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A Hybrid Model for Fitness Influencer Competency Evaluation Framework

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Abstract: Fitness influencers are an emerging profession in recent years. At present, the main research on fitness influencers focuses on their personal traits, professional knowledge and skills, and course content, while there is still a large research gap on the social media marketing strategies of fitness influencers, how they interact with fans, and the reasons for their influence on fans. There is a lack of a comprehensive evaluation framework for fitness influencer research, and there is no clear research on what competencies are required to become a qualified fitness influencer. Therefore, it has become an important issue to establish a comprehensive fitness influencer competency evaluation. In this study, a hybrid model of fitness influencer competency evaluation framework was developed based on government competency standards and expert knowledge using the Multiple Criteria Decision-Making (MCDM) model perspective. This evaluation should expand to include the principles of sustainable development, emphasizing the influencers' role in advocating for environmental responsibility, social equity, and economic viability within the fitness industry. First, the study developed 21 criteria in six dimensions of fitness influencer competencies through a literature survey and interviews with several experts. The 21 criteria resonate with many of the Sustainable Development Goals (SDGs), including SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), SDG 5 (Gender Equality), SDG 10 (Reduced Inequalities), and SDG 11 (Sustainable Cities and Communities). The Bayesian Best-Worst Method (Bayesian BWM) was used to generate the best group weights for fitness influencer competencies. Then, a modified Technique for Order Preference by Similarity to the Ideal Solution Based on Aspiration Level (modified TOPSIS-AL) was applied to evaluate the performance ranking of major fitness influencers in Taiwan by integrating the concept of the aspiration level. The results of the study revealed that behavioral standards were the most important dimension, emphasizing the need for fitness influencers to establish a comprehensive set of norms for their own behavioral standards. The top five criteria for fitness influencers' competencies were self-review, punctuality and prudence, creativity, rapport and motivation, and the need to conform to one's body image. The performance ranking was used to compare the evaluated subjects to the desired level to obtain a basis for improvement. This study effectively identifies key fitness industry competency indicators and refines business performance through the management implications proposed in this study to facilitate the development of the fitness industry.

Keywords: fitness influencer; Multiple Criteria Decision-Making (MCDM); Sustainable Development Goals (SDGs)

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1. Introduction

Due to the accelerated pace of life in modern society, a lack of physical activity can lead to health problems [1]. As people's living standards improve, they have enough time and money to pursue a healthy lifestyle and are becoming aware of the importance of physical fitness [2]. With the increasing emphasis on health, the demand for fitness facilities and services, such as fitness equipment, sportswear, and fitness centers, is increasing, and these demands are driving the fitness industry to flourish, making it one of the fastest-growing industries worldwide [3,4]. Taking into account different ages, genders, body types, and health conditions, the fitness industry offers a wide variety of exercise programs, such as aerobics, weight training, yoga, aerobic dance, outdoor climbing, water sports, etc., thus providing different types of fitness programs to meet various needs [3]. The fitness industry can provide a variety of fitness options to meet the fitness needs of different people and allow more people to participate in fitness activities, thereby improving the health of the population [5]. Secondly, the fitness industry also creates a large number of employment opportunities and contributes to local economic development [6]. In addition, the fitness industry can also promote the development of related industries, such as sports equipment and food and beverage [1]. Finally, the fitness industry can also facilitate social communication, allowing people to build new social relationships in the process of fitness [7].

In recent years, the popularity of social media and online platforms has led to the emergence of fitness influencers as an emerging profession in the fitness industry [8]. Fitness influencers are gradually building their brand and influence by using multiple online social platforms, such as Instagram and YouTube, to share their fitness, diet, and life experiences, offering personal coaching services and online classes on these platforms [6,8]. They are not only good at attracting fans and viewers but also have extensive fitness knowledge and expertise to provide effective fitness instruction and advice [1]. Fitness influencers are more likely to be trusted by consumers than traditional celebrity endorsements when it comes to promoting fitness brands and sports products [7,9–11]. The emergence of fitness influencers brings new business and development opportunities for the fitness industry [12,13]. In this study, a fitness influencer is defined as an individual who commands a significantly and actively engaged following of over 100,000 on major social media platforms, primarily focusing on delivering a range of fitness-related content, from workout routines to health and wellness advice. These influencers are characterized by their commitment to regular updates (at least once a week) to maintain relevance and engagement within the online fitness community. A key aspect of their role is credibility, often supported by certifications, training, or personal achievements in fitness, combined with an authentic approach that resonates with their followers. Their influence is measured not just by the number of followers but also by their ability to positively impact health and fitness behaviors. By adhering to ethical standards, including transparency and respect for the diversity of their audience, they do more than just share information; they embody the principles of health and fitness in their own lives, thereby positioning themselves as positive role models within the community. This study emphasizes the professional and educational roles of fitness influencers, underscoring their commitment to advocating proper training techniques and authentic health and fitness education over engaging in commercial product endorsements.

With the emergence of fitness influencers as a significant influence in the fitness industry, the study of fitness influencers has become one of the most important issues in current fitness industry research. However, there are relatively few studies on fitness influencers, and there is a lack of systematic and in-depth research. In this study, the main research gaps related to fitness influencers were found to include the following:

(i) Fitness influencers' competency development and planning are unclear.
(ii) The key elements of success for fitness influencers are not known.
(iii) It is unclear what professional competencies and knowledge-transfer skills are required to become a fitness influencer.

(iv) There is no clear performance evaluation that shows how underperforming fitness influencers can improve.
(v) Most fitness influencer research methods use statistical methods or qualitative surveys.

To effectively address these research gaps, Multiple Criteria Decision-Making (MCDM) can be used to investigate the problem by focusing on the development of dimensions and criteria, calculation of weights, and evaluation of the performance of alternatives [14]. Compared with traditional statistical applications, MCDM does not require excessive hypothesis tests for criteria or variables, is suitable for a variety of evaluation and selection problems, and has excellent evaluation performance under a wide range of constraints [15]. MCDM has developed many soft computing methods to handle various complex data [14]. Therefore, this study proposes a hybrid model for evaluating fitness influencer competency development from an MCDM perspective. Firstly, this study referred to the concept of occupational competency standards proposed by the Department of Workforce Development, Ministry of Labor, a government agency in Taiwan, and considered the characteristics of fitness influencers through a literature review and expert group research, aggregated six main dimensions: professional competence, major tasks, behavioral indicators, attitude, self-management behavior, and personal characteristics, and subdivided them into 21 criteria. In terms of methodology, the Bayesian Best-Worst Method (Bayesian BWM) proposed by Mohammadi and Rezaei [16] was used to identify the weights of fitness influencers' competency dimensions and criteria. Then, soft computing using a modified Technique for Order Preference by Similarity to Ideal Solution Based on Aspiration Level (modified TOPSIS-AL) introduces the concept of aspiration level into the traditional TOPSIS calculation process, replacing the traditional concept of "relative satisfaction" with "aspiration level" in line with the development trend of MCDM. Finally, a sensitivity analysis was conducted to confirm the robustness of the proposed evaluation framework. Overall, the fitness influencer competency evaluation proposed in this study has five main features and contributions:

(i) This study developed an appropriate framework for evaluating fitness influencer competencies, and all criteria can be clearly defined and supported by the literature.
(ii) The proposed criteria align with several Sustainable Development Goals (SDGs), namely SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), SDG 5 (Gender Equality), SDG 10 (Reduced Inequalities), and SDG 11 (Sustainable Cities and Communities).
(iii) This study uses Bayesian BWM to obtain fitness influencer competency dimensions and criterion weights, which overcomes the shortcomings of AHP and BWM and significantly reduces the number of criterion pairwise comparisons. In addition, this study uses the modified TOPSIS-AL to identify the distances among existing fitness influencers in the ranking.
(iv) Sensitivity analysis is used to illustrate the importance of the weights of the criteria, and the ranking results of the evaluated subjects will change with the weights.

The proposed model contributes to the academic community in that it can be applied to different research topics, to the fitness industry in that it suggests a basis for improving existing fitness influencers, and to the government in that it establishes clear goals for fostering the fitness industry to facilitate counseling and training courses.

The remaining sections of this study are organized as follows: Section 2 reviews the relevant studies on the development of occupational competencies; Section 3 introduces the proposed hybrid model using Bayesian BWM and modified TOPSIS-AL methods and presents the computational process and implementation steps of both methods in detail; Section 4 demonstrates the practicality and sensitivity of the proposed model by evaluating five fitness influencers in Taiwan; Section 5 discusses the management implications; Section 6 provides conclusions and suggested directions for future research.

2. Literature Reviews

This section conducts a literature review, which encompasses two aspects: first, the research developments in the fitness industry, and second, the proposed evaluation framework.

2.1. The Research Developments in the Fitness Industry

As people become more aware of health and fitness, the fitness industry is emerging and becoming a global industry. The growing importance of the fitness industry and its development will help to understand the size of the industry, industry trends, training of trainers, teaching methods, and marketing. In addition, the emergence and influence of fitness influencers are also worth exploring, such as how they influence consumer behavior and impact the fitness equipment and apparel industry [17,18].

The literature searches for this study span from 2020 to the present and were conducted using databases such as Google Scholar, Scopus, and Web of Science. The keywords used in this search include 'fitness industry', 'fitness development', and 'influencers'. To ensure comprehensive coverage, the search strategy was meticulously designed to capture a wide range of relevant studies. This included scrutinizing articles that discuss the evolution of the fitness industry, the role of fitness in health and wellness trends, and the growing impact of influencers in shaping fitness culture.

This study reviewed the literature on the fitness industry for the past three years. The review of the literature reveals that more research on the fitness industry is related to the lifestyle and influencer marketing of the fitness industry, in addition to its impact on physical health. More and more studies are looking at how the content published on social media platforms should be presented or what qualities are more likely to attract people to watch, subscribe, or even purchase digital content. As the fitness industry trends toward lifestyle and digitization, it is important to develop policies to protect it. The results of the literature review are summarized in Table 1.

Table 1. Literature on the fitness industry.

Author(s) (Year)	Research Content and Results	Research Method
Yong et al. [5]	This study develops an intelligent fitness system utilizing Internet of Things (IoT) technology, featuring a unified database and return service, indicative of a broader industry trend. It underscores the burgeoning role of IoT and artificial intelligence in revolutionizing fitness facility management, equipment tracking, and personalized fitness experiences.	Experimental data collection
Dobson and McLuskie [19]	This study examines the entrepreneurial identity of mountain bike trainers, revealing their alignment with a 'lifestyle' entrepreneurial identity over market-driven pursuits. This reflects a growing trend in the fitness industry where passion and lifestyle choices often drive business models more than traditional market opportunities.	Semi-structured interviews
Jones et al. [2]	This study illustrates the connection between fitness, public health, and entrepreneurship, analyzing how these contribute to economic returns. It reflects the fitness industry's increasing focus on holistic well-being and social entrepreneurship as key drivers of economic growth and community impact.	Literature review

Table 1. *Cont.*

Author(s) (Year)	Research Content and Results	Research Method
Jang et al. [20]	Investigating indoor exercise class size, layout, and training intensity, this study highlights their role in COVID-19 transmission. The findings underscore the fitness industry's challenge in redesigning spaces and modifying workout regimes to prioritize health and safety during pandemics.	Statistica
Führer et al. [21]	This study advocates for incorporating resistance and endurance training in physical education, aligning with recent industry trends emphasizing diverse training methodologies to enhance the physical development of younger demographics.	Linear mixed model (LMM)
Rydzik and Ambroży [22]	Establishing a correlation between various training aspects and taekwondo performance, this study reflects the fitness industry's focus on specialized training programs that cater to specific athletic needs, enhancing competitive performance through tailored regimens.	Parametric tests, Shapiro-Wilk test, Levene test, descriptive statistics, Pearson's linear correlation coefficient
Kim [23]	Highlighting consumer reliance on mobile technology, this study aligns with the fitness industry's increasing investment in digital solutions like apps and wearable devices, catering to a tech-savvy consumer base and enhancing user engagement and fitness tracking capabilities.	Principal component analysis, exploratory factor analysis (EFA), Kaiser-Meyer-Olkin test, Bartlett's spherical test
Sokolova and Perez [8]	This study's findings on the significant impact of YouTube fitness influencers on their audience echo a key trend in the fitness industry: leveraging digital platforms for marketing and community building. The positive demeanor of influencers shaping subscriber attitudes and purchase behaviors reflects the growing importance of digital content creation in the fitness sector.	Partial least squares (PLS)
Ahrens et al. [1]	The study underscores the power of celebrity content on Instagram in the fitness industry, highlighting the need for robust content protection policies. This resonates with the industry's growing focus on responsible and ethical content creation, given its influence on consumer behavior and brand reputation.	Chi-square test
Kim [24]	Revealing how fitness comparisons influence user behavior, this study reflects a key aspect of the fitness industry's community dynamics. The motivational impact of such comparisons underscores the importance of creating supportive and aspirational environments in fitness platforms and communities.	Binary logistic regression analysis
Kim [7]	Confirming the significance of content attributes on fitness YouTube channels, this study aligns with the industry's evolving digital marketing strategies. The focus on quality and interaction highlights the fitness industry's need to adapt to digital trends, ensuring engaging and valuable content to retain and attract a digital audience.	Correlation analysis, Kaiser-Meyer-Olkin test, factor analysis, Varimax, quantitative analysis of variance, Bonferroni correction

A review of previous literature reveals that the fitness industry is mostly characterized by qualitative interviews and narrative statistics, with little further exploration of fitness influencer issues and insufficient information to construct a fitness influencer competency evaluation framework [7,8]. What competencies do these fitness influencers possess in order to be successful? What competencies do successful fitness influencers possess? The current research on fitness influencer issues is not clearly identified. Therefore, in order to propose a novel framework for evaluating the occupational competencies of fitness influencers.

2.2. The Proposed Evaluation Framework

This study initially formulated occupational competency standards in alignment with the Workforce Development Administration of the Ministry of Labor in Taiwan. These standards encompass knowledge, skills, key tasks, behavioral indicators, attitudes, and self-management behavioral competencies, as delineated in references [17,25,26]. In addition, considering the online digital nature of social media platforms, the channels of fitness influencers are more likely to be influenced by attributes to attract followers [7].

Ultimately, six dimensions were identified. Professional knowledge and skills (D_1) refer to having fitness-related knowledge and skills and exercise science, as well as an understanding of training methods and techniques [17,25,26]. Course instruction competency (D_2) refers to the ability to develop customized fitness for clients [17,18,25,27]. Behavioral standards (D_3) are designed to define the behavioral attitudes and professional conduct of fitness influencers at work [17,18,27,28]. Attitude towards people (D_4) refers to having good communication skills and the ability to effectively communicate, build relationships, and provide appropriate advice and support to clients [8,25,29] Personal attributes (D_5) refer to having good expression, influence, creativity, learning ability, and other attributes in order to establish good interaction with fans [7,10,30,31]. Self-improvement (D_6) refers to the ability to manage oneself, to manage time and the online community effectively, to innovate, and to continue to maintain a positive work attitude and a good mental state [7,8,31]. Through literature review and expert examination, the 21 criteria were subdivided under dimensions, and the detailed description of the evaluation criteria and their references are shown in Table 2.

Table 2. Description of the criteria and their references.

Dimension	Criterion	Description	References
Professional skills and knowledge (D_1)	Physical fitness skills and knowledge (C_{11})	Having professional skills and professional knowledge in body composition, nutrition, and sports training.	Wang and Chen [17]; De Vos et al. [25]; Hoff et al. [26]
	Social media and software operation skills (C_{12})	Having knowledge of online marketing and community management to build their brand image, awareness, and exposure on social media platforms	Ghosh et al. [32]; De Vos et al. [25]; Oberländer et al. [33]
	Data analysis ability (C_{13})	Able to analyze network traffic and data to understand how to increase impact and add value to themselves.	Sokolova and Perez [8]; Oberländer et al. [33]; Jiménez-Castillo and Sánchez-Fernández [34]
	Online marketing skills (C_{14})	Interacting with users on social media through marketing campaigns to increase value and revenue.	Kim [7]; Sokolova and Perez [8]; Jiménez-Castillo and Sánchez-Fernández [34]

Table 2. *Cont.*

Dimension	Criterion	Description	References
Course instruction competency (D_2)	The courses are easy to understand (C_{21})	The content, format, and teaching style of the courses are easy for the students to understand and master.	Kim [7]; Casaló et al. [35]; Sokolova and Kefi [31]
	Diversity of course content (C_{22})	The topics and content covered in the training are rich and diverse to meet the needs of different trainees.	Leung et al. [10]; Lim et al. [36]; Sokolova and Kefi [31]
	Content validity (C_{23})	The courses are effective in enhancing the professional competence, skills, and knowledge of the trainees.	Kim [7]; Leung et al. [10]; Lim et al. [36]
	Attractive and trustworthy (C_{24})	The courses provide participants with the motivation to actively participate and learn and to achieve tangible benefits and growth in the learning process.	Kim [7]; Leung et al. [10]; Lim et al. [36]; Sokolova and Kefi [31]
Behavioral standards (D_3)	Active innovation (C_{31})	Constantly looking for new ways to teach, train, and provide nutritional counseling, developing new content, and using different forms of media to spread fitness knowledge.	Wang and Chen [17]; Mäkikangas and Schaufeli [18]; De Vos et al. [25];Lazazzara et al. [27]
	Punctuality and discretion (C_{32})	Arriving at the site on time at the scheduled time with the trainee and taking care of the trainee's safety and health during the teaching process.	Kim [7]; Sokolova and Perez [8]; Sokolova and Kefi [31]
	Self-examination (C_{33})	Taking the initiative to review teaching methods and performance during training, to identify problems and room for improvement to improve the quality and effectiveness of their teaching.	Maina et al. [37]; Wang and Chen [17]; Mäkikangas and Schaufeli [18]; De Vos et al. [25]
Attitude towards people (D_4)	Rapport and motivation (C_{41})	Able to establish a good interactive relationship with customers and audiences, build trust with each other, and be able to motivate and support each other.	Flanigan et al. [38]; Kim [7]; Lim et al. [36]; Schwerter et al. [39]
	Continuous interaction and feedback (C_{42})	Continuing to interact with the audience and customers, and being willing to give suggestions and feedback promptly.	Flanigan et al. [38]; Kim [7]; Lim et al. [36]
	Working together to accomplish goals (C_{43})	Able to establish a good cooperative relationship with team members, trainees, or customers, set goals together, and strive to achieve them.	Flanigan et al. [38]; Lim et al. [36]

Table 2. *Cont.*

Dimension	Criterion	Description	References
Individual traits (D_5)	Positive and affectionate (C_{51})	Projecting a positive image and being approachable through the content posted.	Lim et al. [36]; Sokolova and Kefi [31]
	Enthusiastic and generous (C_{52})	Demonstrating a positive, enthusiastic, friendly, and open attitude when interacting with students or fans, and the ability to build rapport with others.	Flanigan et al. [38]; Kim [7]; Leung et al. [10]
	Good physical appearance (C_{53})	Having a healthy, sturdy, aesthetically pleasing physical condition and appearance, and demonstrating fitness knowledge and skills to inspire and guide audiences to a healthy lifestyle through the attractiveness and credibility of their image.	Kim [7]; Lim et al. [36]; Sokolova and Perez [8]; Sokolova and Kefi [31]
	Trustworthy (C_{54})	Having integrity, honesty, and trustworthiness allows students to trust their professional abilities and personal integrity and be willing to follow the guidance of the coach.	Janssen et al. [30]; Kim [7]; Sokolova and Perez [8]; Sokolova and Kefi [31]
Self-improvement (D_6)	Developing professional knowledge (C_{61})	Continuously learning and updating professional knowledge in fitness, exercise, nutrition, and other related fields to provide better fitness advice, instruction, and services.	Wang and Chen [17]; Lazazzara et al. [27]
	Developing professional skills (C_{62})	To accomplish goals more effectively, continuing to learn a wide range of professional skills such as fitness training skills, nutrition knowledge, communication skills, education and training skills, and social media skills.	Wang and Chen [17]; Lazazzara et al. [27]
	Demanding self-image (C_{63})	Maintaining a healthy and positive image by staying in good shape and healthy, so that the audience will have a good impression and trust.	Kim [7]; Sokolova and Kefi [31]

Overall, a review of the literature on fitness influencers will help us gain insight into the current state of the modern fitness industry, and thus establish a direction for the advancement and development of the fitness industry.

3. Methodology

The proposed model has two evaluation stages. First, the Bayesian BWM is used to calculate and prioritize the best weights of the dimensions and criteria based on the proposed dimensions and criteria in Section 2. Bayesian BWM was chosen because it is a novel technique for group decision analysis, and the final weights obtained through the Bayesian iterative computations are better than the average weights of traditional BWM, thus overcoming the disadvantage of using traditional arithmetic means that combine expert opinion with statistical estimation methods. A criterion with a higher weight indicates that it is relatively more important in the evaluation system. Subsequently, the Modified TOPSISAL technique is used to calculate the performance values and ranking results of the alternative (fitness influencers) and to propose strategies to improve the fitness influencer competencies based on the evaluation results.

In the process of implementing modified TOPSIS-AL, the aspiration level and the worst level are considered as two evaluation objects, so that the degree of distance between each alternative and the aspiration level can be known, more management information can be obtained, and improvement suggestions can be made. By integrating the Bayesian BWM with the modified TOPSIS-AL into a hybrid model, this study not only fortified the traditional AHP-TOPSIS approach but also achieved greater assessment accuracy and decision-making quality. Furthermore, this fusion enhances its adaptability, making it suitable for various performance evaluations and other decision-making issues. Figure 1 represents the flowchart of this study.

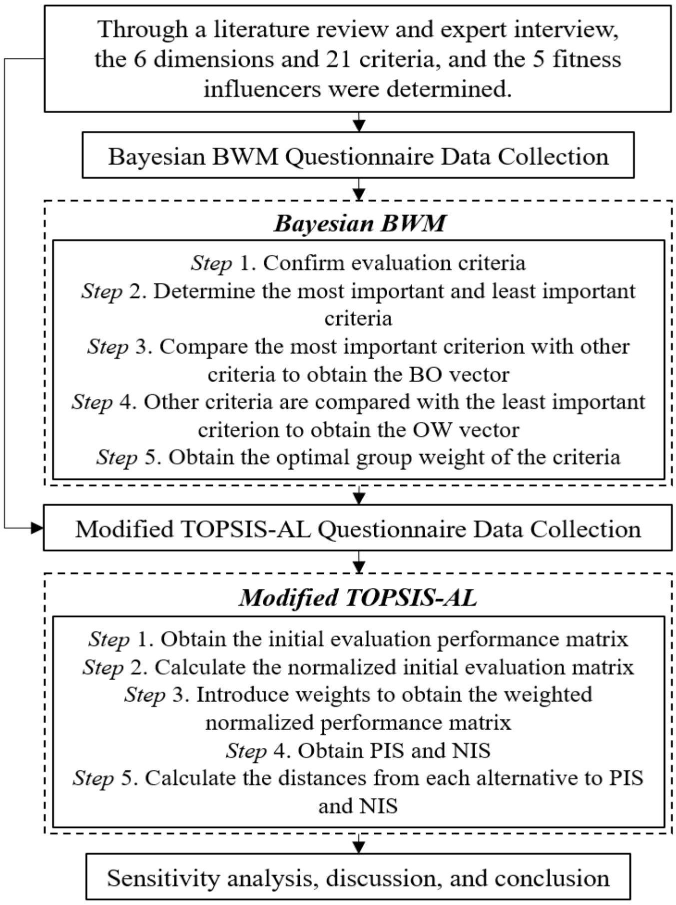

Figure 1. The flowchart of this study.

3.1. Bayesian BWM Technique

The BWM method was proposed by Rezaei in 2015 as a novel pairwise comparison weighting method that effectively improves the limitations of traditional AHP studies by solving the problems of excessive comparisons and unstable consistency [40]. In the BWM data survey phase, structured expert questionnaires are designed to compare these criteria with others on a 9-scale, and two sets of vectors (Best-to-Others and Others-to-Worst vectors) are obtained by pairwise comparisons to identify the best and worst criteria to help decision-makers make more accurate evaluations [41]. The BWM approach has been widely applied in various industrial evaluation projects, such as risk evaluation [42], blockchain [43], and smart cities [44]. However, traditional BWM uses the simplest arithmetic average to integrate the opinions of multiple experts, and if the experts disagree during the evaluation process, the evaluation value obtained by using the arithmetic average can no longer express the real situation [45]. To overcome the limitations of traditional BWM, Mohammadi and Rezaei [16] proposed a new method to optimize the traditional BWM approach, called Bayesian BWM, which is calculated by the concept of probability distribution when integrating group evaluation information to obtain the best set of criteria group weights. The basic criterion for weight generation in MCDM is that the sum of weights is 1, and each weight is greater than the equivalent of 0. From the concept of probability, the criterion can be considered a random event, and the possibility of the criterion occurring is the generation of weight. Therefore, the model is constructed as a probabilistic model. Therefore, it is reasonable to use BWM as the basis for constructing a probabilistic model. Existing studies have widely applied Bayesian BWM to solve the problem of evaluating weights, including school performance evaluation [45], electricity retailers [46], and airport resilience evaluation [41].

This study uses the suite software provided by Mohammadi and Rezaei [16] to perform Bayesian BWM-related calculations. The description and brief steps of Bayesian BWM for this study are as follows:

Step 1. Confirm evaluation criteria

A literature review and expert group discussions are used to identify criteria $c_i = \{c_1, c_2, \ldots, c_n\}$ for evaluating the competencies of n fitness influencers. These criteria can be assigned to six dimensions to form a hierarchical evaluation framework.

Step 2. Determine the most important and least important criteria

Determine the most important (or best) and least important (or worst) criteria from among the n criteria.

Step 3. Compare the most important criterion with other criteria to obtain the BO vector

The expert evaluation uses a scale of 9, which is set from 1 to 9 to present the importance of the most important criteria relative to other criteria. A scale of 1 indicates equal importance compared to the most important criteria, while a scale of 9 indicates absolute importance compared to other criteria. The greater the difference in scale, the greater the difference in relative importance. The BO vector is expressed as

$A_{Bi} = (a_{B1}, a_{B2}, \ldots, a_{Bi}, \ldots, a_{Bn})$ The importance of the criterion is the most important criterion, which is denoted by a_{Bi}.

Step 4. Other criteria are compared with the least important criterion to obtain the OW vector

This step is similar to Step 3, where the experts evaluate the importance of other criteria compared to the least important criterion. The OW vector is expressed as

$A_{iW} = (a_{1W}, a_{2W}, \ldots, a_{iW}, \ldots, a_{nW})^T$ where a_{iW} represents the relative importance of other criterion i compared to the least important criterion W. $a_{BB} = 1$ and $a_{WW} = 1$ are required due to the equal importance of self-comparisons.

Step 5. Obtain the optimal group weight of the criteria

The probability model of polynomial distribution is constructed by A_{Bi} and A_{iW}, so the probability function of polynomial distribution of A_{iW} is as Equation (1).

$$P(A_{iW}|w_i) = \frac{(\sum_{i=1}^{n} a_{iW})!}{\prod_{i=1}^{n} a_{iW}!} \prod_{i=1}^{n} w_i^{a_{iW}} \tag{1}$$

w_i is the probability distribution of weights, and the probability of w_i and a_{iW} is proportional, so Equation (2) can be obtained. The weight probability w_W of the least important criterion is shown in Equations (3) and (4) and can be obtained by combining Equations (2) and (3).

$$w_i \propto \frac{a_{iW}}{\sum_{i=1}^{n} a_{iW}}, \ \forall i = 1, 2, \ldots, n \tag{2}$$

$$w_W \propto \frac{a_{WW}}{\sum_{i=1}^{n} a_{iW}} = \frac{1}{\sum_{i=1}^{n} a_{iW}} \tag{3}$$

$$\frac{w_i}{w_W} \propto a_{iW}, \ \forall i = 1, 2, \ldots, n \tag{4}$$

In addition, the weight probability of the most important criterion is shown in Equation (5).

$$\frac{1}{w_B} \propto \frac{a_{BB}}{\sum_{i=1}^{n} a_{Bi}} = \frac{1}{\sum_{i=1}^{n} a_{Bi}} \Rightarrow \frac{w_B}{w_i} \propto a_{Bi}, \ \forall i = 1, 2, \ldots, n \tag{5}$$

The model is constructed using Dirichlet's probability distribution to obtain the optimal weight value w_i, with Equation (6). as its probability function.

$$Dir(w_i|\alpha) = \frac{1}{B(\alpha)} \prod_{i=1}^{n} w_i^{\alpha_i - 1} \tag{6}$$

α is the parameter of the vector, and usually the value is set to 1. $w_i \geq 0$ and $\sum w_i = 1$ are required to comply with the concept of MCDM.

The Bayesian BWM is a soft computing method that takes into account the survey data of several experts and integrates them to obtain a set of optimal group weights w_i^{agg}. The steps are as follows:

Step 5.1. Construct the joint probability distribution of the group

There are j experts $j = 1, 2, \ldots, J$ in the expert group, and the weight of the individual criterion is w_i^j after the experts' evaluation, and the group weight w_i^{agg} is obtained by integrating all of w_i^j. The BO and OW vectors of the first expert to the Jth expert are denoted by $A_{Bi}^{1:J}$ and $A_{iW}^{1:J}$. These vectors are used to construct the joint probability distribution function of the group decision as in Equation (7).

$$P\left(w_i^{agg}, w_i^{1:J} \middle| A_{Bi}^{1:J}, A_{iW}^{1:J}\right) \tag{7}$$

Step 5.2. Build a Bayesian hierarchical model

The optimal weight w_i^j of each expert is obtained based on the A_{Bi} and A_{iW} vectors of each expert, while the optimal weight w_i^{agg} of the expert group is determined by w_i^j. The Bayesian-level model is constructed based on the Bayesian iterative operations, which means that the A_{Bi} and A_{iW} vectors of the experts generate w_i^j, and the new group optimal weight w_i^{agg} is computed on a rolling basis after the evaluation data of multiple experts are added one after another. Considering that the variables are independent of one another, the joint probability of the Bayesian model is shown in Equation (8).

$$P\left(w_i^{agg}, w_i^{1:J} \middle| A_{Bi}^{1:J}, A_{iW}^{1:J}\right) \propto P\left(A_{Bi}^{1:J}, A_{iW}^{1:J} \middle| w_i^{agg}, w_i^{1:J}\right) P\left(w_i^{agg}, w_i^{1:J}\right) \tag{8}$$

Equation (8) can be further deduced as follows.

$$P\left(A_{Bi}^{1:J}, A_{iW}^{1:J} \middle| w_i^{agg}, w_i^{1:J}\right) P\left(w_i^{agg}, w_i^{1:J}\right) = P\left(w_i^{agg}\right) \prod_{j=1}^{J} P\left(A_{iW}^{j} \middle| w_i^{j}\right) P\left(A_{Bi}^{j} \middle| w_i^{j}\right) P\left(w_i^{j} \middle| w_i^{agg}\right) \tag{9}$$

From Equation (9), the corresponding probability function can be found by specifying the statistical distribution of each variable. The distributions of $A_{Bi}^{j}\middle|w_{i}^{j}$ and $A_{iW}^{j}\middle|w_{i}^{j}$ are shown in Equation (10).

$$A_{B}^{j}\Big|w_{i}^{j} \sim multinomial\left(\frac{1}{w_{i}^{j}}\right),\ \forall_{j} = 1,2,\ldots,J;$$
$$A_{iW}^{j}\Big|w_{i}^{j} \sim multinomial\left(w_{i}^{j}\right),\ \forall_{j} = 1,2,\ldots,J \tag{10}$$

w_{i}^{j} under the condition w_{i}^{agg} can be constructed as a Dirichlet distribution as shown in Equation (11).

$$w_{i}^{j}\Big|w_{i}^{agg} \sim Dir\left(\gamma \times w_{i}^{agg}\right),\ \forall_{j} = 1,2,\ldots,J \tag{11}$$

The mean value of the Dirichlet distribution is, and the non-negative parameter is γ.

The w_{i}^{j} must be in the proximity of w_{i}^{agg} since it is the mean of the distribution, the proximity is determined by the parameter γ, and the distribution of the parameter γ obeys gamma distribution as in Equation (12).

$$\gamma \sim gamma(a,b) \tag{12}$$

The shape and scale parameters of the gamma distribution are a and b, respectively. Finally, the optimal group weight w_{i}^{agg} obeys the Dirichlet distribution as in Equation (13).

$$w_{i}^{agg} \sim Dir(\alpha) \tag{13}$$

The parameter α is set to 1.

After constructing the probability distribution of all variables, the optimal group weight w_{i}^{agg} is obtained by simulating the experiment p times through Markov-chain Monte Carlo (MCMC) technology.

3.2. Modified TOPSIS-AL Technique

TOPSIS is one of the popular MADM methods used in recent years for evaluating performance and ranking alternatives. In this method, the Positive and Negative Ideal Solutions (PIS and NIS) are identified among the combinations of alternatives, and the distance between each alternative and the PIS and NIS is calculated to obtain the relative position of each alternative. The best choice is the alternative closest to the PIS and furthest from the NIS. The TOPSIS method is easy to understand, simple to compute, and has solved many different problems [47,48]. The concept of aspiration level is introduced in this study as TOPSIS-AL. Whereas the original TOPSIS defined the current best alternative as the most desirable solution, TOPSIS-AL defined the aspiration level as PIS and the opposite worst value as NIS. The steps of TOPSIS-AL in this study are as follows:

Step 1. Obtain the initial evaluation performance matrix

There are k fitness influencers $A_p = \{A_1, A_2, \ldots, A_k\}$ and h criteria $c_f = \{c_1, c_2, \ldots, c_h\}$ (in the construction of the performance matrix, the vertical axis of the matrix is the fitness influencer A_p, and the horizontal axis is the criterion c_f). The evaluation value d_{pf} represents the performance of fitness influencer p under criterion f, as in Equation (14).

$$\boldsymbol{D} = \left[d_{pf}\right]_{k \times h} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1f} & \cdots & d_{1h} \\ d_{21} & d_{22} & \cdots & d_{2f} & \cdots & d_{2h} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{p1} & d_{p2} & \cdots & d_{pf} & \cdots & d_{ph} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{k1} & t_{k2} & \cdots & d_{kf} & \cdots & d_{kh} \end{bmatrix}_{k \times h}, p = 1,\ 2, \ldots,\ k; f = 1,\ 2, \ldots,\ h \tag{14}$$

Step 2. Calculate the normalized initial evaluation matrix

To have a uniform unit for all the obtained evaluation criteria and to allow all the performance values in the matrix to converge to a value range between 0 and 1, the normalization method is used to obtain the matrix $\boldsymbol{D}^*$ (Equation (15)). The conventional normalization method is to take the alternative with the best performance under each criterion as the denominator, which will lead to the situation of "picking the best apple from a bucket of rotten apples". Therefore, the concept of aspiration level is introduced in the study to modify the normalization equation, as shown in Equation (16).

$$\boldsymbol{D}^* = \left[d^*_{pf}\right]_{k \times h} \tag{15}$$

$$d^*_{pf} = \frac{d_{pf}}{d_f{}^{aspire}} \tag{16}$$

Step 3. Introduce weights to obtain the weighted normalized performance matrix

Considering the different importance of criteria, the weight obtained in Bayesian BWM is multiplied by the normalized performance matrix to obtain the weighted normalized performance matrix, as shown in Equation (17).

$$\boldsymbol{D}^{**} = \left(w_i^{agg}\right) \cdot (\boldsymbol{D}^*) \tag{17}$$

Step 4. Obtain positive and negative ideal solutions (PIS and NIS)

Based on the concept of aspiration level, after matrix normalization, PIS and NIS should be 1 and 0. Therefore, after considering the weights, the PIS and NIS of the system can be obtained, as in Equations (18) and (19).

$$\text{PIS} = \left(z_1^+, z_2^+, \ldots, z_n^+\right) = \left(w_1^*, w_2^*, \ldots, w_n^*\right) \tag{18}$$

$$\text{NIS} = \left(z_1^-, z_2^-, \ldots, z_n^-\right) = (0,\ 0, \ldots,\ 0) \tag{19}$$

Step 5. Calculate the distances from each alternative to PIS and NIS

In this paper, the Euclidean distances are used to define the separation of fitness influencer p from the PIS and NIS, as in Equations (20) and (21).

$$S_p^+ = \sqrt{\sum_{f=1}^{h}\left(z_f^+ - d_{pf}^{**}\right)^2} \tag{20}$$

$$S_p^- = \sqrt{\sum_{f=1}^{h}\left(d_{pf}^{**} - z_f^-\right)^2} \tag{21}$$

Step 6. Obtain the final TOPSIS performance value and the ranking

The closeness coefficient (CC_p) is proposed by Kuo [48], which improves many shortcomings of conventional TOPSIS to obtain more reliable ranking results, as shown in

Equation (22). The new ranking index has a better judgment basis, with the value range of CC_p ranging from -1 to 1 and the sum of CC_p being 0.

$$CC_p = \frac{w^+ S_p^-}{\sum_{p=1}^{k} S_p^-} - \frac{w^- S_p^+}{\sum_{p=1}^{k} S_p^+} \tag{22}$$

where w^+ and w^- represent the relative importance of PIS and NIS, respectively. Since $w^+ + w^- = 1$, how much w^+ and w^- are set will affect each other. In the absence of special circumstances, such as a particularly optimistic or pessimistic bias, w^+ and w^- are both set to 0.5.

4. An Empirical Study of Fitness Influencer Evaluation

In this section, we introduce the background of the case study and outline the analytical procedure of Bayesian BWM and modified TOPSIS-AL applied to the case.

4.1. Case Illustration

Influencers, recognized for their superior physical conditioning, knowledge, and proficiency, leverage digital platforms to disseminate advice on exercise, nutrition, and healthy living, thereby motivating others to adopt better lifestyle habits and attracting a large audience. Their success has encouraged many people to become involved in the fitness industry; however, current research has not clearly established what competencies are required to become a fitness influencer and which competencies are relatively important in the process of developing occupational competencies. When these questions are solved, they can effectively provide direction for becoming a fitness influencer and facilitate the development of the fitness influencer industry.

Therefore, this study developed 6 dimensions and 21 criteria for their classification through a literature review, reference to the Occupational Competency Standards of the Department of Workforce Development, Ministry of Labor, Taiwan, and discussions with several experts. In this study, 10 experts were invited to form an expert group, which was composed of experts whose backgrounds were mainly gym instructors, influencers, and sports academics. They had sufficient expertise and years of experience in fitness, and they had been in the field for at least 10 years. Table 3 shows the experts' affiliations, positions, work experience, and education. After confirming that the experts understood the content and procedures of the interview, the researcher began asking questions and recording the responses. The Bayesian BWM was then used to identify the importance weights of the 6 dimensions and 21 criteria.

Table 3. Backgrounds of the 10 experts.

Expert	Affiliation	Position	Work Experience	Education
Expert 1	School	P.E. teacher	over 10 years	Bachelor
Expert 2	Gym	Personal trainer	over 10 years	High School
Expert 3	School	P.E. teacher	over 10 years	Bachelor
Expert 4	School	P.E. teacher	over 10 years	Bachelor
Expert 5	Gym	Personal trainer	over 10 years	Bachelor
Expert 6	Gym	Personal trainer	over 10 years	Bachelor
Expert 7	Gym	Personal trainer	over 10 years	Bachelor
Expert 8	Gym	Personal trainer	over 10 years	Bachelor
Expert 9	Gym	Personal trainer	over 10 years	Bachelor
Expert 10	Gym	Gym owner	over 10 years	Master

In addition, five Taiwanese fitness influencers with more than 100,000 followers on social media platforms were selected through discussion group decisions by entering relevant keywords from various social media platforms, including A_1, A_2, A_3, A_4, and A_5. The influencers selected for this study all conform to the definition of an influencer as described in Section 1. Information about these five fitness influencers is shown in Table 4. The five fitness influencers will be evaluated through the modified TOPSIS software to determine the ranking order of the five fitness influencers and to develop management implications and recommendations for improvement.

Table 4. Fitness influencers' brief biographies and numbers of fans.

Alternative	Brief Biography	Social Media Platform (Number of Fans)
A_1	The CEO of the 'G' group, who owns several gyms and founded a related fitness product brand, also boasts extensive training experience in aerobic and boxing exercises. His background includes many years of dedicated practice in these disciplines. This expertise complements his business acumen, demonstrated by winning several Google YouTube annual ranking awards, showcasing a unique blend of hands-on fitness experience and entrepreneurial success.	Facebook: 1.48 million Instagram: 750,000 YouTube: 400,000
A_2	This individual, who has collaborated with or been sponsored by various fitness-related brands, possesses extensive experience in both general fitness and bodybuilding. With a focus primarily on muscle-building training, they have spent many years mastering and applying techniques aimed at increasing muscle mass.	Facebook: 100,000 Instagram: 190,000 YouTube: 810,000
A_3	This individual, who has collaborated with or been sponsored by various fitness-related product brands, specializes in conducting research that integrates diet with fitness regimes. Their expertise lies in exploring the synergistic effects of nutrition and exercise on overall health and physical performance.	Instagram: 150,000
A_4	This individual, who has collaborated with or been sponsored by various fitness-related brands, stands as the first professional fitness athlete in Taiwan. With a background as a seasoned fitness competitor, they have dedicated many years to self-training and have participated in numerous fitness competitions.	Instagram: 190,000 YouTube: 220,000
A_5	This individual, the founder of several fitness-related brands and owner of a fitness website, has developed a systematic approach to fitness training. He has designed comprehensive fitness programs, including specialized training plans tailored specifically for women.	Facebook: 170,000 Instagram: 200,000 YouTube: 680,000

4.2. Using Bayesian BWM to Calculate the Criteria Weights

This study demonstrates the advantages of Bayesian BWM and its computational process according to Section 3.1. First, the experts were asked to select the most and least important dimensions and criteria among the fitness influencers' competency development factors to obtain the 10 experts' BO vectors, as shown in Table A1, and OW vectors, as shown in Table A2, according to the Bayesian BWM evaluation scale. The Bayesian BWM used in this study has a hierarchical framework with a total of 4 surveys containing 6 dimensions and 21 criteria under the dimensions. For example, Expert 4 in Tables A1 and A2 considered D_5 as the best dimension, so the BO vector formed by comparing D_5 with the other dimensions is $A_{Bi,5}$ = (2, 2, 2, 2, 2, 1, 2). Similarly, D_1 is chosen as the worst dimension and the OW vector is $A_{iW,5}$ = (1, 1, 1, 1, 1, 2, 1). All experts follow the same way to obtain information about the expert group.

All Bayesian BWM questionnaires are subjected to a consistency test to ensure that the experts are logical and reasonable in the process of completing the questionnaires. The consistent ratio (CR) of each questionnaire in this study was less than 0.03, and the average *CR* of the 10 questionnaires in this study was 0.0016, which indicates a significant consensus among experts in questionnaire completion [40]. Unlike the original BWM, the calculation does not require individual computation of the BWM questionnaire data of the 10 experts, and the Bayesian BWM is used to estimate the optimal criterion weights of the group through a statistical probability model. By solving Equations (1)–(13), the weights of each dimension and criterion can be determined. The algorithmic software for performing Bayesian BWM in this study is applying the program provided by Mohammadi and Rezaei [16], and the overall weighting results are shown in Table 5. According to Table 5, behavioral criteria (D_3) is the most important dimension, with a weight of 0.2187. In addition, online marketing skills (C_{14}), attractiveness and trustworthiness (C_{24}), self-examination (C_{33}), rapport and motivation (C_{41}), good physical appearance (C_{53}), and demanding self-image (C_{63}) are the most important criteria for each of the six dimensions. In terms of the overall evaluation framework, the top five criteria are self-examination (C_{33}),$\succ$ punctuality and discretion (C_{32}),$\succ$ active innovation (C_{31}),$\succ$ rapport, and motivation (C_{41}), and $\succ$ demanding self-image (C_{63}).

Table 5. Weighting results of Bayesian BWM calculation.

Dimension	Local Weight	Rank	Criterion	Local Weight	Rank	Global Weight	Rank
D_1	0.1225	6	C_{11}	0.2236	3	0.0274	20
			C_{12}	0.2535	2	0.0310	18
			C_{13}	0.2185	4	0.0268	21
			C_{14}	0.3044	1	0.0373	16
D_2	0.1427	4	C_{21}	0.2202	3	0.0314	17
			C_{22}	0.2033	4	0.0290	19
			C_{23}	0.2800	2	0.0399	14
			C_{24}	0.2965	1	0.0423	13
D_3	0.2187	1	C_{31}	0.3116	3	0.0682	3
			C_{32}	0.3391	2	0.0742	2
			C_{33}	0.3493	1	0.0764	1
D_4	0.1641	3	C_{41}	0.3933	1	0.0645	4
			C_{42}	0.3150	2	0.0517	9
			C_{43}	0.2917	3	0.0479	11
D_5	0.2120	2	C_{51}	0.2503	3	0.0531	8
			C_{52}	0.2331	4	0.0494	10
			C_{53}	0.2657	1	0.0563	6
			C_{54}	0.2508	2	0.0532	7
D_6	0.1400	5	C_{61}	0.2782	3	0.0390	15
			C_{62}	0.3101	2	0.0434	12
			C_{63}	0.4117	1	0.0577	5

In order to examine the reliability of the calculated optimal group weights with their criterion ranking, a ranking confidence check is provided for this Bayesian BWM. In terms of dimensions, as in Figure 2, the confidence that D_3 is more important than D_1 is 98.63%. The average confidence in the ranking of the overall evaluation framework is 81.77%, indicating a high level of confidence in the ranking of the dimensions and criteria. Next, modified TOPSIS-AL is applied to integrate the evaluated performance values of the five fitness influencers.

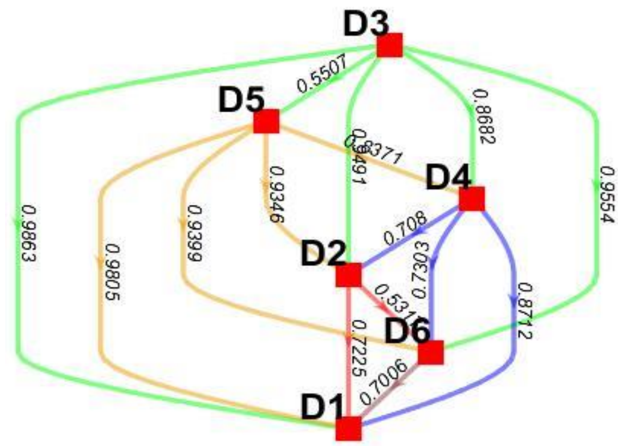

Figure 2. Confidence in the ranking of the dimensions.

4.3. Using Modified TOPSIS-AL to Calculate Fitness Influencer Function Benchmark Performance

The modified TOPSIS-AL proposed in this study introduces the concept of aspiration level to avoid considering only the relative preference solution of the current alternatives. The efficiency of the model calculation is not affected by the ranking value due to the number of alternatives. First, Table A3 presents the average survey results of the 10 experts and converts the interview results into quantifiable computational data using soft computing. By using the modified TOPSIS-AL computational procedure introduced in Section 3.2, the distance between D^* and positive ideal solutions (PIS), the distance between D^- and negative ideal solutions (NIS), and the CC value for each alternative can be obtained by solving Equations (14)–(22). The CC values and final ranking of the five fitness influencers can be found in Table 6. Here, the aspiration level and the worst level are considered alternatives, and their scores are 1 and 0, respectively. In addition, the distances of fitness influencers from the PIS and NIS (D^+ and D^-) can be determined. In particular, the distance between the aspiration level and the PIS must be 0. Conversely, the distance between the worst level and the NIS is also 0. The distance between the aspiration level and the worst level is 1. The CC values range from -1 to 1, and this coefficient gives a clearer indication of how much room for improvement there is for the alternatives. The overall performance of the five fitness influencers is significantly higher than the normal level (CC = 0), and the distance between the first-ranked A_2 and the aspiration level is 0.050 ($1 - 0.050 = 0.050$) indicating that A_2 still has significant room for improvement. Further discussion and improvement suggestions will be made in response to the study results.

Table 6. Summary of modified TOPSIS-AL results for the Fitness influencers.

	D^+	D^-	CC	Rank
A_1	0.204	0.796	0.028	3
A_2	0.140	0.860	0.050	1
A_3	0.253	0.747	0.010	5
A_4	0.215	0.785	0.024	4
A_5	0.168	0.832	0.041	2
Aspiration	0.000	1.000	0.100	
Worst	1.000	0.000	−0.253	

5. Discussion

In this study, sensitivity analysis was used to understand whether the results of the evaluation would differ due to changes in a particular variable. The sensitivity analysis is used to check the robustness of the proposed model. By exploring whether a change in the weight of a criterion affects the ranking of alternatives. In the MCDM problem, the weights of the criteria are an important conditional variable in the evaluation system. Based on the weighting results presented in Section 4.2, C_{33} has the highest weighting value of all the criteria. Therefore, it is important to understand whether a change in C_{33} significantly affects the results of the overall analysis. The weight of C_{33} was adjusted from 0.1 to 0.9, and the other criteria were adjusted proportionally. The adjustment process requires that the weights of each run be summed to 1. Table 7 shows the nine different criterion weight changes. Then, a total of nine sensitivity analyses of modified TOPSISAL-AL were performed by combining the weights, and the results of the ranking of the alternatives are presented in Table 8. The ranking of Run 1 to Run 9 is still $A_2 \succ A_5 \succ A_1 \succ A_4 \succ A_3$. Obviously, the ranking remained stable after nine sensitivity analyses. The ranking of the alternatives is not affected by the change in the weights, which indicates the robustness of the proposed hybrid model.

Table 7. Criteria weighting for nine runs of sensitivity analysis.

	Bayesian BWM	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9
C_{11}	0.0274	0.0293	0.0290	0.0288	0.0285	0.0282	0.0279	0.0276	0.0273	0.0270
C_{12}	0.0310	0.0333	0.0329	0.0326	0.0323	0.0319	0.0316	0.0313	0.0309	0.0306
C_{13}	0.0268	0.0287	0.0284	0.0281	0.0278	0.0275	0.0272	0.0269	0.0267	0.0264
C_{14}	0.0373	0.0400	0.0396	0.0391	0.0387	0.0383	0.0379	0.0375	0.0371	0.0367
C_{21}	0.0314	0.0337	0.0333	0.0330	0.0327	0.0323	0.0320	0.0316	0.0313	0.0310
C_{22}	0.0290	0.0311	0.0308	0.0305	0.0302	0.0298	0.0295	0.0292	0.0289	0.0286
C_{23}	0.0399	0.0428	0.0424	0.0420	0.0415	0.0411	0.0407	0.0402	0.0398	0.0394
C_{24}	0.0423	0.0453	0.0449	0.0444	0.0440	0.0435	0.0431	0.0426	0.0421	0.0417
C_{31}	0.0682	0.0731	0.0723	0.0716	0.0708	0.0701	0.0694	0.0686	0.0679	0.0671
C_{32}	0.0742	0.0795	0.0787	0.0779	0.0771	0.0763	0.0755	0.0747	0.0739	0.0731
C_{33}	0.0764	0.0100	0.0200	0.0300	0.0400	0.0500	0.0600	0.0700	0.0800	0.0900
C_{41}	0.0645	0.0692	0.0685	0.0678	0.0671	0.0664	0.0657	0.0650	0.0643	0.0636
C_{42}	0.0517	0.0554	0.0548	0.0543	0.0537	0.0532	0.0526	0.0520	0.0515	0.0509
C_{43}	0.0479	0.0513	0.0508	0.0503	0.0497	0.0492	0.0487	0.0482	0.0477	0.0471
C_{51}	0.0531	0.0569	0.0563	0.0558	0.0552	0.0546	0.0540	0.0535	0.0529	0.0523
C_{52}	0.0494	0.0530	0.0525	0.0519	0.0514	0.0509	0.0503	0.0498	0.0492	0.0487
C_{53}	0.0563	0.0604	0.0598	0.0592	0.0586	0.0580	0.0573	0.0567	0.0561	0.0555
C_{54}	0.0532	0.0570	0.0564	0.0559	0.0553	0.0547	0.0541	0.0536	0.0530	0.0524
C_{61}	0.0390	0.0418	0.0413	0.0409	0.0405	0.0401	0.0397	0.0392	0.0388	0.0384
C_{62}	0.0434	0.0465	0.0461	0.0456	0.0451	0.0447	0.0442	0.0437	0.0433	0.0428
C_{63}	0.0577	0.0618	0.0612	0.0605	0.0599	0.0593	0.0587	0.0581	0.0574	0.0568

Table 8. Ranking results after nine runs of sensitivity analysis.

	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9
A_1	3	3	3	3	3	3	3	3	3
A_2	1	1	1	1	1	1	1	1	1
A_3	5	5	5	5	5	5	5	5	5
A_4	4	4	4	4	4	4	4	4	4
A_5	2	2	2	2	2	2	2	2	2

As part of the fitness industry, fitness influencers are a rapidly developing profession, and the development and management of their competencies are of paramount importance. In this study, the most important dimension of fitness influencer competency evaluation is behavioral standards (D_3), which emphasizes the need for fitness influencers to establish a comprehensive set of regulations for their own behavioral standards, including the requirements of instructor ethics, teaching norms, safety and hygiene, and professional skills, to ensure that fitness influencers have a high professional standard in their work and can provide safe, effective, and appropriate training and instruction to their trainees. In addition, the regulations can help professional organizations in the industry or relevant government departments monitor and evaluate fitness influencers, to ensure that they have a good image and reputation in the fitness industry.

According to the Bayesian BWM analysis, self-examination (C_{33}),$\succ$ punctuality and discretion (C_{32}),$\succ$ active innovation (C_{31}),$\succ$ rapport and motivation (C_{41}),$\succ$ and demanding self-image (C_{63}) are the most important fitness influencer competency criteria. The criteria were determined by the 10 experts, whose opinions on all criteria were obtained through questionnaires and personal interviews. The first important criterion is self-examination (C_{33}), whether one cares about one's own teaching and performance during teaching and identifies problems for improvement [17,18,25,37], which has become the top criterion for students to choose a trainer. Only by continuously improving the quality and effectiveness of their teaching can students achieve their goals. This introspection is not just about identifying areas for improvement but is integral to evolving the quality and impact of their instruction, ultimately aiding students in achieving their fitness goals. This aspect of continuous self-improvement has become a paramount factor for clients when choosing a trainer.

The second most important criterion is punctuality and discretion (C_{32}). In addition to the quality of teaching, the ability to show up on time at the appointed time and be careful about the safety and health of the students during the teaching process is also one of the keys to being a good coach [7,8,31]. It underscores the importance of reliability and attentiveness to student safety and health during sessions, marking these traits as crucial in defining a responsible and trustworthy coach.

The third important criterion is active innovation (C_{31}). Only through continuous innovation in teaching, training, and nutrition knowledge and presenting it in different media can the students feel that the coach is committed to the course [17,18,25,27]. The ability to dynamically present this evolving knowledge across various media platforms is pivotal in demonstrating commitment and keeping students engaged and informed.

The fourth important criterion is rapport and motivation (C_{41}), which is to build a good relationship with clients and audiences so that participants and coaches can trust each other and motivate and support each other [7,36,38,39]. Interaction with the audience in the digital age is no longer the one-way process that it used to be, and providing appropriate encouragement when interacting with the audience is one of the ways to build a good relationship.

Lastly, it is important to demand self-image (C_{63}), and in the case of live or video teaching, maintaining a good body shape, a healthy state, and a positive image [7,31] is more likely to convince the audience of one's own condition. This embodiment of a fit and healthy lifestyle is a tangible demonstration of the benefits of fitness, reinforcing the influencer's message through personal example.

In sum, these criteria collectively deepen the understanding of effective fitness influencer management, underscoring aspects that go beyond traditional coaching to include digital engagement, personal branding, and continuous professional development. These competencies reflect a holistic approach to fitness influence, where personal development, client relations, and adaptability in the digital age are as important as physical fitness and technical knowledge.

In the performance ranking, the modified TOPSIS-AL was used to effectively evaluate and prioritize the alternatives, and the results of the performance ranking showed that A_2 was the better fitness influencer among the alternatives. This fitness influencer's overall comprehensive score was significantly higher than the rest of the evaluated subjects, but there was still a significant gap in comparison to the aspiration level. Therefore, it is recommended that A_2 continue to learn and develop to keep up with the latest trends and technologies. For example, he can increase his professional knowledge and skills by attending courses, reading relevant articles or books, and attending seminars. Next, it is recommended that he better understand the personal preferences and goals of his audience and clients, and provide customized programs and guidance, which would result in a positive experience of good guidance and feedback for his audience and clients. Furthermore, it is recommended that he use more social media and other online platforms for marketing and brand building to increase exposure and popularity. Finally, it is recommended that he regularly evaluate and track audience and customer satisfaction and make adjustments in a timely manner. Overall, this study provides a novel hybrid fitness influencer competency evaluation system that can improve the accuracy of decision-makers and practitioners in developing strategies.

6. Conclusions

This study creates a comprehensive evaluation framework for fitness influencer competency development, and the proposed hybrid model takes into account the fitness influencer's professional attributes during the competency construction process. The Bayesian BWM effectively improves on the methodological limitations of traditional BWM by analyzing expert opinions in a systematic manner. Behavioral standards (D_3) are the most important dimension in the overall evaluation framework, and self-examination (C_{33}), punctuality and discretion (C_{32}), active innovation (C_{31}), rapport and motivation (C_{41}), and demanding self-image (C_{63}) are the top five most important criteria. In the performance ranking, this study uses modified TOPSIS-AL to introduce the concept of aspiration level, avoiding the traditional TOPSIS method gap that only considers the relative preference solution of the current alternatives and ignores the potential room for improvement.

In summary, this study provides the fitness industry with invaluable tools and insights to not just navigate its current landscape but also to shape its future in a way that prioritizes professionalism, growth, and continuous improvement. The specific research contributions are summarized as follows:

(i) This study has crafted a well-defined framework for assessing fitness influencer abilities.
(ii) This study has addressed the limitations of AHP and BWM by employing Bayesian BWM.
(iii) This study has identified the relative rankings of contemporary fitness influencers by using the modified TOPSIS-AL.
(iv) The robustness of the hybrid model has been confirmed through sensitivity analysis.

Although this study is innovative and contributes to the development of fitness influencers' competencies, there are still some limitations that need to be overcome and extended. This study suggests that the independence of dimensions and criteria was not considered in terms of their interdependence and that future research could consider the mutual influence relationships among dimensions and criteria through the use of interdependent research methods, such as the Decision-making Trial and Evaluation Laboratory (DEMATEL) technique. In the case of expert evaluations that do not take into account the ambiguity and uncertainty of the evaluation environment, the study can incorporate fuzzy theory to better match the actual evaluation status of the expert. Multiple model comparisons can be conducted to present the reliability and robustness of the model in this study. In addition, the analysis process of this study can be replicated for other multi-criteria decision-making problems by simply modifying the dimensions and criteria according to the industry sector.

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Appendix A

Table A1. BO vectors for the dimensions.

BO Vectors	Best	D_1	D_2	D_3	D_4	D_5	D_6
Expert 1.	D_1	1	1	1	1	1	1
Expert 2.	D_1	1	1	1	1	1	1
Expert 3.	D_1	1	1	1	1	1	1
Expert 4.	D_5	2	2	2	2	1	2
Expert 5.	D_3	4	4	1	2	1	2
Expert 6.	D_3	4	4	1	1	1	4
Expert 7.	D_1	1	1	1	1	1	1
Expert 8.	D_1	1	1	1	1	3	1
Expert 9.	D_2	2	1	1	1	2	1
Expert 10.	D_5	7	4	2	7	1	7

Table A2. OW vectors of the transposed dimensions.

OW	Worst	D_1	D_2	D_3	D_4	D_5	D_6
Expert 1.	D_2	1	1	1	1	1	1
Expert 2.	D_2	1	1	1	1	1	1
Expert 3.	D_2	1	1	1	1	1	1
Expert 4.	D_1	1	1	1	1	2	1
Expert 5.	D_1	1	1	4	2	4	2
Expert 6.	D_1	1	1	4	4	4	1
Expert 7.	D_2	1	1	1	1	1	1
Expert 8.	D_1	3	3	3	3	1	3
Expert 9.	D_1	1	2	2	2	1	2
Expert 10.	D_1	1	2	4	1	7	1

Table A3. Average decision matrix for the 10 experts.

	A_1	A_2	A_3	A_4	A_5	Aspiration Level	Worst Level
C_{11}	7.7	8.2	5.9	6.7	7.4	10	0
C_{12}	7.8	7.6	6.1	5.9	7.2	10	0
C_{13}	5.8	6.6	5.3	5.4	6.6	10	0
C_{14}	6.0	7.0	5.8	5.9	6.6	10	0
C_{21}	6.5	7.7	6.6	7.0	7.6	10	0
C_{22}	6.3	7.7	6.7	6.8	7.2	10	0
C_{23}	6.5	7.5	6.7	6.7	7.1	10	0
C_{24}	7.9	8.0	6.5	6.3	7.0	10	0
C_{31}	7.5	7.8	6.3	6.5	7.4	10	0
C_{32}	7.5	7.5	6.6	6.7	7.5	10	0
C_{33}	6.7	7.2	6.1	6.7	7.3	10	0
C_{41}	6.6	7.8	6.8	7.3	7.6	10	0
C_{42}	6.3	7.9	6.8	7.3	7.5	10	0
C_{43}	6.9	7.5	6.4	6.8	7.2	10	0
C_{51}	6.9	8.0	7.2	7.1	7.7	10	0
C_{52}	7.4	7.9	7.7	7.6	7.8	10	0
C_{53}	8.5	8.3	7.4	8.2	8.0	10	0
C_{54}	7.9	7.9	7.3	8.1	8.0	10	0
C_{61}	7.2	7.8	7.2	7.6	7.5	10	0
C_{62}	7.0	7.9	6.9	7.6	7.8	10	0
C_{63}	8.3	8.3	7.6	8.4	8.2	10	0

References

1. Ahrens, J.; Brennan, F.; Eaglesham, S.; Buelo, A.; Laird, Y.; Manner, J.; Newman, E.; Sharpe, H. A Longitudinal and Comparative Content Analysis of Instagram Fitness Posts. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6845. [CrossRef]
2. Jones, P.; Ratten, V.; Hayduk, T. Sport, Fitness, and Lifestyle Entrepreneurship. *Int. Entrep. Manag. J.* **2020**, *16*, 783–793. [CrossRef]
3. Söderström, T. A 20-year analysis of motives and training patterns of Swedish gym-goers. *Ann. Leis. Res.* **2023**, *26*, 521–544. [CrossRef]
4. Storm, R.K.; Hansen, B.O.R. Commercial fitness centres in Denmark: A study on development, determinants of provision and substitution effects. *Ann. Leis. Res.* **2021**, *24*, 468–491. [CrossRef]
5. Yong, B.; Xu, Z.; Wang, X.; Cheng, L.; Li, X.; Wu, X.; Zhou, Q. IoT-based intelligent fitness system. *J. Parallel Distrib. Comput.* **2018**, *118*, 14–21. [CrossRef]
6. De Veirman, M.; Cauberghe, V.; Hudders, L. Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitude. *Int. J. Advert.* **2017**, *36*, 798–828. [CrossRef]
7. Kim, M. How can I Be as attractive as a Fitness YouTuber in the era of COVID-19? The impact of digital attributes on flow experience, satisfaction, and behavioral intention. *J. Retail. Consum. Serv.* **2022**, *64*, 102778. [CrossRef]
8. Sokolova, K.; Perez, C. You follow fitness influencers on YouTube. But do you actually exercise? How parasocial relationships, and watching fitness influencers, relate to intentions to exercise. *J. Retail. Consum. Serv.* **2021**, *58*, 102276. [CrossRef]
9. Femenia-Serra, F.; Gretzel, U.; Alzua-Sorzabal, A. Instagram travel influencers in #quarantine: Communicative practices and roles during COVID-19. *Tour. Manag.* **2022**, *89*, 104454. [PubMed]
10. Leung, F.F.; Gu, F.F.; Palmatier, R.W. Online Influencer Marketing. *J. Acad. Mark. Sci.* **2022**, *50*, 226–251. [CrossRef]
11. Muñoz, M.M.; Rojas-de-Gracia, M.M.; Navas-Sarasola, C. Measuring engagement on twitter using a composite index: An application to social media influencers. *J. Inf. Technol.* **2022**, *16*, 101323. [CrossRef]
12. Liu, J.W.; Chang, C.W.; Wang, Y.J.; Liu, Y.H. Constructing a Decision Model for Health Club Members to Purchase Coaching Programs during the COVID-19 Epidemic. *Sustainability* **2022**, *14*, 13497. [CrossRef]
13. Branley-Bell, D.; Talbot, C.V. Exploring the impact of the COVID-19 pandemic and UK lockdown on individuals with experience of eating disorders. *J. Eat. Disord.* **2020**, *8*, 44. [CrossRef] [PubMed]
14. Chang, T.; Pai, C.; Lo, H.; Hu, S. A hybrid decision-making model for sustainable supplier evaluation in electronics manufacturing. *Comput. Ind. Eng.* **2021**, *156*, 107283. [CrossRef]
15. Shao, Q.; Lo, H.W.; Liou, J.J.; Tzeng, G.H. A Data-Driven Model to Construct the Influential Factors of Online Product Satisfaction. *Int. J. Inf. Technol. Decis. Mak.* **2023**, 1–31. [CrossRef]
16. Mohammadi, M.; Rezaei, J. Bayesian best-worst method: A probabilistic group decision making model. *Omega* **2019**, *96*, 102075. [CrossRef]
17. Wang, L.; Chen, Y. Success or growth? Distinctive roles of extrinsic and intrinsic career goals in high-performance work systems, job crafting, and job performance. *J. Vocat. Educ. Train.* **2022**, *135*, 103714. [CrossRef]
18. Mäkikangas, A.; Schaufeli, W. A person-centered investigation of two dominant job crafting theoretical frameworks and their work-related implications. *J. Vocat. Behav.* **2021**, *131*, 103658. [CrossRef]
19. Dobson, S.; McLuskie, P. Performative entrepreneurship: Identity, behaviour and place in adventure sports Enterprise. *Int. Entrep. Manag. J.* **2020**, *16*, 879–895. [CrossRef]
20. Jang, S.; Han, S.H.; Rhee, J.Y. Cluster of coronavirus disease associated with fitness dance classes, South Korea. *Emerg. Infect. Dis.* **2020**, *26*, 1917–1920. [CrossRef]
21. Führer, T.; Kliegl, R.; Arntz, F.; Kriemler, S.; Granacher, U. An Update on Secular Trends in Physical Fitness of Children and Adolescents from 1972 to 2015: A Systematic Review. *Sports Med.* **2021**, *51*, 303–320. [CrossRef] [PubMed]
22. Rydzik, Ł.; Ambrozy, T. Physical fitness and the level of technical and tactical training of kickboxers. *Int. J. Environ. Res. Public Health* **2021**, *18*, 3088. [CrossRef] [PubMed]
23. Kim, M. Conceptualization of e-servicescapes in the fitness applications and wearable devices context: Multi-dimensions, consumer satisfaction, and behavioral intention. *J. Retail. Consum. Serv.* **2021**, *61*, 102562. [CrossRef]
24. Kim, H. Social comparison of fitness social media postings by fitness app users. *Comput. Hum. Behav.* **2022**, *131*, 107204. [CrossRef]
25. De Vos, A.; van der Heijden, B.I.J.M.; Akkermans, J. Sustainable careers: Towards a conceptual model. *J. Vocat. Behav.* **2020**, *117*, 103196. [CrossRef]
26. Hoff, K.A.; Song, Q.C.; Wee, C.J.M.; Phan, W.M.J.; Rounds, J. Interest fit and job satisfaction: A systematic review and metaanalysis. *J. Vocat. Behav.* **2020**, *123*, 103503. [CrossRef]
27. Lazazzara, A.; Tims, M.; de Gennaro, D. The process of reinventing a job: A meta–synthesis of qualitative job crafting research. *J. Vocat. Behav.* **2020**, *116*, 103267. [CrossRef]
28. Sun, C.; Shute, V.J.; Stewart, A.; Yonehiro, J.; Duran, N.; D'Mello, S. Towards a generalized competency model of collaborative problem solving. *Comput. Educ.* **2020**, *143*, 103672. [CrossRef]
29. Gruman, J.A.; Budworth, M.-H. Positive psychology and human resource management: Building an HR architecture to support human flourishing. *Hum. Resour. Manag. Rev.* **2022**, *32*, 100911. [CrossRef]
30. Janssen, L.; Schouten, A.P.; Croes, E.A.J. Influencer Advertising on Instagram: Product-Influencer Fit and Number of Followers Affect Advertising Outcomes and Influencer Evaluations Via Credibility and Identification. *Int. J. Advert.* **2022**, *41*, 101–127. [CrossRef]

31. Sokolova, K.; Kefi, H. Instagram and YouTube Bloggers Promote It, Why Should I Buy? How Credibility and Parasocial Interaction Influence Purchase Intentions. *J. Retail. Consum. Serv.* **2020**, *53*, 101742. [CrossRef]
32. Ghosh, S.; Hughes, M.; Hodgkinson, I.; Hughes, P. Digital transformation of industrial businesses: A dynamic capability approach. *Technovation* **2021**, *113*, 102414. [CrossRef]
33. Oberländer, M.; Beinicke, A.; Bipp, T. Digital Competences: A Review of the Literature and Applications in the Workplace. *Comput. Educ.* **2020**, *146*, 103752. [CrossRef]
34. Jiménez-Castillo, D.; Sánchez-Fernández, R. The role of digital influencers in brand recommendation: Examining their impact on engagement, expected value and purchase intention. *Int. J. Inf. Manag.* **2019**, *49*, 366–376. [CrossRef]
35. Casaló, L.V.; Flavian, C.; Ibáñez-Sánchez, S. Influencers on Instagram: Antecedents and consequences of opinion leadership. *J. Bus. Res.* **2020**, *117*, 510–519. [CrossRef]
36. Lim, M.S.C.; Molenaar, A.; Brennan, L.; Reid, M.; McCaffrey, T. Young adults' use of different social media platforms for health information: Insights from web-based conversations. *J. Med. Internet Res.* **2022**, *24*, e23656. [CrossRef] [PubMed]
37. Maina, M.F.; Ortiz, L.G.; Mancini, F.; Melo, M.M. A Micro-Credentialing Methodology for Improved Recognition of HE Employability Skills. *Int. J. Educ. Technol. High. Educ.* **2022**, *19*, 10. [CrossRef] [PubMed]
38. Flanigan, A.E.; Akcaoglu, M.; Ray, E. Initiating and maintaining student-instructor rapport in online classes. *Internet High. Educ.* **2022**, *53*, 100844. [CrossRef]
39. Schwerter, J.; Dimpfl, T.; Bleher, J.; Murayama, K. Benefits of Additional Online Practice Opportunities in Higher Education. *Internet High. Educ.* **2022**, *53*, 100834. [CrossRef]
40. Rezaei, J. Best-worst multi-criteria decision-making method. *Omega* **2015**, *53*, 49–57. [CrossRef]
41. Huang, C.-N.; Liou, J.J.; Lo, H.-W.; Chang, F.-J. Building an assessment model for measuring airport resilience. *J. Air Transp. Manag.* **2021**, *95*, 102101. [CrossRef]
42. Aydin, N.; Seker, S.; Şen, C. A new risk assessment framework for safety in oil and gas industry: Application of FMEA and BWM based picture fuzzy MABAC. *J. Pet. Sci. Eng.* **2022**, *219*, 111059. [CrossRef]
43. Munim, Z.H.; Balasubramaniyan, S.; Kouhizadeh, M.; Hossain, N.U.I. Assessing blockchain technology adoption in the Norwegian oil and gas industry using Bayesian Best Worst Method. *J. Ind. Inf. Integr.* **2022**, *28*, 100346. [CrossRef]
44. Vieira, F.C.; Ferreira, F.A.F.; Govindan, K.; Ferreira, N.C.M.Q.F.; Banaitis, A. Measuring Urban Digitalization Using Cognitive Mapping and the Best Worst Method (BWM). *Technol. Soc.* **2022**, *71*, 102131. [CrossRef]
45. Gül, M.; Yücesan, M. Performance evaluation of Turkish Universities by an integrated Bayesian BWM-TOPSIS model. *Socio-Econ. Plan. Sci.* **2022**, *80*, 101173. [CrossRef]
46. Zhang, Y.; Zhao, H.; Li, B.; Zhao, Y.; Qi, Z. Research on credit rating and risk measurement of electricity retailers based on Bayesian Best Worst Method-Cloud Model and improved Credit Metrics model in China's power market. *Energy* **2022**, *252*, 124088. [CrossRef]
47. Lo, H.W.; Liou, J.; Huang, C.N.; Chuang, Y.C. A novel failure mode and effect analysis model for machine tool risk analysis. Reliab. *Eng. Syst. Saf.* **2019**, *183*, 173–183. [CrossRef]
48. Kuo, T. A modified TOPSIS with a different ranking index. *Eur. J. Oper. Res.* **2017**, *260*, 152–160. [CrossRef]