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Article

Algorithm for Determination of Indicators Predicting Health Status for Health Monitoring Process Optimization

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Abstract: This article proposes an algorithm that allows the selection of prognostic variables from a set of 21 variables describing the health statuses of male and female students. The set of variables could be divided into two groups—body condition indicators and body activity indicators. For this purpose, we propose applying the multiple criteria decision methods WEBIRA, entropy-ARAS, and SAW in modelling the general health index, a latent variable describing health status, which is used to rank the alternatives. In the next stage, applying multiple regression analysis, the most informative indicators influencing health status are selected by reducing the indicator's number to 9–11, and predictor indicators by reducing their number to 5. A methodology for grouping students into three groups is proposed, using selected influencing indicators and predictor indicators in regression equations with the dependent variable of group number. Our study revealed that two body condition indicators and three body activity indicators have the greatest influence on men's general health index. It was established that two body condition indicators have the greatest influence on women's general health index. The determination of the most informative indicators is important for predicting health status and optimizing the health monitoring process.

Keywords: body condition; body activity; MCDM methods; entropy; regression analysis

MSC: 90-10

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1. Introduction

The public's interest in their body condition and its influence on lifestyle factors is increasing. Lifestyle factors are closely related not only to the state of health but also to the efficiency of professional activities and the quality of personal life [1]. Lifestyle factors influence body parameters and mentality. Lifestyle is the typical way of life of an individual, group, or culture [2]. A healthy lifestyle is a way of life that reduces the risk of serious illness or early death [3]. Personal health indicators can be conditionally divided into indicators describing the physical condition and indicators of healthy behavior [4]. Physical condition is the state of the body or body functions. Healthy behavior is the individual maintaining or enhancing health, preventing health problems, or achieving a positive body image. It is important to understand which information are the most informative for assessing a person's health: a person's healthy behavior indicators or indicators of the physical condition of the body [5]. The bases of self-assessment can be subjective (self-assessment based on a checklist) and objective (measurements and tests). Health self-assessment provides an opportunity to understand vital information about body conditions and changes [6]. It can motivate people to take action to change their lifestyle [7]. There is an increasing number of methodologies and devices on the market that help monitor and manage body activity and lifestyle factors [8,9]. The abundance of healthy lifestyle score methodologies that focus on a lot of behavioral and body condition indicators makes self-monitoring a complex and difficult process for the average ordinary user [10–12]. It is important to move toward better understanding of healthy behavior and physical condition indicators. Relevant empirical research is needed on a wide range of behavioral and physical condition indicators [13]. An important problem is to determine the most informative indicators of a healthy lifestyle, thanks to which it would be possible to make decisions about lifestyle adjustment not only for individuals, but also for social groups [14,15]. The abundance of human body condition indicators complicates control and operational management [16]. To effectively manage the process of improving health and the state of the body, it is necessary to divide the indicators into groups according to their greatest influence on the state of the body.

Process monitoring and evaluation are key factors in their planning and implementation. Three main aspects of planning and implementation are distinguished: (1) monitoring of parameters; (2) recording and evaluation of parameter deviations from optimal values; (3) process adjustment [17]. Indicators form the basis of process monitoring and evaluation. Indicators are divided according to criteria: (1) performance [18], (2) lead [19], (3) trends [20].

In order to optimize the process, it is necessary to determine indicators of high informativeness [21], which help to quickly identify undesirable changes and evaluate the implementation of goals. It is necessary to ensure that indicators selected for the evaluation correspond to the desired goal and inform about the essential changes in the process, that is, they play the role of a trigger in management (signals about the need to make a decision on corrections) [22,23]. The trigger indicators selected for monitoring must be linked to specific criteria and targeted results. Trigger indicators, due to their informativeness, can reflect systemic or critical changes and their progress. Trigger indicators make it possible to identify a critical deviation from the goal in the course of the process, after which undesirable changes may occur that prevent the achievement of the intended goal. The readings of the trigger indicators, upon reaching which corrective measures are taken, are set in such a range that there is enough time to correct the course of the process before the limit of irreversibility is reached. By determining the critical readings of the trigger indicators, one can identify real changes.

It is ineffective to collect complex and abundant information if there are no opportunities to analyze and use it to adjust processes. Information provided by the evaluated indicators must be understandable to process coordinators and executors. Thus, the evaluated indicators must meet the criteria of SMART indicators: specific, measurable, achievable, relevant, and time bound [24]. The SMART indicator best reflects the success of the process implementation [25].

It is important that the selected indicators meet the objectives of the plan adaptation and are not selected because other researchers use them.

A key question raised by this study is: how to identify informative indicators of a healthy lifestyle in order to promptly monitor and manage processes of the body condition and how to distinguish them according to informativeness identifying triggers?

The following methods are used in the article to achieve the set goals. MCDM methods WEBIRA, entropy-ARAS, and SAW are applied in the article. Weight-balancing indicator ranks accordance (WEBIRA) [26–29] is a modification of another method—the KEmeny median indicator ranks accordance (KEMIRA) [30], in which entropy is usually used to prioritize criteria. WEBIRA is adapted to search for the best alternative, when the set of variables is divided into two related groups. WEBIRA proposes a technique of criteria weights calculation through weight-balancing procedure when the optimization problem of maximizing compatibility of two subsets of criteria, is solved.

The additive ratio assessment (ARAS) method [31] is a convenient method in which the most acceptable alternative is determined on the basis of degree of utility, calculated for each alternative as the ratio of overall performance index of i-th alternative and overall performance index of optimal alternative. In this article, criteria weights are calculated by applying entropy approach [32].

The simple additive weighting method (SAW) proposed in [33] is one of the oldest and simplest MCDM methods. It uses a simple aggregation procedure based on weighted average and is also known as weighted linear combination method. For simplicity of method demonstration, equal weights of variables are used in this article. A comprehensive review of contemporary MCDM methods is given in Zavadskas et al. [34].

Final ranking of alternatives was calculated for men and women via averaging rankings obtained using WEBIRA, ARAS, and SAW methods. Then, the most informative indicators for evaluation of students' health states and predictor indicators, were selected using the stepwise multivariate regression procedure [35].

Finally, the most informative and predictive indicators were used for classifying the alternatives into three groups, according to their health status.

This paper presents the original approach for ranking the alternatives according to the set of given indicators, which can be applied for solving similar problems in various areas. Applied MCDM methods can vary, the methods best suited to the structure and specifics of the data under investigation, may be used. The novelty of the proposed method is that we use synthesis of objective and subjective methods, when the calculations include experimental results and the best indicator values proposed by experts. In addition, the method uses hybrid technology, when the MCDM approach is mixed with the stepwise regression procedure for revealing the most informative prognostic indicators and for classifying students into groups according to their health level. To our knowledge, the proposed methodology has not yet been described in the literature.

The rest of the article is organized as follows. In Section 2, the indicators influencing student's health status are described and research methodology is presented. In Section 3, final ranking of students was established on the basis of three MCDM methods rankings –WEBIRA, entropy-ARAS, and SAW. Regression analysis and classification results are presented in Section 4. The most informative indicators selection results are discussed in Section 5. Discussion and conclusions are given in Section 6.

2. Data Preparation for the Analysis

2.1. Study Design

Participants in the research composition were 106 male students (21.358 $\pm$ 1.106 years old) and 51 female students (21.333 $\pm$ 1.089 years old), who were randomly selected from the second–third courses of bachelor studies at different faculties of Vilnius Gediminas Technical University.

Selected students carried out self-testing, self-observation, and self-evaluation according to 21 criteria over a 7-day period. Students who participated in the research were instructed and trained in the methods for test data collection and accounting. The subjects' reports were anonymized by assigning codes. All subjects were informed of the study research procedures, requirements, benefits, and risks. Informed consent was obtained from all participants. The obtained data were grouped and summarized.

A total of 21 evaluation criteria were classified into two groups of competencies (variables) regarding the features analyzed, as follows:

1. Body condition indicators (X1):
   (1) Body mass index, (units), [36];
   (2) Waist-to-hip ratio, (units), [37];
   (3) Body fat percentage, (%), [38–40];
   (4) Body muscle percentage, (%), [41,42];
   (5) Ruffier–Dickson index, (units), [43];
   (6) Resting heart rate, (units), [44];
   (7) VO_2max, (mL/kg/min), [45].
2. Body activity indicators (X2) (seven days average):
   (1) Duration of sleep per day, (min), [46];
   (2) Number of meals per day, (units), [47];

(3) Duration of one meal, (min), [48];
(4) Food and water consumption per day, (g), [49];
(5) Energy intake per day, (Kcal), [50];
(6) Carbohydrate intake, (%), [51];
(7) Protein intake, (%), [51];
(8) Fat intake, (%), [51];
(9) Expenditure of energy per day, (Kcal), [50];
(10) Physical activity, METs < 3, (%), [52,53];
(11) Physical activity, METs = from 3 to 6, (%), [52,53];
(12) Physical activity, METs > 6, (%), [52,53];
(13) Time of physical activity, METs = from 3 to 6, (units), [52,53];
(14) Time of physical activity, METs > 6, (units), [52,53].

2.2. The Indicators

Each investigated participant performed self-monitoring and self-testing using standardized methodology and submitted a report. The reports were summarized, and the data were processed using the selected mathematical methods. In Tables 1 and 2, minimum, maximum, average ($\overline{X}$), standard deviation (*SD*), and optimal values of indicators are presented for male and female students. Optimal data values for men and women of this age group were chosen for evaluation based on research data and recommendations of other authors [36–53].

Table 1. Values of indicator variables for men (optimal indicators of parameters are determined according to research data from sources [36–53]).

No	Indicator	Indicator Abbreviation	Minimum Value	Maximum Value	$\overline{X} \pm$ SD	Optimal Value
			Body condition indicators (X1)			
1	Body mass index, (units)	A	18.922	34.903	23.682 ± 2.516	22
2	Waist-to-hip ratio, (units)	B	0.783	1.190	0.940 ± 0.061	0.95
3	Body fat percentage, (%)	C	10.630	29.475	16.457 ± 3.529	21
4	Body muscle percentage, (%)	D	39.767	55.295	48.183 ± 2.733	42
5	Ruffier–Dickson index, (units)	E	−1.200	15.200	5.704 ± 2.700	6
6	Resting heart rate, (units)	F	44	88	66.547 ± 8.564	60
7	VO_2max, (mL/kg/min)	G	33	68	47.321 ± 6.922	47
			Body activity indicators (X2)			
8	Duration of sleep per day, (min)	H	360	589	479.802 ± 46.996	420
9	Number of meals per day, (units)	I	3	6	3.811 ± 0.558	4
10	Duration of one meal, (min)	J	6	25	13.882 ± 4.123	20
11	Food and water consumption per day, (g)	K	1105.714	2485.714	1697.764 ± 352.502	2300
12	Energy intake per day, (Kcal)	L	1837.519	3832.953	2501.877 ± 389.332	2400
13	Carbohydrate intake, (%)	M	33.717	89.471	57.526 ± 7.041	55
14	Protein intake, (%)	N	7.081	44.036	23.378 ± 5.279	30
15	Fat intake, (%)	O	3.447	32.437	19.096 ± 5.378	15
16	Expenditure of energy per day, (Kcal)	P	1823.571	4200.714	2725.974 ± 393.138	2300
17	Physical activity, METs < 3, (%)	Q	17.289	96.736	74.475 ± 13.224	39
18	Physical activity, METs = from 3 to 6, (%)	R	0	56.139	15.961 ± 11.889	60
19	Physical activity, METs > 6, (%)	S	0	41.793	9.563 ± 8.958	1
20	Time of physical activity, METs = from 3 to 6, (units)	T	0	14	5.425 ± 3.380	7
21	Time of physical activity, METs > 6, (units)	U	0	9	2.528 ± 2.466	3

Table 2. Values of indicator variables for women (optimal indicators of parameters are determined according to research data from sources [36–53]).

No	Indicator	Indicator Abbreviation	Minimum Value	Maximum Value	$\overline{X} \pm$ SD	Optimal Value
		Body condition indicators (X1)				
1	Body mass index, (units)	A	15.055	31.572	21.423 ± 3.214	21
2	Waist-to-hip ratio, (units)	B	0.628	0.953	0.795 ± 0.073	0.8
3	Body fat percentage, (%)	C	11.073	37.731	20.974 ± 6.296	28
4	Body muscle percentage, (%)	D	36.805	52.388	43.317 ± 3.353	32
5	Ruffier–Dickson index, (units)	E	0.8	15.2	7.302 ± 2.851	7
6	Resting heart rate, (units)	F	52	92	70.510 ± 7.998	70
7	VO_2max, (mL/kg/min)	G	32.0	58.0	42.980 ± 5.634	43
		Body activity indicators (X2)				
8	Duration of sleep per day, (min)	H	360	593	488.549 ± 53.547	420
9	Number of meals per day, (units)	I	2	7	3.922 ± 0.821	4
10	Duration of one meal, (min)	J	8	34	15.078 ± 6.273	20
11	Food and water consumption per day, (g)	K	818.466	2910.237	1484.210 ± 486.845	1800
12	Energy intake per day, (Kcal)	L	1442.921	2451.713	1793.340 ± 327.930	1800
13	Carbohydrate intake, (%)	M	39.508	86.604	60.067 ± 6.937	55
14	Protein intake, (%)	N	6.631	30.953	21.908 ± 4.878	30
15	Fat intake, (%)	O	6.766	29.539	18.024 ± 4.176	15
16	Expenditure of energy per day, (Kcal)	P	1505.198	2938.365	2275.450 ± 269.487	2000
17	Physical activity, METs < 3, (%)	Q	55.930	99.176	77.130 ± 11.336	39
18	Physical activity, METs = from 3 to 6, (%)	R	0	31.816	15.206 ± 9.872	60
19	Physical activity, METs>6, (%)	S	0	31.018	7.665 ± 7.260	1
20	Time of physical activity, METs = from 3 to 6, (units)	T	0	22	7.216 ± 5.029	7
21	Time of physical activity, METs > 6, (units)	U	0	8	2.333 ± 1.987	3

2.3. Algorithm of Data Transformation

The data under investigation could be divided into three groups:

(i) The optimal value is the largest;
(ii) The optimal value is the smallest;
(iii) The optimal value is intermediate value between the smallest and the largest.

There are two data matrices: first data matrix $(X_m)_{106\times21}$ for men and second data matrix $(X_w)_{51\times21}$ for women, where each column corresponds to one of 21 variables. The algorithm of column data $\{x_j\}$ transformation to the integers $\{y_j\} \in \{0, 1, \ldots, 100\}$ is as follows:

The optimal value can be the largest one, while the smallest and intermediate value are between the smallest and the largest. In all cases, the transformation algorithm is given as below:

1. Calculate two values m and M, $m < M$, as follows:

$$m = \max\{m_1, m_2\},\ \ m_1 = \min\{x_j\},\ m_2 = \overline{x} - 2\sigma, \tag{1}$$

$$M = \min\{M_1, M_2\},\ \ M_1 = \max\{x_j\},\ \ M_2 = \overline{x} + 2\sigma, \tag{2}$$

where $\overline{x} = \frac{1}{n}\sum_{j=1}^{n} x_j, \sigma = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_j - \overline{x}\right)^2}$.

2. Suppose that X is specified optimal value for given indicator (see Tables 1 and 2). If $M < X$, then we assign $M = X$.

$$y(x) = \begin{cases} \left[100 \cdot \frac{x-m}{X-m} + 0.499\right],\ if\ x \in [m, X], \\ \left[100 \cdot \frac{M-x}{M-X} + 0.499\right],\ if\ x \in [X, M], \\ 0,\ if\ x \notin [m, M], \end{cases} \quad (3)$$

where $[\ldots]$ is an integer part of a number. This allows us to truncate a number to an integer by removing its fractional part, for example, $[8.37 + 0.499] = [8.869] = 8$ or $[8.57 + 0.499] = [9.069] = 9$. As a result, we have transformed data $\{y_j\} \in \{0, 1, \ldots, 100\}$, and all indicators are benefit type indicators, i.e., their bigger values are better. Further, the transformed data $\{y_j\}$ will be used directly, or, if it is necessary (for example, when applying MCDM methods), $\{y_j\}$ are normalised so that we get data from the interval $[0, 1]$.

We do the data transformation not only so that all indicators are benefit type, but also so that they are not overloaded with redundant information. The data in this study were obtained by survey, their accuracy is not high; we believe that an accuracy to two digits is sufficient. Therefore, we transformed the data into whole numbers, writing them down compactly. A value of 2σ (an interval of 4σ length) contains 95% of normally distributed values. We think that this is enough, since the accuracy of the data is not high; therefore, we filter more values (leave fewer values). Future comparisons could be made using 3σ filtering, but this is unlikely to significantly change the results.

2.4. Research Methodology

After data transformation, three MCDM methods were applied to the initial data matrix. As a result, we received four rankings of alternatives—two by WEBIRA, one by entropy-ARAS, and one ranking from the SAW method. Averaging these four rankings gives a final ranking of the alternatives. However, the question of which criteria are most informative for men and women in determining their health status remains unanswered. In the next step, regression analysis is applied to the final rank of the student (dependent variable) and the whole set of indicators (independent variables). Then, the set of independent variables was reduced to the most informative subsets of indicators—influencing and predictor indicators. The corresponding regression equations were obtained. Finally, regression models for grouping variables were created. This demonstrated how alternatives could be classified into three groups according to values of influencing and predictor indicators.

The description of the most informative indicators selection and alternatives classification procedure is given below:

1. Collecting information for initial data matrix.
2. Data transformation to the benefit type integers $\{y_j\} \in \{0, 1, \ldots, 100\}$.
3. Calculation of alternatives ranks according to three methods: WEBIRA, entropy-ARAS, and SAW.
4. Calculation of final ranks of alternatives by averaging ranks obtained by selected methods.
5. Implementation of stepwise regression procedure, where the final rank is a dependent variable, for determining 9–11 most informative (influencing) indicators.
6. Implementation of the stepwise regression procedure for revealing the five most informative indicators (predictors).
7. Classification of alternatives into three groups according to their health status on the basis of regression where the group is dependent variable, and the most informative indicators are independent variables.

2.5. Methodological Limitations

About 2% of students from different faculties were randomly selected to participate in the study at Vilnius Gediminas University of Technology. All participants solved tasks assigned anonymously. To assess the health status of other universities, extensive research is necessary, it is necessary to conduct research with dependent samples (the same research subjects at the beginning of the first year and the end of the fourth year). Only assumptions can be made when evaluating the self-esteem data independent samples. We plan to perform research with dependent samples in the future. This aspect should also be investigated in the future. The authors of the tests provide rating scales and do not specify target audiences; therefore, specialized research is necessary based on which target rating scales are created. To ensure the internal validity of the research, approved tests were used. The research participants were introduced to the test tasks just before performing them. To exclude erroneous data, tests with values outside the 3SD mean were excluded from the study.

3. MCDM Methods for Obtaining Criteria Weights and Ranking Results

In this section, students ranking was performed via three MCDM methods: WEBIRA (weight-balancing indicator ranks accordance), ARAS (additive ratio assessment), and SAW (simple additive weighting). All these methods implement full cycle of MCDM procedures:

1. Determining priorities for evaluation criteria;
2. Calculation of criteria weights;
3. Ranking the alternatives.

3.1. The WEBIRA Method

WEBIRA is one of the MCDM methods designed to work with data arrays, where a whole set of indicators can be divided into two groups of the same nature, for example, external and internal, objective and subjective indicators, etc. Likewise, in this research, the variables (indicators) could be naturally divided into two groups: indicators describing students physical condition $\left(X_j^1, j = 1,\ 2, \ldots,\ n_1\right)$ and indicators describing students healthy behavior $\left(X_j^2,\ j = 1,\ 2,\ \ldots, n_2\right)$. The decision matrix is given in Equation (4):

$$D = \left[\begin{array}{ccc|ccc} x_{11}^1 & \cdots & x_{1n_1}^1 & x_{11}^2 & \cdots & x_{1n_2}^2 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ x_{m1}^1 & \cdots & x_{mn_1}^1 & x_{m1}^2 & \cdots & x_{mn_2}^2 \end{array}\right], \tag{4}$$

where m is the number of observations (51 for women and 106 for men), $n_1 = 7$ is the number of indicators in the first group, and $n_2 = 14$ is the number of indicators in the second group. Data in matrix D are transformed according to algorithm described in Section 2.3.

Transformed data are normalized using the direct min-max normalization formula, where a higher value is considered preferable, as follows:

$$\hat{x}_{ij}^{1,2} = \frac{x_{ij}^{1,2} - x_j^-}{x_j^+ - x_j^-}, \tag{5}$$

$$x_j^- = \min_{i=1,2,\ldots,m} x_{ij}^{1,2},\ x_j^+ = \max_{i=1,2,\ldots,m} x_{ij}^{1,2},\ j = 1,2,\ldots,n_{1,2},$$

The obtained normalized values $\hat{x}_{ij}^{1,2}$ are in the interval $[0,1]$. In the first step of WEBIRA, criteria priority is determined separately in each group of criteria according to the decreasing value of entropy. Thus, the weight of similar data (when the values of the criteria do not differ considerably) obtained by WEBIRA is low. The large weight corresponds to the criterion with non-homogeneous data. Suppose that $\hat{x}_j, (j = 1,\ 2, \ldots, m)$ are normalized values of an indicator, calculated by Equation (5). Denote $\overline{x_j}, (j = 1, 2, \ldots, k)$ different values of $\hat{x}_j$ and $d_j, j = 1, 2, \ldots, k$–frequencies of these values. Then, relative frequency of value $\hat{x}_j$ is equal to $\frac{d_j}{m}$ $\left(\sum_{j=1}^k d_j = m\right)$. Entropy of the criterion $X = (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_m)$ is calculated as follows [28]:

$$e_X = -\frac{1}{\ln m}\sum_{j=1}^{k} \frac{d_j}{m} \ln\left(\frac{d_j}{m}\right). \tag{6}$$

Here, we treat X as a discrete random variable that takes on values $\hat{x}_j$, and relative frequencies $\frac{d_j}{m}$ are considered as probabilities of corresponding values of this random variable. Note, that $\sum_{j=1}^{k} \frac{d_j}{m} = 1$.

In Table 3, entropy values and priorities of indicators for men and women are presented, determined in two separate groups: X^1 and X^2. The priorities of body activity indicators are similar for men and women. Only the first five positions vary—K, N, L, M, O for men and M, O, L, N, K for women. These indicators reflect consumption of food, water, energy, and various types of food macronutrients. For men, the indicators with the highest priority are food and water consumption per day, protein intake, and energy intake. For women they are carbohydrate intake, fat intake, and energy intake. The priorities of body condition indicators are also similar for both men and women, except A (body mass index), which is the most important indicator for women and the least important for men.

Table 3. Entropy values and priority of indicators for men and women.

Men				Women			
Indicator	**Indicator Abbreviation**	**Entropy**	**Priority**	**Indicator**	**Indicator Abbreviation**	**Entropy**	**Priority**
Body condition indicators (X1)							
Body fat percentage	C	0.871489	1	Body mass index	A	0.921343	1
Body muscle percentage	D	0.854115	2	Body muscle percentage	D	0.907517	2
Waist-to-hip ratio	B	0.818183	3	Body fat percentage	C	0.888126	3
Ruffier–Dickson index	E	0.661923	4	Waist-to-hip ratio	B	0.881558	4
VO_2max	G	0.6098	5	Ruffier–Dickson index	E	0.773987	5
Resting heart rate	F	0.449279	6	VO_2max	G	0.667622	6
Body mass index	A	0.268122	7	Resting heart rate	F	0.503433	7
Body activity indicators (X2)							
Food and water consumption per day	K	0.894807	1	Carbohydrate intake	M	0.917039	1
Protein intake	N	0.861841	2	Fat intake	O	0.911475	2
Energy intake	L	0.847308	3	Energy intake	L	0.907517	3
Carbohydrate intake	M	0.841269	4	Protein intake	N	0.907517	4
Fat intake	O	0.832915	5	Food and water consumption per day	K	0.89369	5
Physical activity, METs < 3	Q	0.832635	6	Physical activity, METs < 3	Q	0.888471	6
Expenditure of energy per day	P	0.802044	7	Expenditure of energy per day	P	0.874299	7
Physical activity, METs = from 3 to 6	R	0.782924	8	Physical activity, METs = from 3 to 6	R	0.853559	8
Physical activity, METs > 6	S	0.723188	9	Physical activity, METs > 6	S	0.802901	9
Duration of sleep per day	H	0.645677	10	Duration of sleep per day	H	0.778861	10
Duration of one meal	J	0.554215	11	Duration of one meal	J	0.653795	11
Time of physical activity, METs = from 3 to 6	T	0.524263	12	Time of physical activity, METs = from 3 to 6	T	0.640313	12
Time of physical activity, METs > 6	U	0.368857	13	Time of physical activity, METs > 6	U	0.438689	13
Number of meals per day	I	0.229003	14	Number of meals per day	I	0.273371	14

Indicators will be assigned weights based on their entropy value. Indicators with the highest entropy provide the most quantity of information about the student; indicators with the lowest entropy, as a rule, have few different values and are the least informative. Such indicators will be given small weights, for example, the least informative indicator in the body activity (X^2) group is number of meals per day. The weight of this indicator should be the lowest in both the male and female groups.

In the second step of WEBIRA, the criteria weights are calculated. Criteria (indicators) $x_1^{1,2}, x_2^{1,2}, \ldots, x_{n_{1,2}}^{1,2}$ are arranged in descending order of their priority. The criterion with the highest priority, i.e., the one with the highest entropy, must have the highest weight and vice versa.

Two weighted sums are calculated for each row of matrix D:

$$S_{X^1}^{(i)} = \sum_{j=1}^{n_1} w_{x_j^1} x_{ij}^1, \quad S_{X^2}^{(i)} = \sum_{j=1}^{n_2} w_{x_j^2} x_{ij}^2, i = 1, 2, \ldots, m, \tag{7}$$

where coefficients $W_{X^1} = \left(w_{x_1^1}, w_{x_2^1}, \ldots, w_{x_{n_1}^1}\right)$ and $W_{X^2} = \left(w_{x_1^2}, w_{x_2^2}, \ldots, w_{x_{n_2}^2}\right)$ must satisfy the following conditions:

$$1 \geq w_{x_1^1} \geq w_{x_2^1} \geq \ldots \geq w_{x_{n_1}^1} \geq 0; 1 \geq w_{x_1^2} \geq w_{x_2^2} \geq \ldots \geq w_{x_{n_2}^2} \geq 0 \tag{8}$$

and

$$\sum_{j=1}^{n_1} w_{x_j^1} = \sum_{j=1}^{n_2} w_{x_j^2} = 1. \tag{9}$$

Denote $R_{X^1}^{(i)}$ and $R_{X^2}^{(i)}$ as the two separate interim rankings created according to values of weighted sums (7), i.e., according to body condition indicators (X^1) and body activity indicators (X^2). For example, in the first ranking, alternative with the highest value of weighted sum $S_{X^1}^{(i)}$ will be assigned a rank 1, alternative with the second highest value will be assigned a rank 2, and so on. Analogously, we obtained a ranking of alternatives according to values of the weighted sum $S_{X^2}^{(i)}$. The procedure for calculating weighted sums $S_{X^1}^{(i)}$ and $S_{X^2}^{(i)}$ and ranks $R_{X^1}^{(i)}$ and $R_{X^2}^{(i)}$ is performed many times until a solution to the optimization problem (10) or (11) is found, i.e., until we found sets of weights (8) that minimize the objective functions.

The essence of WEBIRA method, i.e., that criteria weights must minimize the objective function, which measures the discrepancy between the two rankings of objects, one by the first group of criteria and the other by the second. The distance between the two rankings could be measured using various formulas. In Equation (10), the distance function is the sum of the absolute values of the differences between $S_{X^1}^{(i)}$ and $S_{X^2}^{(i)}$ and sum of the absolute values of the differences in their ranks $R_{X^1}^{(i)}$ and $R_{X^2}^{(i)}$. The weights satisfying conditions (8) and (9) are sought by solving the following optimization problem:

$$s_1(W_{X^1}, W_{X^2}) = \min_{W_{X^1}, W_{X^2}} \frac{1}{m} \sum_{i=1}^{m} \left(\left| S_{X^1}^{(i)} - S_{X^2}^{(i)} \right| + \left| R_{X^1}^{(i)} - R_{X^2}^{(i)} \right| \right), \tag{10}$$

where the value $s_1(W_{X^1}, W_{X^2})$ measures the similarity of alternatives rankings while using only the first (X^1) and only the second (X^2) group of criteria. The procedure of calculating criteria weights is called the weight-balancing procedure. Alternatively, we calculated weights of criteria using Equation (11), where the distance function is the sum of the squared differences between $S_{X^1}^{(i)}$ and $S_{X^2}^{(i)}$ and the sum of the squared differences in their ranks, as follows:

$$s_2(W_{X^1}, W_{X^2}) = \min_{W_{X^1}, W_{X^2}} \frac{1}{m} \sum_{i=1}^{m} \left(\left(S_{X^1}^{(i)} - S_{X^2}^{(i)} \right)^2 + \left(R_{X^1}^{(i)} - R_{X^2}^{(i)} \right)^2 \right). \tag{11}$$

Criteria weights for men and women calculated using Equations (10) and (11) are presented in Table 4.

When the weights of the criteria are found, the final values of the weighted sums $S_{X^1}^{(i)}$ and $S_{X^2}^{(i)}$ are calculated and it is then possible to calculate alternative ranks.

Table 4. Criteria weights for men and women calculated using Equations (10) and (11).

Men				Women			
Indicator	**Indicator Abbreviation**	**Weight Equation (10)**	**Weight Equation (11)**	**Indicator**	**Indicator Abbreviation**	**Weight Equation (10)**	**Weight Equation (11)**
Body condition indicators (X1)							
Body fat percentage	C	0.4410	0.4933	Body mass index	A	0.2798	0.1571
Body muscle percentage	D	0.3296	0.4759	Body muscle percentage	D	0.1509	0.1479
Waist-to-hip ratio	B	0.0522	0.0062	Body fat percentage	C	0.1171	0.1479
Ruffier–Dickson index	E	0.0522	0.0062	Waist-to-hip ratio	B	0.1171	0.1391
VO_2max	G	0.0522	0.0062	Ruffier–Dickson index	E	0.1171	0.1391
Resting heart rate	F	0.0522	0.0061	VO_2max	G	0.1170	0.1390
Body mass index	A	0.0205	0.0060	Resting heart rate	F	0.1010	0.1299
Body activity indicators (X2)							
Food and water consumption per day	K	0.7696	0.7522	Carbohydrate intake	M	0.3144	0.4507
Protein intake	N	0.1995	0.2033	Fat intake	O	0.3135	0.4506
Energy intake	L	0.0039	0.0089	Energy intake	L	0.2641	0.0177
Carbohydrate intake	M	0.0039	0.0089	Protein intake	N	0.0120	0.0102
Fat intake	O	0.0039	0.0032	Food and water consumption per day	K	0.0120	0.0102
Physical activity, METs < 3	Q	0.0038	0.0032	Physical activity, METs < 3	Q	0.0120	0.0102
Expenditure of energy per day	P	0.0037	0.0032	Expenditure of energy per day	P	0.0118	0.0101
Physical activity, METs = from 3 to 6	R	0.0036	0.0032	Physical activity, METs = from 3 to 6	R	0.0117	0.0101
Physical activity, METs > 6	S	0.0035	0.0032	Physical activity, METs > 6	S	0.0108	0.0101
Duration of sleep per day	H	0.0034	0.0032	Duration of sleep per day	H	0.0107	0.0101
Duration of one meal	J	0.0003	0.0032	Duration of one meal	J	0.0107	0.0101
Time of physical activity, METs = from 3 to 6	T	0.0003	0.0018	Time of physical activity, METs = from 3 to 6	T	0.0096	0.0001
Time of physical activity, METs > 6	U	0.0002	0.0012	Time of physical activity, METs > 6	U	0.0068	0.0001
Number of meals per day	I	0.0001	0.0012	Number of meals per day	I	0	0

In the third step of WEBIRA, we rank the alternatives. The WEBIRA method constructs two sums $S^{(i)}_{X^1}$, $S^{(i)}_{X^2}$ (see Formula (7)), that are maximally matched with respect to the objective function (10) or (11). These sums provide two rankings of alternatives that need to be combined into one. The simplest, though not a unique method, is to rank the alternatives by the value of their sums $S^{(i)}_{X^1} + S^{(i)}_{X^2}$. All similar rankings (for example, $\max\left\{S^{(i)}_{X^1}, S^{(i)}_{X^2}\right\}$, $\min\left\{S^{(i)}_{X^1}, S^{(i)}_{X^2}\right\}$, $S^{(i)}_{X^1} \cdot S^{(i)}_{X^2}$, etc.) require some methodological justification. In this paper, we use α-cuts and analyse already constructed sets of alternatives without applying new algebraic operations. Ranks of alternatives are obtained by performing an α-cuts recursive procedure. This procedure ensures the interrelation between two groups of indicators—body condition and body activity indicators.

Let α be a positive number satisfying condition $0 < \alpha < 1$. Denote A_α—the set of alternatives $i^{(1)}, i^{(2)}, \ldots, i^{(k_\alpha)}$, which satisfy the following conditions:

$$S^{(i)}_{X^1} = \sum_{j=1}^{n_1} w_{x^1_j} x^1_{ij} \geq \alpha \text{ and } S^{(i)}_{X^2} = \sum_{j=1}^{n_2} w_{x^2_j} x^2_{ij} \geq \alpha, i \in A_\alpha. \tag{12}$$

We call A_α the α-cut of the set of alternatives $A = \{1, 2, \ldots, m\}$. A_α is the subset of the set A containing all the alternatives, with weighted sums $S^{(i)}_{X^1}$, $S^{(i)}_{X^2}$ greaterthan the threshold α. These alternatives are the best according to both groups of criteria—X^1 and X^2. Let initial value of α be equal to 1. A_1 is an empty set, i.e., $A_1 = \varnothing$. By gradually reducing the value of α, we will obtain α-cuts (sets of the alternatives) containing, respectively, $1, 2, \ldots, m$ alternatives. The procedure continues until all alternatives fall into the set A_α, i.e., with such α value, when Equation (12) is satisfied for all m alternatives. Alternatives that enter sets A_α one after another, acquire the respective ranks $1,\ 2, \ldots, m$. Since the number of alternatives m is finite, there exists a finite number of α-cuts $\alpha_1 > \alpha_2 > \alpha_3 > \ldots$. This allows us to obtain all different sets of alternatives $A_{\{\alpha_j\}}$. These sets naturally define the ranks of alternatives. Rank 1 (maximum) has an alternative $j_1 \in A_{\{\alpha_1\}}$, Rank 2 has an alternative $j_2 \in A_{\{\alpha_2\}} \setminus A_{\{\alpha_1\}}$, etc. Thus, the proposed ranking method does not require additional methodological considerations, analyses already obtained information and is best adapted to the WEBIRA method.

A detailed description of the α-cuts recursive procedure is provided in Krylovas et al. [28], where a ranking of 18 European countries according to the interrelation between two groups of criteria—children's physical activity in the countries and the countries' human development—was performed using the α-cuts recursive procedure.

As a result, we have two rankings of alternatives: $WEBIRA\ R_1$, when criteria weights set according to Formula (10); and $WEBIRA\ R_2$, according to Formula (11). The measures of similarity of alternatives rankings could be chosen in various ways. We proposed Formulas (10) and (11) for this purpose. We did not observe significant differences between alternative rankings when indicator weights were found using Equations (10) and (11). The Spearman correlation coefficient between the two rankings is 0.987 for men and 0.729 for women, (p-values < 0.001).

3.2. The Entropy-ARAS Method

Next, we used the entropy-ARAS method for alternatives ranking. The entropy method [32] is applied to calculate criteria weights. Then, following to the additive ratio assessment (ARAS) method, we calculated optimality function values, which are the basis for alternative rankings.

Shannon's entropy method is used to determine the significance of criteria in many MCDM problems. Entropy identifies the amount of uncertainty associated with an appropriate criterion. Suppose that x_{ij} are values of an indicator, $i = 1, 2, \ldots, m$ are the alternatives and $j = 1, 2, \ldots, n$ are the criteria. This method of entropy was described by

Claude E. Shannon [54]. The entropy of random variable X with probability distribution $p(x)$ is calculated as follows:

$$H(X) = -\sum_{x \in X} p(x) \log p(x).$$

Entropy-ARAS method proposes the original approach when values of criteria are normalized so that one will further deal with normalized values (13) as discrete probability distribution. Thus, the authors proposed an analogue of Shannon's entropy formula. The weights of the criteria are determined as follows:

1. The values of criteria are normalized using the following equation:

$$\hat{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \tag{13}$$

2. The analogue of entropy of each criterion is calculated as follows:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} \hat{x}_{ij} \ln\left(\hat{x}_{ij}\right),\ j = 1, \ldots, n,\ 0 < E_j < 1.$$

3. The extent of variation in each criterion is determined as follows:

$$d_j = 1 - E_j,\ j = 1, \ldots, n.$$

4. The normalized d_j values are taken for the weights obtained using the following entropy method:

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j}. \tag{14}$$

Note that the criteria weights obtained using Shannon's entropy method differ from the weights calculated according using Formula (6), for which we did not use the values of decision matrix x_{ij} but rather the frequencies of the values. The weights obtained using Formula (14) reflect the structure of the data (i.e., the elements of the decision matrix) and their non-homogeneity. The weight of non-homogeneous data with the values of the criteria differing considerably obtained by the entropy method (14) is about zero and does not have a strong influence on the evaluation.

For the ARAS method, criteria weights calculated using the entropy method (14) are used. The ARAS method has a utility function value determining the complex relative efficiency of a reasonable alternative, which is directly proportional to the relative effect of values and weights of the main criteria considered in a project [31]. The most acceptable alternative is determined on the basis of optimality function values Q_i, calculated using the following formula:

$$Q_i = \frac{S_i}{S_0},\ i = 1, \ldots, m, \tag{15}$$

where S_i is the overall performance index of the i-th alternative and S_0 is the overall performance index of the optimal alternative. The overall performance index of the i-th alternative can be determined as follows:

$$S_i = \sum_{j=1}^{n} w_j \hat{x}_{ij},\ i = 1, \ldots, m, \tag{16}$$

w_j are criteria weights, calculated using the entropy method (14), and $\hat{x}_{ij}$ are normalised values of criteria (13). The alternatives are ranked on the basis of their Q_i in ascending order, and the alternative with the highest value of Q_i is the best ranked.

3.3. The SAW Method

The simple additive weighting (SAW) method [33], is probably the simplest, best known and most often used MCDM method. The SAW method uses a simple aggregation procedure, which can be described using the following formula:

$$Q_i = \sum_{j=1}^{n} w_j \hat{x}_{ij}, \, i = 1, \ldots, m, \tag{17}$$

where Q_i is the overall ranking index of the i-th alternative; w_j is the weight of the j-th criterion; and $\hat{x}_{ij}$ is the normalized performance of the i-th alternative with respect to the j-th criterion, $i = 1, \ldots, m$ and $j = 1,\ 2,\ \ldots,\ n$. For the maximization case, the best alternative is the one that yields the maximum overall ranking index Q_i.

We used normalization Formula (13) to calculate $\hat{x}_{ij}$, as follows:

$$w_j = \frac{1}{n}, \, j = 1, \ldots, n \tag{18}$$

Equal weights were applied in our further calculations for method demonstration purposes only. Let us note that when applying the proposed methodology, the methods of determining the weights of the indicators, as well as the methods of ranking the alternatives, can be different and may be chosen by the researcher depending on the structure and nature of the data.

3.4. Ranking Results

Ranks of alternatives were calculated using four MCDM methods: two rankings according to WEBIR, $WEBIRA1$ when criteria weights were set according to Formula (10) and $WEBIRA2$ when using Formula (11); one ranking according to the entropy-ARAS method (Equation (16)); and one ranking according to the SAW method (Equation (17)). Then, a final ranking was calculated for men and women by averaging these four rankings (Table 5). To compare the rankings calculated using the four MCDM methods, we have provided Spearman's correlation coefficients for men and women in Table 6.

Table 5. Ranks calculated using WEBIRA1, WEBIRA2, ARAS, and SAW.

			Men			
No	**WEBIRA1**	**WEBIRA2**	**ARAS**	**SAW**	**Final rank**	**Group**
1	15	10	2	17	3	1
2	23	34	12	9	9	1
3	98	106	80	60	94	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮
104	77	74	83	73	84	3
105	33	32	30	28	27	1
106	38	39	11	5	13	1
			Women			
No	**WEBIRA1**	**WEBIRA2**	**ARAS**	**SAW**	**Final rank**	**Group**
1	16	20	33	28	24	2
2	9	23	11	17	9	1
3	45	48	45	42	48	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	46	47	26	31	42	3
50	39	40	23	23	32	2
51	33	38	14	13	25	2

Table 6. The Spearman correlation coefficients between rankings calculated using WEBIRA1, WEBIRA2, ARAS, and SAW and their significance levels.

		Men		
	Webira1	**Webira2**	**ARAS**	**SAW**
Webira1	1	0.987 (0.000)	0.563 (0.001)	0.621 (0.000)
Webira2	0.987 (0.000)	1	0.615 (0.000)	0.637 (0.000)
ARAS	0.563 (0.001)	0.615 (0.000)	1	0.871 (0.000)
SAW	0.621 (0.000)	0.637 (0.000)	0.871 (0.000)	1
		Women		
	Webira1	**Webira2**	**ARAS**	**SAW**
Webira1	1	0.880 (0.000)	0.468 (0.001)	0.520 (0.000)
Webira2	0.880 (0.000)	1	0.415 (0.001)	0.505 (0.000)
ARAS	0.468 (0.001)	0.415 (0.001)	1	0.732 (0.000)
SAW	0.520 (0.000)	0.505 (0.000)	0.732 (0.000)	1

Since WEBIRA is a method created for tasks in which the set of criteria is naturally divided into two subsets and the weights of the criteria are chosen in such a way as to minimize the discrepancy between two rankings by separate criteria groups, therefore we see lower correlations between WEBIRA and other methods, which deal with a set of indicators as a whole. This fact was described by the authors of [28].

4. Regression Analysis and Classification Results

Multiple linear regression analysis was performed for women and men according to the obtained ranks, denote as *Rank* (the average of the ranks of the four MCDM methods). The indicators with the greatest influence on the variable *Rank* were selected from all 21 indicators. In the first step, we selected 9–11 regressors and 5 regressors in the second step. Let us remember that the values of all indicators vary from 0 to 100.

We began from the model with all 21 indicators included; next, regressors were removed from the model one by one considering p-values and t-test values of indicators, adjusted R-squared value, and searching for the smallest value of Akaike information criterion (AIC).

Coefficient of determination $R^2 = 1 - \frac{SSE}{SST}$ is a measure of goodness of fit for a regression model (SSE is sum of squared errors and SST—total sum of squares).

However, adding more variables always increases the R^2 regardless of whether they are relevant or not. An alternative measure of goodness of fit is the adjusted R squared, as follows:

$$\overline{R}^2 = 1 - \frac{\frac{SSE}{N-K}}{\frac{SST}{N-1}}, \tag{19}$$

where N is the number of observations and K is the number of predictor variables. $\overline{R}^2$ increases when relevant variables are added and decreases if the irrelevant variables are added to the model.

The Akaike information criterion (AIC) is an alternative measure of goodness of fit. AIC is given by the following formula:

$$AIC = \ln\left(\frac{SSE}{N}\right) + \frac{2K}{N}, \tag{20}$$

where K is the number of predictor variables, N is the number of observations. The model with the smallest AIC is preferred. The AIC penalizes extra variables, since the second term becomes larger, when *K* increases [35]. This procedure of selecting the most informative regressors is a kind of manual work and stepwise regression mixture.

Scatter plots showing the dependence of the rank on the primary indicators for women and men presented in Figure 1.

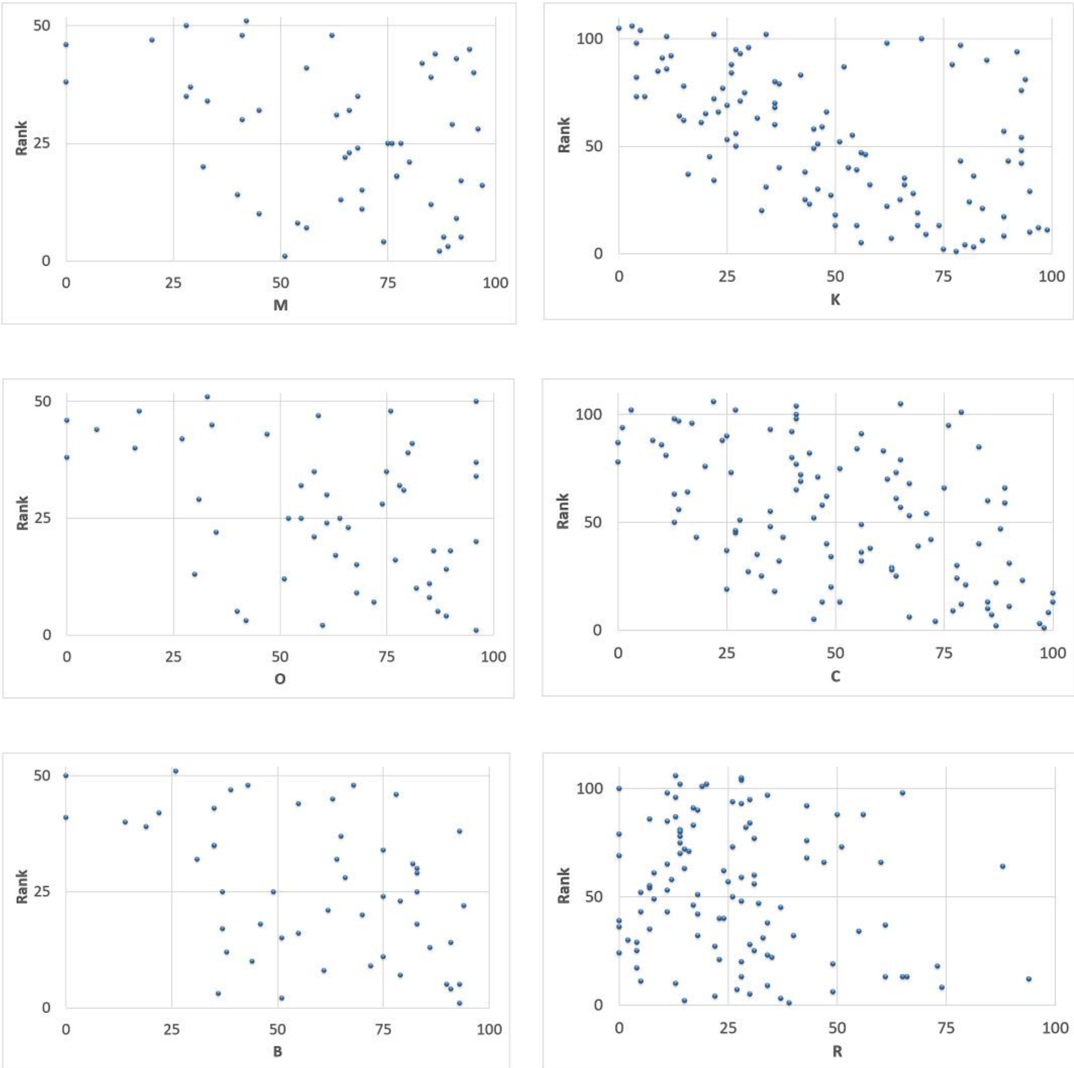

Figure 1. Scatter plots of variable rank and regressors M, O, B for women (**left**); variable rank and regressors K, C, R for men (**right**).

4.1. Regression Analysis Results for Women

In the first step, the dependent variable is *Rank*. For women, the nine most important predictors of the *Rank* variable were identified: A, B, C, E, L, M, O, R, U.

Value of $\overline{R}^2$ of this model is equal to 0.822. All nine selected regressors are significant, the significance levels of all variables are less than or equal to 0.01.

Then, five most informative predictors of variable *Rank* were selected from 21 indicators: B, C, M, O, U. The value of $\overline{R}^2$ of this model is equal to 0.639 and significance levels of all variables are less than or equal to 0.001.

After selecting the most important indicators, they were used as predictors for grouping the girls into three groups according to the magnitude of the *Rank* variable. The new variable *Group* was created according to the values of variable *Rank* for men and women (Table 5). For women, the first group consisted of ranks from 1 to 17 (the strongest group), the second of ranks from 18 to 34 (the average group), and the third of ranks from 35 to

51 (the weakest group). Now, *Group* variable taking the values 1, 2, 3 was considered to be a dependent variable, and the selected indicators were the regressors. The obtained regression equation for women with nine regressors is as follows:

$$\begin{aligned} Group = 6.509 - 0.007 \cdot A - 0.009 \cdot B - 0.006 \cdot C - 0.014 \cdot E - 0.007 \cdot L \\ -0.011 \cdot M - 0.011 \cdot O - 0.012 \cdot R - 0.007 \cdot U. \end{aligned} \quad (21)$$

Regression equation with five regressors is follows:

$$Group = 5.147 - 0.014 \cdot B - 0.006 \cdot C - 0.013 \cdot M - 0.013 \cdot O - 0.007 \cdot U. \quad (22)$$

The significance levels of all variables in Equation (21) are less than or equal to 0.025, while in Equation (22) they are less than or equal to 0.02.

All regression coefficients are negative, because higher values of the indicators lead to a better state of health, such students are assigned to a group with a lower number (Group = 1 (the strongest group), Group = 2 (the average group), and Group = 3 (the weakest group)). Also, students with a better state of health were assigned a lower rank (the best student had Rank = 1).

Equations (21) and (22) were summarized in Tables 7 and 8, where, along with the abbreviations, full names of indicators are presented. The regressors are listed in the tables in the order of decreasing absolute values of the coefficients.

Table 7. Indicators influencing health status (assessment indicators).

No	Male Indicators	Abbrev.	Coef.	No	Female Indicators	Abbrev.	Coef.
	Constant		5.513		Constant		6.509
			Body condition indicators (X1)				
1.	Body muscle percentage	D	−0.012	1.	Ruffier–Dickson index	E	−0.014
2.	Body fat percentage	C	−0.010	2.	Waist-to-hip ratio	B	−0.009
3.	Resting heart rate	F	−0.006	3.	Body mass index	A	−0.007
4.	Body mass index	A	−0.003	4.	Body fat percentage	C	−0.006
			Bodyactivity indicators (X2)				
1.	Food and water consumption per day	K	−0.011	1.	Physical activity, METs = from 3 to 6	R	−0.012
2.	Physical activity, METs = from 3 to 6	R	−0.009	2.	Carbohydrate intake	M	−0.011
3.	Time of physical activity, METs > 6	U	−0.007	3.	Fat intake	O	−0.011
4.	Protein intake	N	−0.006	4.	Time of physical activity, METs > 6	U	−0.007
5.	Duration of one meal	J	−0.005	5.	Energy intake	L	−0.007
6.	Fat intake	O	−0.004				
7.	Physical activity, METs > 6	S	−0.004				

Table 8. Indicators making significant impact of health status (predictor indicators).

Nr.	Male Indicators	Abbrev.	Coef.	Female Indicators	Abbrev.	Coef.
	Constant		4.239	Constant		5.147
			Body condition indicators (X1)			
1.	Body muscle percentage	D	−0.012	Waist-to-hip ratio	B	−0.014
2.	Body fat percentage	C	−0.011	Body fat percentage	C	−0.006
			Bodyactivity indicators (X2)			
1.	Food and water consumption per day	K	−0.011	Carbohydrate intake	M	−0.013
2.	Time of physical activity, METs > 6	U	−0.009	Fat intake	O	−0.013
3.	Physical activity, METs = from 3 to 6	R	−0.009	Time of physical activity, METs > 6	U	−0.007

4.2. Regression Analysis Results for Men

For men, the 11 most important regressors of variable *Rank* were identified: A, C, D, F, J, K, N, O, R, S, U. Value of $\overline{R}^2$ of this model is equal to 0.904. All 11 selected regressors are significant, significance levels of all variables are less than or equal to 0.002.

Then, five most informative predictors were selected from 21 indicators: C, D, K, R, U. Value of $\overline{R}^2$ of this model is equal to 0.777 and significance levels of all variables are less than or equal to 0.001.

Again, the variable *Group* was constructed, acquiring the values 1, 2, 3 (the dependent variable). Accordingly, men with ranks from 1 to 35 entered the first group (the strongest group), those with ranks from 36 to 70 entered the second (average) group, and those with ranks from 71 to 106 entered the third (weakest) group. The obtained regression equation with selected 11 regressors is as follows:

$$\begin{aligned} Group = 5.513 - 0.003 \cdot A - 0.010 \cdot C - 0.012 \cdot D - 0.006 \cdot F - 0.005 \cdot J - 0.011 \cdot K \\ -0.006 \cdot N - 0.004 \cdot O - 0.009 \cdot R - 0.004 \cdot S - 0.007 \cdot U. \end{aligned} \tag{23}$$

Regression equation with five regressors is as follows:

$$Group = 4.239 - 0.011 \cdot C - 0.012 \cdot D - 0.011 \cdot K - 0.009 \cdot R - 0.009 \cdot U. \tag{24}$$

Significance levels of all variables in Equation (23) are less than or equal to 0.007, while in Equation (24) they are less than 0.001.

As in the case of women, Equations (23) and (24) are summarized in Tables 7 and 8, where abbreviations and full names of predictors are given.

Among indicators influencing health status for women, there are four body condition indicators and five body activity indicators. Men's assessment indicators are four body condition and seven body activity indicators. Among indicators making significant impact of health status for both men and women there are two body condition and three body activity indicators.

4.3. Classification Results for Women and Men

According to regression Equations (21) and (22), the values of the *Group* variable were calculated for each female and male student, then rounding these values to whole numbers. Two assignments of female students to three classifications were obtained—according to nine (Equation (21)) and to five (Equation (22)) indicators—see Table 9. One can compare these classifications with the actual group (see *Group* variable in Table 9).

Spearman rank correlation coefficients were calculated between the actual group variable and classifications obtained using Formulas (21) and (22). They are equal to 0.861 and 0.682, respectively. Another measure of similarity is the distance between the actual group and other classifications. Distances between the two classifications are calculated using the following formula:

$$d = \frac{1}{2N} \sum_{i=1}^{N} \left| Group_i^{(1)} - Group_i^{(2)} \right|, \tag{25}$$

where N is the number of subjects (observations). Distance is normalised by the maximum distance between two classifications. For females, maximum distance is $2 \cdot 51 = 102$, for males—$2 \cdot 106 = 212$.

The distance between the reference group and Formula (21) classification is 0.098039, the distance between the reference group and Formula (22) classification is 0.186275.

According to regression Equations (23) and (24), values of the Group variable were calculated for each male student, then rounding these values to whole numbers. Two classifications were obtained according to 11 and to 5 indicators, see Table 9.

Table 9. Students' classification into three groups when the regression equation for men has 11 and 5 regressors and 9 and 5 regressors for women.

Men				Women			
Student No.	*Group*	*Group*$^{(1)}$ **11 Regressors Equation (23)**	*Group*$^{(2)}$ **5 Regressors Equation (24)**	**Student No**	*Group*	*Group*$^{(1)}$ **9 Regressors Equation (21)**	*Group*$^{(2)}$ **5 Regressors Equation (22)**
1	1	1	1	1	2	2	2
2	1	1	1	2	1	1	2
3	3	3	3	3	3	3	3
4	3	3	3	4	3	3	3
5	3	2	2	5	3	3	3
6	3	3	3	6	2	2	1
7	3	2	3	7	3	3	3
8	1	2	2	8	3	3	2
9	1	1	1	9	3	3	3
10	3	3	3	10	2	2	2
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
104	3	3	3	49	3	3	3
105	1	2	2	50	2	2	2
106	1	1	2	51	2	2	2

Spearman rank correlation coefficients between the actual Group variable and classifications obtained using Equations (23) and (24) are 0.878 and 0.730, respectively. The distance between actual grouping and classification using Formula (23) is 0.080189, while the distance between actual grouping and classification using Formula (24) is 0.165094. Predictions made using regression equations are more accurate for men. Better results for men can be explained via the greater number of observations.

Thus, based on the regression results with a smaller number of indicators, 9 or 5 for women, and 11 or 5 for men (instead of 21), it is possible to determine with sufficient accuracy which of the three groups a student belongs to.

5. Evaluation of the Results of the Most Informative Indicators Selection

The study revealed indicators that influence the health of the subjects (Table 7). Nine parameters have the greatest impact on the wellness of female students including four indicators for the body condition evaluation: Ruffier–Dickson index, waist-to-hip ratio, body mass index, and body fat percentage; and five behavior indicators: physical activity; METs=from 3 to 6; carbohydrate intake; fat intake; times of physical activity, METs > 6; and energy intake. In assessing the influence of the indicators under investigation on women's wellness, it can be argued that physical condition has a greater influence on health than behavior. For wellness assessment, 57% of the body condition indicators acquired the status of affecting health, while only 36% of the behavior indicators have acquired this status. Indicators affecting health were prioritized by the absolute values of the regression coefficients. Thus, in order to estimate the wellness of the women studied, the Ruffier–Dickson index (how the cardiovascular system responds to standard exertion) became the indicator with the highest weight. Behavior indicators reflecting the scope of moderate physical activity and the peculiarities of nutrition (carbohydrate and fat consumption) also have a high weight.

The list of indicators that make the greatest influence on men's wellness is longer, consisting of 11 units from which four indicators were received to evaluate the body condition: body muscle percentage, body fat percentage, resting heart rate, and body mass index; and seven behavior indicators: food and water consumption per day; physical activity, METs = from three to six; times of physical activity, METs > 6; protein intake; duration of one meal; fat intake; and physical activity, METs > 6.

Evaluating the influence of the studied indicators on men's health, it can be said that physical condition has a greater influence on health than healthy behavior. For wellness assessment, 57% of the body condition indicators acquired the status of affecting health, and 50% of the investigated behavior indicators have acquired this status. In ranking the indicators affecting health just as in the case of women, the values of the regression coefficients have been applied. Body muscle percentage (proportion of skeletal muscle) and body fat percentage (the percentage of body fat in proportion to lean mass, organs, tissues, and water) became the indicators with the greatest weight. Nutritional characteristics (food and water consumption per day) also have great weight.

When comparing men and women indicators affecting health, a significant difference is observed. Only 4 of the 9 and 11 indicators coincide with two body condition indicators (body fat percentage and body mass index) and two behavior indicators (physical activity, METs = from three to six and fat intake). The ranking positions of coincident indicators are radically different. The overlap between the indicators for men and women that influence their health is lower than 45%. This testifies to the fundamental differences between women and men health systems. In order to optimize the assessment of health, we identified five indicators that have the greatest influence on the general health index (Tables 7 and 8). Reducing the number of indicators allows avoiding spending a lot of time and is necessary for operational monitoring. It was established that two body condition indicators have the greatest influence on women's general health index (waist-to-hip ratio and body fat percentage) as well as three behavior indicators (carbohydrate intake; fat intake; time of physical activity, METs > 6). Meanwhile, the greatest influence on men's general health index has two physical condition indicators (body muscle percentage and body fat percentage) and three behavior indicators (food and water consumption per day; times of physical activity, METs > 6; physical activity, METs = from 3 to 6). The indicators that have the greatest influence on the general health index of women and men have fundamental differences (in their factors and their ranking). If the most informative health indicator for women is waist-to-hip ratio, for men it is the body muscle percentage. In summary, it can be said that the health of the women studied is most influenced by the amount of fat in the body and its distribution. Evaluating the contribution of the factors that have the greatest influence on the general indicator of health, it can be said that both body condition and behavior have a similar influence on the health of studied men and women. However, the conducted research can be characterized as a pilot in terms of the subjects. The main goals of the research were as follows: (1) to propose an algorithm for identifying the weights of health factors, (2) to reveal the most informative factors influencing students' health status, and (3) to cluster students into several groups according to their level of health. The obtained results show that the proposed methodology allows for sufficiently accurate assessment of students' health status as well as for predicting student's health status with a significantly smaller number of indicators.

In this article, we presented a template that can be flexibly adapted to the specifics of the existing data; for example, instead of the mentioned MCDM methods WEBIRA, entropy-ARAS, and SAW, other methods that better fit the data can be used. In addition, when determining the final ranks, the ranks obtained using separate methods may be averaged with different weights.

The proposed methodology for evaluating the studied health parameters using MCDM and statistical methods should be verified by wider studies with larger samples of subjects of different social groups (age, status, etc.) using a larger number of health research methods and applying alternative MCDM methods. To obtain fundamental research data, further research is necessary.

6. Discussion and Conclusions

Poor personal conditions and irrational behavior can be manifested independently and concurrently [55]. The condition and behavior of humans can affect the results of one or the other, or it can be the result of a combination of the two. Irrational behavior and poor body conditions are responsible for most health disorders. Irrational behavior also worsens bad body conditions. When irrational/rational behavior encourages poor/good body conditions, this initiates a closed cycle of the condition–behavior–condition process [56]. The risk of a negative result on health increases when multiple key behavior and body condition factors are at play. When an improper body condition exists, persons must further alter their behavior to negotiate it safely [57]. Human health deviations as a system disorder occur and intensify when body conditions and behavior indicators reach critical parameters [58]. The principle component algorithm used for monitoring and analyzing individuals' body behavior and condition for application in modern technologies may be useful for lifestyle planning [59].

Monitoring indicators that influence health status is expensive and requires a lot of time, effort, and special skills. Therefore, it is very important to be able to reduce the number of informative indicators without losing the accuracy of the mathematical model and the ability to predict the state of human health. This study presents an algorithm for selecting the most informative body condition and body activity indicators, which determine the state of health. Three MCDM methods were applied to create students ranking according to the latent variable describing health status. One of these methods—WEBIRA—maximizes the interdependence between two groups of indicators: body condition and body activity. After that, a regression model was created with the dependent variable student's rank, in which, by stepwise reducing the number of influencing variables, their number was decreased to 9–11 and then to 5. Finally, all students were divided into three groups based on their health status rating, and regression models were created to assign students to one of the three groups based on the values of 9–11 or 5 prognostic variables. The accuracy of this classification has been evaluated.

The role of a person in the changing state of health is the assessment of information indicators of the body condition and behavior and their adjustment. The study revealed that the informative list of health assessment indicators and their ranking for men and women have significant differences. However, body condition indicators have a greater influence on the health assessment of men and women. Meanwhile, more healthy behavior indicators entered the list of informative indicators in both groups of men and women. After determining health prediction indicators, body condition and healthy behavior indicators are distributed similarly, but body condition indicators have a higher ranking and a greater weight.

The conducted research presents an indicator selection algorithm for health monitoring systems. This algorithm provides an opportunity to determine informative and prognostic indicators for health assessment. The experiment was conducted on the target group (university students). In order to assess the stability of the applied methodology, it is necessary to repeat this study with different target groups.

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References

1. Ferrans, C.E.; Zerwic, J.J.; Wilbur, J.E.; Larson, J.L. Conceptual model of health-related quality of life. *J. Nurs. Scholarsh.* **2005**, *37*, 336–342. [CrossRef] [PubMed]
2. Merriam-Webster. n.d. Lifestyle. Available online: https://www.merriam-webster.com/dictionary/lifestyle/ (accessed on 15 April 2024).
3. World Health Organization. Healthy Living: What Is a Healthy Lifestyle? *WHO Regional Office for Europe: WHO Regional Office for Europe.* 1999. Available online: https://iris.who.int/handle/10665/108180 (accessed on 15 April 2024).
4. Bussmann, J.B.; van den Berg-Emons, R.J. To total amount of activity. . ... and beyond: Perspectives on measuring physical behavior. *Front. Psychol.* **2013**, *4*, 463.
5. Noar, S.M.; Zimmerman, R.S. Health Behavior Theory and cumulative knowledge regarding health behaviors: Are we moving in the right direction? *Health Educ. Res.* **2005**, *20*, 275–290. [CrossRef] [PubMed]
6. Garrity, T.F.; Somes, G.W.; Marx, M.B. Factors influencing self-assessment of health. *Soc. Sci. Med. Part A Med. Psychol. Med. Sociol.* **1978**, *12*, 77–81.
7. Murray, J.; Dunn, G.; Tarnopolsky, A. Self-assessment of health: An exploration of the effects of physical and psychological symptoms. *Psychol. Med.* **1982**, *12*, 371–378. [CrossRef]
8. Mihrshahi, S.; Gow, M.L.; Baur, L.A. Contemporary approaches to the prevention and management of paediatric obesity: An Australian focus. *Med. J. Aust.* **2018**, *209*, 267–274. [CrossRef] [PubMed]
9. Wadden, T.A.; Tronieri, J.S.; Butryn, M.L. Lifestyle modification approaches for the treatment of obesity in adults. *Am. Psychol.* **2020**, *75*, 235. [CrossRef] [PubMed]
10. Boufford, J.I.; Cassel, C.K.; Bender, K.W.; Berkman, L.; Bigby, J.; Burke, T. *The Future of the Public's Health in the 21st Century*; Institute of Medicine of the National Academies: Washington, DC, USA, 2002.
11. Curry, L. The Future of the Public's Health in the 21st Century. *Gener. J.* **2005**, *29*, 82.
12. Toomey, M.T. Understanding the Determinants of Health for Australian High-Performance Athletes: A Mixed-Methods Exploration of a Multi-Disciplinary, Multi-Sport Panel of Expert High-Performance Sport Health Practitioners. Ph.D. Thesis, Victoria University, Melbourne, Australia, 2022.
13. Weinstein, N.D. Testing four competing theories of health-protective behavior. *Health Psychol.* **1993**, *12*, 324. [CrossRef] [PubMed]
14. Weaver, I.I.I.J.B.; Mays, D.; Weaver, S.S.; Hopkins, G.L.; Eroğlu, D.; Bernhardt, J.M. Health information–seeking behaviors, health indicators, and health risks. *Am. J. Public Health* **2010**, *100*, 1520–1525. [CrossRef]
15. Webster, P.; Sanderson, D. Healthy cities indicators—A suitable instrument to measure health? *J. Urban Health* **2013**, *90*, 52–61. [CrossRef]
16. McKenzie, J.F.; Neiger, B.L.; Thackeray, R. *Planning, Implementing and Evaluating Health Promotion Programs*; Jones & Bartlett Learning: Burlington, MA, USA, 2022.
17. Qaffou, I. Optimization of the process of parameter adjustment: Image processing as a case study. In Proceedings of the 2020 IEEE 6th International Conference on Optimization and Applications (ICOA), Beni Mellal, Morocco, 20–21 April 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–4.
18. Dolence, M.G.; Norris, D.M. Using Key Performance Indicators to Drive Strategic Decision Making. *New Dir. Institutional Res.* **1994**, *82*, 63–80. [CrossRef]
19. Hamilton, J.D.; Perez-Quiros, G. What do the leading indicators lead? *J. Bus.* **1996**, *69*, 27–49. [CrossRef]
20. Fontanills, G.A.; Gentile, T. *The Stock Market Course*; John Wiley & Sons: Hoboken, NJ, USA, 2002.
21. Ghafarian, S.H.; Yazdi, H.S. Identifying crisis-related informative tweets using learning on distributions. *Inf. Process. Manag.* **2020**, *57*, 102145. [CrossRef]
22. Rabbitt, P.A. Errors and error correction in choice-response tasks. *J. Exp. Psychol.* **1966**, *71*, 264. [CrossRef] [PubMed]
23. Ehinger, B.V.; Dimigen, O. Unfold: An integrated toolbox for overlap correction, non-linear modeling, and regression-based EEG analysis. *PeerJ* **2019**, *7*, e7838. [CrossRef] [PubMed]
24. Doran, G.T. There'sa SMART way to write management's goals and objectives. *Manag. Rev.* **1981**, *70*, 35–36.
25. Abdulmyanov, V.; Sivtsov, A.; Fomichyov, N. Architecting a Geo-Enabled CRM: The Way to Seamless Integration. *Procedia Comput. Sci.* **2017**, *112*, 1651–1657. [CrossRef]
26. Krylovas, A.; Dadelo, S.; Kosareva, N.; Zavadskas, E.K. Entropy–KEMIRA approach for MCDM problem solution in human resources selection task. *Int. J. Inf. Technol. Decis. Mak.* **2017**, *16*, 1183–1209. [CrossRef]
27. Krylovas, A.; Dadelienė, R.; Kosareva, N.; Dadelo, S. Comparative evaluation and ranking of the European countries based on the interdependence between human development and internal security indicators. *Mathematics* **2019**, *7*, 293. [CrossRef]
28. Krylovas, A.; Kosareva, N.; Dadelo, S. European countries ranking and clustering solution by children's physical activity and human development index using entropy-based methods. *Mathematics* **2020**, *8*, 1705. [CrossRef]

29. Krylovas, A.; Kosareva, N.; Zavadskas, E.K. WEBIRA-comparative analysis of weight balancing method. *Int. J. Comput. Commun. Control* **2017**, *12*, 238–253. [CrossRef]
30. Kosareva, N.; Zavadskas, E.K.; Krylovas, A.; Dadelo, S. Personnel ranking and selection problem solution by application of KEMIRA method. *Int. J. Comput. Commun. Control* **2016**, *11*, 51–66. [CrossRef]
31. Zavadskas, E.K.; Turskis, Z. A new additive ratio assessment (ARAS) method in multicriteria decision-making. *Technol. Econ. Dev. Econ.* **2010**, *16*, 159–172. [CrossRef]
32. Zavadskas, E.K.; Podvezko, V. Integrated determination of objective criteria weights in MCDM. *Int. J. Inf. Technol. Decis. Mak.* **2016**, *15*, 267–283. [CrossRef]
33. MacCrimmon, K.R. *Decisionmaking among Multiple-Attribute Alternatives: A Survey and Consolidated Approach*; Rand Corporation: Santa Monica, CA, USA, 1968.
34. Zavadskas, E.K.; Turskis, Z.; Kildienė, S. State of art surveys of overviews on MCDM/MADM methods. *Technol. Econ. Dev. Econ.* **2014**, *20*, 165–179. [CrossRef]
35. Hill, R.C.; Griffiths, W.E.; Lim, G.C. *Principles of Econometrics*; John Wiley & Sons: Hoboken, NJ, USA, 2018.
36. Peterson, C.M.; Thomas, D.M.; Blackburn, G.L.; Heymsfield, S.B. Universal equation for estimating ideal body weight and body weight at any BMI. *Am. J. Clin. Nutr.* **2016**, *103*, 1197–1203. [CrossRef] [PubMed]
37. World Health Organization. *Healthy Diet (No. WHO-EM/NUT/282/E)*; World Health Organization, Regional Office for the Eastern Mediterranean: Geneva, Switzerland, 2019.
38. Gallagher, D.; Heymsfield, S.B.; Heo, M.; Jebb, S.A.; Murgatroyd, P.R.; Sakamoto, Y. Healthy percentage body fat ranges: An approach for developing guidelines based on body mass index. *Am. J. Clin. Nutr.* **2000**, *72*, 694–701. [CrossRef] [PubMed]
39. Latour, A.W.; Peterson, D.D.; Riner, D.D. Comparing Alternate Percent Body Fat Estimation Techniques for United States Navy Body Composition Assessment. *Int. J. Kinesiol. High. Educ.* **2019**, *3*, 93–105. [CrossRef]
40. Looney, D.P.; Potter, A.W.; Arcidiacono, D.M.; Santee, W.R.; Friedl, K.E. Body surface area equations for physically active men and women. *Am. J. Hum. Biol.* **2023**, *35*, e23823. [CrossRef]
41. Janssen, I.; Heymsfield, S.B.; Wang, Z.; Ross, R. Skeletal muscle mass and distribution in 468 men and women aged 18–88 yr. *J. Appl. Physiol.* **2000**, *89*, 81–88. [CrossRef]
42. Fragala, M.S.; Cadore, E.L.; Dorgo, S.; Izquierdo, M.; Kraemer, W.J.; Peterson, M.D.; Ryan, E.D. Resistance training for older adults: Position statement from the national strength and conditioning association. *J. Strength Cond. Res.* **2019**, *33*, 2019–2052. [CrossRef]
43. Zanevskyy, I. A model of Dickson index corrected for pupils. *Int. J. Sport Cult. Sci.* **2018**, *6*, 224–234. [CrossRef]
44. Gonzales, T.I.; Jeon, J.Y.; Lindsay, T.; Westgate, K.; Perez-Pozuelo, I.; Hollidge, S.; Wijndaele, K.; Rennie, K.; Forouhi, N.; Griffin, S.; et al. Resting heart rate as a biomarker for tracking change in cardiorespiratory fitness of UK adults: The Fenland Study. *MedRxiv* **2020**. [CrossRef]
45. Uth, N.; Sørensen, H.; Overgaard, K.; Pedersen, P.K. Estimation of VO_{2max} from the ratio between HR max and HR rest–the Heart Rate Ratio Method. *Eur. J. Appl. Physiol.* **2004**, *91*, 111–115. [CrossRef] [PubMed]
46. Watson, N.F.; Badr, M.S.; Belenky, G.; Bliwise, D.L.; Buxton, O.M.; Buysse, D.; Dinges, D.F.; Gangwisch, J.; Grandner, M.A.; Kushida, C. Consensus Conference Panel: Joint consensus statement of the American Academy of Sleep Medicine and Sleep Research Society on the recommended amount of sleep for a healthy adult: Methodology and discussion. *J. Clin. Sleep Med.* **2015**, *11*, 931–952. [PubMed]
47. Verboeket-Van De Venne, W.P.; Westerterp, K.R.; Kester, A.D. Effect of the pattern of food intake on human energy metabolism. *Br. J. Nutr.* **1993**, *70*, 103–115. [CrossRef]
48. Ansu Baidoo, V.Y.; Zee, P.C.; Knutson, K.L. Racial and Ethnic Differences in Eating Duration and Meal Timing: Findings from NHANES 2011–2018. *Nutrients* **2022**, *14*, 2428. [CrossRef] [PubMed]
49. Faizan, U.; Rouster, A.S. *Nutrition and Hydration Requirements in Children and Adults*; StatPearls Publishing: Treasure Island, FL, USA, 2020.
50. Britten, P.; Marcoe, K.; Yamini, S.; Davis, C. Development of food intake patterns for the MyPyramid Food Guidance System. *J. Nutr. Educ. Behav.* **2006**, *38*, S78–S92. [CrossRef] [PubMed]
51. World Health Organization. *Waist Circumference and Waist-Hip Ratio: Report of a WHO Expert Consultation*; World Health Organization: Geneva, Switzerland, 2008.
52. Ainsworth, B.E.; Haskell, W.L.; Herrmann, S.D.; Meckes, N.; Bassett, D.R., Jr.; Tudor-Locke, C.; Greer, J.L.; Vezina, J.; Whitt-Glover, M.C.; Leon, A.S. Compendium of Physical Activities: A second update of codes and MET values. *Med. Sci. Sports Exerc.* **2011**, *43*, 1575–1581. [CrossRef]
53. Piercy, K.L.; Troiano, R.P.; Ballard, R.M.; Carlson, S.A.; Fulton, J.E.; Galuska, D.A.; George, S.M.; Olson, R.D. The physical activity guidelines for Americans. *JAMA* **2018**, *320*, 2020–2028. [CrossRef]
54. Shannon, C.E. A mathematical theory of communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [CrossRef]
55. Ariely, D.; Jones, S. *Predictably Irrational*; HarperCollins: New York, NY, USA, 2008.
56. Lindstrom, K.N.; Tucker, J.A.; McVay, M. Nudges and choice architecture to promote healthy food purchases in adults: A systematized review. *Psychol. Addict. Behav.* **2023**, *37*, 87. [CrossRef] [PubMed]

57. Vuchinich, R.E.; Tucker, J.A.; Acuff, S.F.; Reed, D.D.; Buscemi, J.; Murphy, J.G. Matching, behavioral economics, and teleological behaviorism: Final cause analysis of substance use and health behavior. *J. Exp. Anal. Behav.* **2023**, *119*, 240–258. [CrossRef] [PubMed]
58. Anikwe, C.V.; Nweke, H.F.; Ikegwu, A.C.; Egwuonwu, C.A.; Onu, F.U.; Alo, U.R.; Teh, Y.W. Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. *Expert Syst. Appl.* **2022**, *202*, 117362. [CrossRef]
59. Dadeliene, R.; Dadelo, S.; Pozniak, N.; Sakalauskas, L. Analysis of top kayakers' training-intensity distribution and physiological adaptation based on structural modelling. *Ann. Oper. Res.* **2020**, *289*, 195–210. [CrossRef]

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