold values.
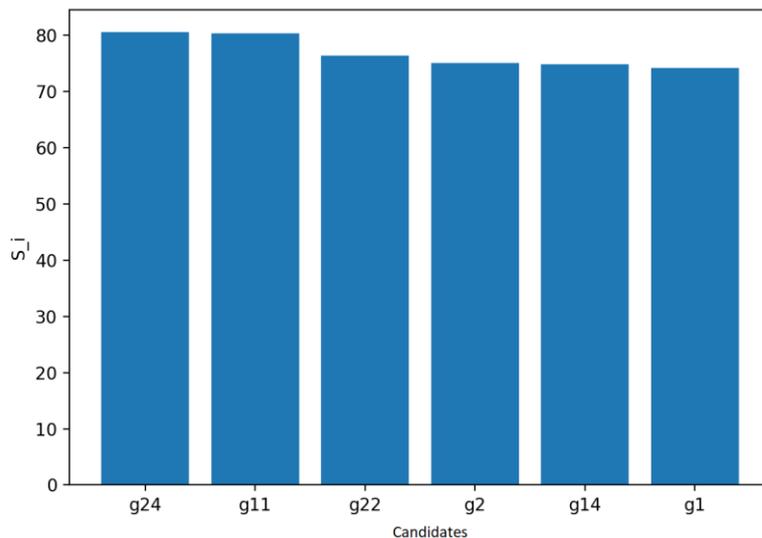


**Fig.3. Top 6 candidates based on overall assessment of prospects**

Thus, the choice of threshold values $\theta_1$ та $\theta_1$ in the experiment is the result of an analysis of the specific distribution of integral assessments and ensures adequate classification of candidates according to their level of promise. This confirms the adaptive nature of the proposed model and its suitability for use in intelligent decision support systems for youth selection tasks.

Figure 4 shows the change in the integral assessment of prospects $S_i$ or candidates g24, g11 and g22 when varying the controlled parameter α, which determines the balance between the current level of preparedness and the dynamics of development.
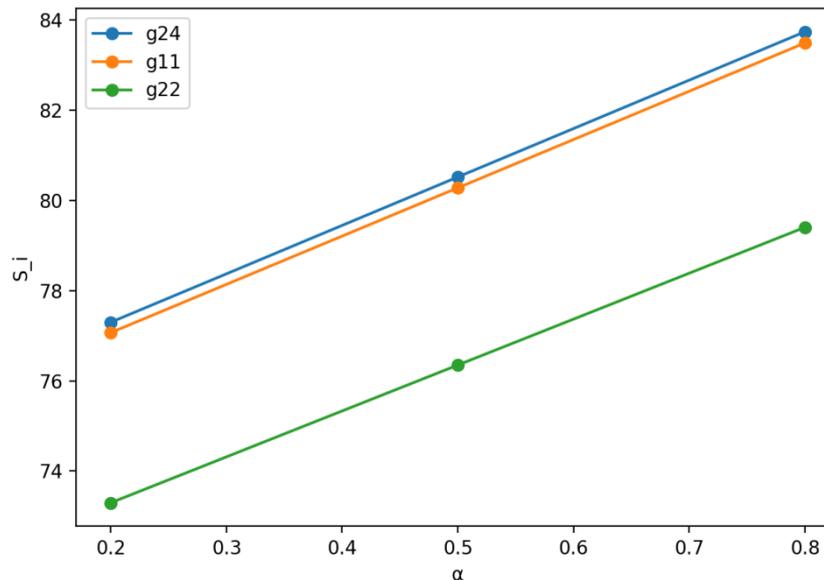


**Fig.4. Dependence of the integral assessment of prospects on parameter**

Analysis of the graph shows that with an increase in the value of α from 0.2 to 0.8, there is an increase in the integral assessment, which corresponds to the strengthening of the influence of development dynamics indicators in the generalised criterion. At the same time, the ranking of candidates remains unchanged, which indicates the stability of the model to moderate changes in controlled parameters and confirms its robustness and controllability.

The results of experimental studies have shown that the use of normalisation and a hierarchical multi-criteria model ensures the stability and reproducibility of candidate assessment. A comparison of the selection results obtained using the proposed model with expert assessments demonstrated a high level of consistency, which indicates the adequacy of the model to the actual decision-making process.

In addition, the experiment confirmed the expediency of considering the selection of young people taking into account not only the current values of indicators, but also their comprehensive combination within a formalised model. The proposed solutions make it possible to reduce the influence of subjective factors and increase the transparency of the selection process in an intelligent information system for decision support in the process of sports selection.

The results obtained indicate the effective integration of multi-criteria assessment and the method of hierarchy analysis within the intellectual information system for decision support. The proposed approach provides the possibility of adapting criteria and weighting coefficients to different conditions and requirements, which is especially important for the task of selecting young people with high development potential.

Thus, experimental studies have confirmed the practical applicability of the proposed model and the feasibility of its use as a decision support tool in weakly formalised selection tasks.

## Conclusions

The modern development of information technologies, intelligent data analysis and decision support systems creates the prerequisites for the formalisation and automation of sports selection processes. At the same time, analysis of scientific publications shows that most existing models of multi-criteria assessment of athletes are static in nature and focused on analysing the current level of preparedness, without taking into account the dynamics of changes in characteristics over time. This is a significant limitation in the selection of young candidates, for whom development potential is crucial.

Therefore, the paper proposes an adaptive multi-criteria decision support model for sports selection tasks, which combines the assessment of the current level of preparedness of candidates with formalised consideration of the dynamics of their characteristics.

A mathematical apparatus for forming an integral assessment of prospects has been developed, based on the hierarchical aggregation of normalised indicators and the use of the hierarchy analysis method to determine weighting coefficients. The proposed approach ensures the transparency, reproducibility and interpretability of the assessment results. For the first time, a generalised performance indicator has been introduced into the youth selection process, which takes into account both normalised values and the rate of change over time, allowing for an assessment of future potential rather than just current results. Within the framework of an experimental study on a sample of 24 candidates, it was shown that the distribution of integral assessments has a heterogeneous structure, which justifies the use of

adaptive threshold values for classifying candidates according to their level of prospects. The use of statistically justified thresholds made it possible to form a group of the most promising candidates without introducing strict regulatory restrictions. The analysis of the model's sensitivity to changes in the α parameter confirmed its controllability and stability. A change in the balance between current indicators and development dynamics affects the absolute values of the integral assessment, but does not violate the overall structure of candidate ranking.

The results obtained indicate the practical applicability of the proposed model for use in intelligent decision support systems for youth selection tasks and confirm the feasibility of using formalised multi-criteria analysis methods.

## ADDITIONAL INFORMATION

### AUTHOR CONTRIBUTIONS
**Hnatchuk Alina** – developing a research concept, creating a methodology, performing formal analysis, obtaining and processing new scientific results, implementing methods in software, conducting experimental research, preparing an original manuscript, visualizing and interpreting data.
**Hnatchuk Yaroslav** – consultations on methodology and experimental part, verification and validation of results, ensuring scientific accuracy and integrity of research.

### DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS
In the preparation of this work, the authors used ChatGPT and Grammarly for grammar and spelling checks, paraphrasing, and rephrasing of individual sentences. After using these tools/services, the authors reviewed and edited the content and take full responsibility for the content of this publication.

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# АДАПТИВНА БАГАТОКРИТЕРІАЛЬНА МОДЕЛЬ ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ В ЗАДАЧАХ СПОРТИВНОГО ВІДБОРУ

У сучасних умовах розвитку інформаційних технологій, інтелектуального аналізу даних та систем підтримки прийняття рішень виникає потреба у формалізації та автоматизації процесів спортивного відбору. Існуючі моделі багатокритеріальної оцінки спортсменів, як правило, мають статичний характер і орієнтовані лише на аналіз поточного рівня підготовленості, що обмежує їх ефективність при відборі молодих кандидатів, для яких важливим є потенціал розвитку. У роботі запропоновано адаптивну багатокритеріальну модель підтримки прийняття рішень, яка інтегрує оцінку поточного рівня характеристик кандидатів з формалізованим урахуванням динаміки їх розвитку у часі. Розроблено математичний апарат формування інтегральної оцінки перспективності, що базується на ієрархічній агрегації нормалізованих показників та застосуванні методу аналізу ієрархій для визначення вагових коефіцієнтів. Вперше введено узагальнений показник характеристики, який поєднує нормалізовані значення показників та темп їх змін, що дозволяє оцінювати не лише поточні результати, а й перспективність розвитку. Експериментальне дослідження на вибірці з 24 кандидатів показало неоднорідну структуру розподілу інтегральних оцінок, що підтверджує доцільність використання адаптивних порогів для класифікації кандидатів за рівнем перспективності. Проведено аналіз чутливості моделі до зміни параметра α, що дозволяє регулювати баланс між поточними показниками та динамікою розвитку. Результати підтвердили стійкість моделі та незмінність загальної структури ранжування кандидатів при зміні вагових параметрів. Запропонована модель забезпечує прозорість, відтворюваність та інтерпретованість оцінювання, що робить її придатною для використання в інтелектуальних системах підтримки прийняття рішень у задачах спортивного відбору молоді. Практична користь моделі полягає у тому, що вона дозволяє тренерам і спеціалістам зі спортивного відбору ефективно та об'єктивно визначати кандидатів з високим потенціалом розвитку, враховуючи як поточний рівень підготовленості, так і динаміку їх характеристик. Модель може бути інтегрована в інтелектуальні системи підтримки прийняття рішень для планування тренувального процесу та стратегічного формування команд молодих спортсменів.

Ключові слова: системи підтримки прийняття рішень, багатокритеріальна оцінка, інтегральна оцінка перспективності, адаптивна модель, динаміка розвитку, спортивний відбір, метод аналізу ієрархій.