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Adaptive Balanced Entropy Weighting for Mitigating Criterion Weight Imbalance in Multi-Criteria Decision Making

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ABSTRACT

Multi-Criteria Decision Making (MCDM) relies on criterion weights to represent the relative importance of evaluation criteria in ranking alternatives. However, conventional Entropy Weighting may generate highly imbalanced weights when criteria exhibit substantially different levels of information variation, potentially causing excessive dominance of particular criteria. This study proposes Adaptive Balanced Entropy (A-Entropy), an objective weighting method that integrates the information-based principle of Entropy Weighting with an adaptive balancing mechanism. The method derives entropy-based weights, measures weight imbalance using a Weight Imbalance Index, and adaptively adjusts the weights according to the identified imbalance level. The effectiveness of A-Entropy is evaluated through two MCDM case studies involving lecturer selection and leasing customer selection. The resulting weights are compared with conventional Entropy Weighting, while their effects on alternative rankings are evaluated using MOORA and PIV, respectively. The results show that A-Entropy substantially reduces weight concentration in the lecturer selection case, where the highest weight decreases from 0.4368 to 0.3333 and the lowest weight increases from 0.0042 to 0.0665. In the leasing customer selection case, the adjustment is more moderate due to its comparatively lower initial imbalance. Furthermore, A-Entropy produces higher Spearman correlations with the original rankings than Entropy, increasing from 0.8303 to 0.9030 for lecturer selection and from 0.9758 to 0.9879 for leasing customer selection. These findings indicate that A-Entropy reduces excessive criterion weight imbalance while preserving meaningful differences in criterion importance and maintaining high ranking consistency. Therefore, A-Entropy provides an adaptive objective weighting approach for MCDM-based Decision Support Systems.

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I. Introduction

Multi-Criteria Decision Making (MCDM) is an approach that's commonly used in decision-making when alternatives need to be evaluated based on several criteria at the same time[1], [2]. In these situations, each criterion can have different characteristics, scales, and levels of importance, so you need a way to represent each criterion's relative contribution to the final decision. Weighting the criteria is one of the core parts of MCDM because the weight values determine how much influence each criterion has in the process of aggregating and ranking the alternatives. The differences in the weights produced will directly affect the final value of the alternatives and the ranking positions obtained. Therefore, the quality of a weighting method is not only determined by its ability to generate weight values but also by its ability to create a weight distribution that fits the information and characteristics of the data[3], [4]. Disproportionate weighting can make a criterion's contribution too dominant or too small, which ultimately can affect how the decision-making results are represented. This situation makes developing weighting methods that can produce informative and proportional weights an important aspect of improving the quality of the MCDM process.

Objective weighting provides an alternative to subjective approaches by determining weights based on the information contained in the data without directly relying on the decision-maker's preferences[5]-[7]. This approach uses the statistical characteristics of the decision matrix, such as variation, distribution, or the level of information each criterion has, to determine its importance. In this way, the weights obtained can reflect the actual characteristics of the dataset and offer a more systematic and reproducible weighting process. One widely used objective weighting approach is Entropy Weighting, which determines weights based on the level of information or diversity present in each criterion[8]-[10]. Criteria that provide more information to distinguish between alternatives tend to get higher weights, while criteria with relatively uniform information get lower weights. This mechanism makes Entropy Weighting appealing for various MCDM problems because it can determine weights in a data-driven way[11]-[13]. However, its strong reliance on information distribution can also lead to situations where the difference in weights between criteria becomes very large.

Problems arise when the characteristics of information between criteria have extreme differences, causing Entropy Weighting to produce a very uneven weight distribution. Criteria with high information variation can get much larger weights compared to other criteria, while criteria with more uniform distribution can end up with very small weights. Mathematically, this condition is a consequence of the entropy principle, which gives more reward to criteria with higher discriminative ability. However, in the context of decision-making, a distribution that is too extreme can become a problem when all criteria still have relevance for evaluating alternatives. Criteria with dominant weights have the potential to exert a much greater influence on the aggregated results, while the contribution of criteria with low weights becomes increasingly limited. Therefore, statistically valid objective weighting doesn't necessarily produce a balanced distribution of importance for use in the decision-making process, especially when there are huge differences in data characteristics between criteria.

Imbalance in criteria weights can affect the aggregation process because weights act as controllers of each criterion's contribution to the overall value of alternatives[14], [15]. When one criterion gets a much larger weight than others, an alternative's performance on that criterion can become the main factor in determining the aggregated score and ranking position. As a result, the strengths or weaknesses of alternatives on criteria with low weights may become less noticeable, even though those criteria are substantially relevant to the decision problem. This situation can lead to a ranking structure that reflects the influence of dominant criteria more than the collective contribution of all criteria[16], [17]. Besides that, the ranking that forms can become more sensitive to changes in criteria with high weights, so even small changes in data or weights can potentially lead to bigger shifts in the position of alternatives. So, criterion weight imbalance isn’t just about how the weights are distributed, it can also affect the aggregation, consistency, and stability of the ranking produced by MCDM methods.

Efforts to reduce weight inequality can be carried out through various balancing or adjustment mechanisms once the initial weights have been obtained. These approaches can include weight redistribution, smoothing, re-normalization, or applying certain limits to the weight values. While they can reduce extreme differences, static adjustment approaches may apply the same level of correction to datasets with different imbalance characteristics. On the other hand, adjustments that are too aggressive can make the weights too uniform and reduce the discriminatory information derived from the data. This shows that the balancing process needs to consider the actual level of imbalance in the weight distribution, rather than just applying the same correction rule in every situation. In other words, the balancing mechanism ideally can figure out when a distribution needs a small, medium, or stronger

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correction based on the characteristics of the resulting weights. This limitation is what underlines the need for a more adaptive balancing approach in objective weighting.

Based on this discussion, there's still room for research in developing objective weighting that simultaneously preserves the objective information from the data and controls the imbalance in weight distribution. Entropy Weighting can identify the information level of each criterion, but it doesn't specifically provide a mechanism to evaluate and control the level of imbalance in the final weights. Meanwhile, the existing balancing approaches tend to use certain adjustment mechanisms that don't fully take into account variations in imbalance levels across datasets. As a result, there's still a need for an approach that can determine adjustment levels based on the weight distribution conditions dynamically. The research gap in this study lies in the need to integrate the information-based weighting process with adaptive balancing so that the resulting weights still maintain differences in importance among criteria, but don’t become overly dominated. This approach is expected to provide a more flexible weighting mechanism when dealing with datasets that have different information characteristics.

To address this gap, this study proposes Adaptive Balanced Entropy (A-Entropy) as an approach that combines the principles of Entropy Weighting with a balancing mechanism adjusted based on the weight distribution conditions. The main idea of A-Entropy is that balancing doesn't need to be applied with the same level of correction in all cases, but can be adjusted according to the degree of identified imbalance. With this mechanism, the weight distribution can be corrected proportionally without losing the information that formed the original weights. A-Entropy aims to maintain the data-driven characteristics of entropy while providing control over weights that are too dominant or too low. This approach is expected to produce a more balanced weight distribution while still being able to distinguish the importance levels between criteria. So, the development of A-Entropy isn't meant to make all criteria have the same weight, but to achieve a balance between representing objective information and the proportional contribution of each criterion in the decision-making process.

This study aims to develop A-Entropy and evaluate its effectiveness as a method for weighting criteria in MCDM. The evaluation focuses on A-Entropy's ability to produce a more balanced distribution of weights while maintaining discriminative power between criteria when applied to different data conditions. The main contribution of this study is the formulation of the A-Entropy method as an objective weighting approach with an adaptive balancing mechanism, along with an empirical evaluation of weight characteristics and their impact on the ranking of alternatives. This study provides a new approach to handling criterion weight imbalance without ignoring the information obtained from the entropy process.

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II. Preliminaries

2.1. Multi-Criteria Decision Making

Multi-Criteria Decision Making (MCDM) refers to a decision-making framework designed to evaluate a set of alternatives based on multiple criteria that may differ in their characteristics, measurement scales, and relative importance[18]-[20]. Let A = {A1, A2, ..., Am} denote a set of m alternatives evaluated according to C = {C1, C2, ..., Cn}, representing a set of n criteria. The decision information is generally represented by a decision matrix X = [xij]m×n, where xij denotes the performance value of alternative Ai with respect to criterion Cj. Because the criteria may have different units and ranges, the decision matrix is commonly transformed into a normalized form before the evaluation process. A central component of MCDM is the criterion weight vector W = {w1, w2, ..., wn}, where wj ≥ 0 and the sum of all criterion weights is equal to 1. These weights determine the relative contribution of each criterion to the aggregation process and, consequently, influence the final evaluation and ranking of alternatives. Therefore, the quality and distribution of criterion weights are essential factors in ensuring that the resulting decision appropriately reflects the information contained in the decision problem[21]-[24].

2.2. Objective Criterion Weighting

Objective criterion weighting determines the relative importance of criteria directly from the characteristics of the decision data without relying on subjective preferences provided by decision-makers or experts[25], [26]. The underlying principle is that the importance of a criterion can be derived from the amount of information it contributes to differentiating the available alternatives. Depending on the method, this information may be associated with data dispersion, contrast intensity, statistical variation, inter-criterion relationships, or uncertainty. In general, a criterion that provides greater discriminatory information is assigned a higher weight, whereas a criterion with limited variation or lower informational contribution receives a smaller weight. This data-driven mechanism makes objective weighting particularly useful when subjective judgments are unavailable, inconsistent, or undesirable[27], [28]. However, because the resulting weights are strongly determined by the statistical characteristics of the data, substantial differences in information among criteria may produce highly heterogeneous weight distributions. Consequently, objective weighting methods should not only be assessed based on their ability to identify informative criteria but also on the resulting distribution of weights and its implications for subsequent aggregation and ranking processes.

2.3. Entropy Weighting Principle

Entropy Weighting is an objective weighting approach based on the concept of information uncertainty[29]. The method evaluates the

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distribution of normalized values for each criterion to determine the amount of information provided by that criterion. When the performance values of a criterion are relatively similar across alternatives, the criterion contains a higher degree of uncertainty and provides limited discriminatory information. Conversely, greater differences among alternative values indicate lower uncertainty and greater information utility. Based on this principle, Entropy Weighting first derives the relative distribution of each criterion, then calculates its entropy value and corresponding degree of diversification. The criterion weights are subsequently obtained by normalizing the diversification values so that their total equals one. As a result, criteria with greater discriminatory capability generally receive larger weights, while criteria with more homogeneous distributions receive smaller weights. Although this mechanism provides an objective and systematic basis for weighting, large differences in the informational characteristics of criteria may also lead to considerable disparities among the resulting weights.

2.4. Weight Balancing and Adaptive Adjustment

Weight balancing refers to an adjustment process intended to reduce excessive disparities in a criterion weight distribution while preserving the relative importance information generated by the initial weighting procedure[30], [31]. A balancing mechanism should therefore avoid two opposite conditions: insufficient adjustment that leaves extreme dominance unchanged and excessive adjustment that forces the weights toward an artificially uniform distribution. Conventional adjustment strategies may apply a fixed transformation, redistribution rule, or predefined correction intensity to the initial weights. However, a fixed adjustment may not be equally appropriate for different decision matrices because the degree of weight imbalance can vary according to the underlying data structure. Adaptive adjustment addresses this limitation by linking the intensity of the balancing process to the observed characteristics of the weight distribution. Under this concept, a relatively balanced distribution requires limited correction, whereas a highly concentrated distribution may require a stronger adjustment. The purpose of adaptive balancing is therefore to preserve meaningful differences among criteria while proportionally mitigating excessive weight concentration, providing the conceptual basis for the proposed Adaptive Balanced Entropy Weighting approach.

2.5. Notation and Definitions

To facilitate the formulation of the proposed method, the main notations and definitions used throughout this study are summarized as follows. Let Ai denote the i-th alternative, where i = 1, 2, ..., m, and let Cj denote the j-th criterion, where j = 1, 2, ..., n. The original decision matrix is represented as X = [xij]m×n, in which xij indicates the performance of alternative Ai under criterion Cj. The normalized decision value is denoted by rij, while pij represents the proportional

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distribution value used in the entropy calculation. The entropy value of criterion Cj is denoted by ej, and its corresponding degree of diversification is represented by dj. The initial weight generated from the Entropy Weighting procedure is denoted by wjE, whereas the balanced weight produced after the adaptive adjustment process is represented by wjA. The complete criterion weight vector is expressed as W = [w1, w2, ..., wn], subject to wj ≥ 0 and the sum of all criterion weights being equal to 1. These definitions provide a consistent mathematical representation for describing the weighting process, evaluating the level of weight imbalance, and formulating the adaptive balancing mechanism in the proposed method.

III. Proposed Adaptive Balanced Entropy Weighting Method

The proposed A-Entropy weighting method is developed to provide an objective criterion weighting mechanism that integrates the information-based principle of Entropy Weighting with an adaptive strategy for controlling excessive disparities among criterion weights. The method begins by deriving the initial criterion weights from the information distribution of the decision matrix and subsequently evaluates the resulting weight structure to identify the degree of imbalance. Based on the detected imbalance, an adaptive adjustment mechanism is applied to regulate the weight distribution while preserving the relative information contained in the original entropy-based weights. The adjustment is designed to avoid excessive concentration on a limited number of criteria without forcing all criteria toward an identical level of importance. Consequently, A-Entropy aims to establish a balanced relationship between objective information content and proportional criterion contribution, providing a more controlled weighting structure for subsequent MCDM aggregation and ranking processes.

3.1. Framework of the Proposed Method

The proposed adaptive balanced entropy weighting method is structured as a systematic weighting framework that combines objective information measurement with an adaptive mechanism for controlling criterion weight imbalance. The framework is designed to obtain criterion weights from the decision data while maintaining an appropriate distribution of importance among criteria. The overall process provides the foundation for calculating the final ABEW weights, which can subsequently be applied in MCDM-based evaluation and ranking. The complete framework of the proposed method is presented in Figure 1.

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Figure 1. Research Adaptive Balanced Entropy Weighting Method

The framework proposed in Figure 1 introduces the A-Entropy Weighting Method as a systematic approach for determining objective and balanced criteria weights. The framework is designed to process decision-making data sequentially, beginning with the construction of the decision matrix and data transformation through normalization, followed by entropy-based information measurement and diversification analysis. The initial criteria weights obtained from the entropy process are subsequently evaluated using the Weight Imbalance Index to identify potential disparities among criteria. An adaptive adjustment mechanism is then applied to refine the weight distribution, resulting in balanced final criteria weights that can be used in subsequent decision-making or alternative-ranking processes. Overall, the proposed framework consists of eight main stages, as follows.

The decision matrix represents the initial data structure used in the proposed weighting method, as shown in (1). The matrix contains a set of alternatives that are evaluated based on various criteria. Each entry represents the performance of an alternative against a specific criterion. This matrix serves as the main input for the subsequent steps in the proposed weighting procedure, to ensure that the evaluation process is based on the original characteristics of the decision-making problem.

$$X = [x_{ij}]_{mxn} \quad (1)$$

Normalization is performed to transform the original performance values into a comparable scale across all criteria, as presented in (2). This process is necessary because the criteria may have different measurement units, numerical ranges, and magnitudes. The normalization procedure produces dimensionless values while maintaining the relative performance characteristics of the alternatives. The resulting

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normalized values are then used as the basis for the subsequent entropy calculation.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

The entropy calculation is conducted to measure the degree of variation and uncertainty contained within each criterion, as presented in (3). The distribution of normalized performance values across the alternatives is used to determine the information characteristics of each criterion. A relatively uniform distribution indicates limited discriminatory capability, whereas greater variation among alternatives indicates stronger discriminatory information. This stage enables the objective assessment of criterion information based solely on the characteristics of the available data.

$$E_j = -\frac{1}{ln(m)} \sum_{i=1}^{m} (p_{ij}\ ln(p_{ij})) \tag{3}$$

The information degree is determined based on the entropy values obtained in the previous stage, as presented in (4). This stage identifies the effective discriminatory information provided by each criterion. Criteria associated with lower entropy values obtain greater information degrees, indicating a stronger ability to differentiate among alternatives. Conversely, criteria with higher entropy values provide relatively less discriminatory information. The resulting information degrees are subsequently used to determine the initial entropy-based weights.

$$D_j = 1 - E_j \tag{4}$$

The original entropy weights are calculated by normalizing the information degrees across all criteria, as presented in (5). This procedure assigns greater importance to criteria that contain higher levels of discriminatory information and lower importance to criteria with less information. The resulting weight distribution represents the conventional entropy-based weighting approach. However, when the information characteristics of one criterion differ substantially from those of the other criteria, the entropy method may generate a highly concentrated weight distribution, which can cause excessive influence from a particular criterion in the subsequent decision-making process.

$$w_j{}^E = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{5}$$

The weight imbalance detection stage is introduced to evaluate the degree of concentration in the entropy-derived weight distribution, as presented in (6). The imbalance measure assesses the deviation of the obtained weight distribution from an equal-weight reference distribution. A lower value indicates a relatively balanced distribution, whereas a higher value indicates greater concentration among one or more criteria. This stage provides an objective basis for determining the extent of balancing required, eliminating the need to specify the correction intensity arbitrarily.

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$$BI = \frac{\sqrt{\sum_{j=1}^{n} (w_j{}^E - \frac{1}{n})^2}}{\sqrt{\frac{n-1}{n}}} \tag{6}$$

The balance correction stage adjusts the original entropy-derived weights according to the level of imbalance identified in the previous stage, as presented in (7). The correction mechanism combines the information obtained from the conventional entropy weighting process with an equal-weight reference according to the detected degree of imbalance. When the weight distribution is relatively balanced, the adjustment remains limited and the original entropy information is largely preserved. When substantial imbalance is detected, a stronger correction is applied to reduce excessive dominance by highly weighted criteria while increasing the relative contribution of criteria with lower weights.

$$C_j = (1 - BI) w_j{}^E + \frac{BI}{n} \tag{7}$$

The final weighting stage normalizes the corrected weight values to obtain the final entropy-based balanced weights, as presented in (8). This process ensures that the resulting weights form a valid distribution that can be directly incorporated into the subsequent MCDM ranking procedure. The final weighting structure represents a balance between the discriminatory information identified by the conventional entropy method and the need to mitigate excessive weight concentration. Consequently, the proposed approach retains the data-driven characteristics of entropy weighting while producing a more balanced distribution of criterion importance.

$$w_j{}^{EB} = \frac{C_j}{\sum_{i=1}^{m} C_j} \tag{8}$$

Overall, the proposed weighting procedure integrates conventional entropy-based information measurement with an adaptive balancing mechanism to address excessive concentration in criterion weights. The approach first derives objective weights from the information characteristics of the evaluation data and subsequently assesses the degree of imbalance in the resulting weight distribution. The identified imbalance is then used to determine the intensity of the balancing correction, allowing the method to adapt to the characteristics of each dataset rather than relying on a manually predefined adjustment parameter. Through this mechanism, the proposed method aims to preserve the discriminatory information captured by entropy while reducing excessive dominance of individual criteria, resulting in a more balanced and robust criterion weight distribution for subsequent multi-criteria decision-making analysis.

3.2. Final Weight Generation

The Final Weight Generation stage is designed to transform the initial entropy-based weights into a more balanced and reliable set of criteria weights. Although entropy weighting provides an objective

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measure of the information contained in each criterion, the resulting weights may exhibit substantial differences when certain criteria contain greater variation than others. Therefore, the proposed A-Entropy Weighting Method incorporates an adaptive balancing mechanism to reduce excessive weight disparities while preserving the information characteristics obtained from the entropy analysis. This stage consists of three main processes: (1) integration of entropy weights with adaptive balancing, (2) normalization of the final weights, and (3) evaluation of the properties of the proposed weighting scheme.

First, the entropy weights are integrated with the adaptive balancing mechanism based on the Weight Imbalance Index. The index identifies the degree of disparity among the initial criteria weights and provides a basis for determining the extent of adjustment required. Criteria with disproportionately high or low weights are adaptively modified to obtain a more equitable distribution. The adjustment process is performed without completely eliminating the information derived from the entropy calculation, ensuring that the final weights remain data-driven while reducing potential dominance by particular criteria.

Second, the adjusted weights are normalized to ensure that the total weight across all criteria is equal to one. This normalization provides a consistent scale for all criteria and ensures that the final weights can be directly incorporated into subsequent multi-criteria decision-making and alternative-ranking processes. The normalized weights represent the final relative importance of each criterion after considering both the objective information obtained from entropy analysis and the balancing requirements identified through the adaptive mechanism.

Finally, the properties of the proposed weighting scheme are evaluated to determine whether the generated weights provide an appropriate balance between objectivity, discrimination, and weight stability. The proposed scheme is expected to maintain the information contribution of individual criteria while preventing excessive concentration of importance in a small number of criteria. A more balanced weight distribution can improve the reliability of subsequent decision-making by reducing the risk that the ranking results are disproportionately influenced by a single criterion. Thus, the final weight generation stage provides the basis for obtaining a robust set of criteria weights that can be applied consistently in the subsequent alternative evaluation and ranking process.

IV. Experimental Design

4.1. Dataset and Case Study

The dataset and case study provide the empirical foundation for evaluating the proposed method and demonstrating its applicability to a real-world multi-criteria decision-making problem. This section describes the characteristics of the dataset, including the evaluated alternatives, decision criteria, criterion types, and data structure

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used in the analysis. The case study is selected to represent a practical decision environment in which alternatives must be assessed based on multiple criteria with different levels of importance and characteristics. The dataset is subsequently used to implement the proposed method, generate the resulting preference rankings, and conduct comparative and sensitivity analyses to examine the effectiveness, consistency, and robustness of the proposed approach.

The dataset used in this study represents a lecturer selection problem from [32], in which several candidates are evaluated based on multiple academic and professional criteria. The dataset consists of 10 alternatives, with each alternative assigned numerical evaluation scores across five criteria. The criteria include TOEFL Score (C1), TKDA Score (C2), Number of Publications (C3), Interview Score (C4), and Teaching Ability Score (C5). These criteria reflect different aspects of candidates' academic qualifications, research productivity, communication ability, and teaching competence. The complete assessment data for all alternatives and criteria are presented in Table 1, which serves as the decision matrix for the subsequent weighting and ranking analysis using the MOORA-based approach.

Table 1. Lecturer Selection Assessment Data[32]

Alternatives	C1	C2	C3	C4	C5
SA Candidates	620	750	12	90	9
CF Candidates	600	720	15	88	8
RF Candidates	650	800	10	93	8
TR Candidates	580	670	14	85	7
IH Candidates	630	790	13	91	9
AK Candidate	610	740	11	87	8
GM Candidates	590	650	9	84	6
MF Candidates	640	770	16	89	9
SH Candidates	600	700	11	86	7
DG Candidates	610	680	13	88	8

The dataset in Table 1 has numerical data characteristics with different scales and value ranges across the criteria. C1 has a range of 580–650, C2 has 650–800, C3 has 9–16, C4 has 84–93, and C5 has 6–9. These differences in range and scale show that the data characteristics are heterogeneous, so the dataset is suitable for testing the ability of MCDM methods to normalize, weight, and aggregate criteria with different value distributions. In addition, each criterion shows a different level of variation, with C3 and C5 having relatively narrow ranges, while C1 and C2 have larger value ranges. This is important because differences in variation levels can affect the contribution of each criterion to the weighting results.

The next dataset represents a leasing customer selection problem from [33], in which multiple prospective customers are evaluated based on several financial and non-financial criteria related to credit risk. The dataset consists of 15 customer alternatives, denoted as Customer Candidate 1 to Customer Candidate 15, and seven evaluation criteria, namely Monthly Income (CR-1), Employment Type (CR-2), Credit History

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(CR-3), Installment Ratio (CR-4), Collateral Value (CR-5), Customer Age (CR-6), and Home Ownership Status (CR-7). These criteria represent different aspects of customer financial capability, employment stability, credit history, repayment burden, collateral strength, age-related stability, and residential ownership. The dataset contains heterogeneous numerical values across the criteria and includes both benefit and cost characteristics, making it suitable for evaluating objective weighting and multi-criteria ranking methods. The complete assessment data for all alternatives across the seven criteria are presented in Table 2.

Table 2. Leasing Customer Selection Assessment Data[33]

Alternatives	CR-1	CR-2	CR-3	CR-4	CR-5	CR-6	CR-7
Customer Candidate 1	6500000	4	4	32	120000000	32	3
Customer Candidate 2	5800000	3	3	35	100000000	29	2
Customer Candidate 3	7200000	6	5	28	150000000	41	3
Customer Candidate 4	4900000	2	3	40	90000000	27	1
Customer Candidate 5	8000000	7	5	25	180000000	45	3
Customer Candidate 6	6000000	5	4	30	130000000	38	2
Customer Candidate 7	5200000	3	2	42	85000000	26	1
Customer Candidate 8	7500000	6	5	27	160000000	40	3
Customer Candidate 9	6800000	4	4	33	140000000	35	2
Customer Candidate 10	4500000	2	2	45	80000000	25	1
Customer Candidate 11	8300000	8	5	22	200000000	48	3
Customer Candidate 12	5600000	4	3	36	110000000	31	2
Customer Candidate 13	6900000	5	4	31	145000000	37	3
Customer Candidate 14	7800000	7	5	26	170000000	43	3
Customer Candidate 15	5000000	3	3	38	95000000	28	2

The data characteristics of the dataset presented in Table 2 show a numerical structure consisting of 15 alternatives and 7 criteria, with different value ranges and measurement characteristics across criteria. The criteria include Monthly Income (CR-1), Employment Type (CR-2), Credit History (CR-3), Installment Ratio (CR-4), Collateral Value (CR-5), Customer Age (CR-6), and Home Ownership Status (CR-7). The differences in measurement scales, value ranges, and variation levels indicate heterogeneity among the criteria, making the dataset suitable for evaluating weighting and ranking methods that require normalization. In terms of preference direction, CR-1, CR-2, CR-3, CR-5, CR-6, and CR-7 are classified as benefit criteria, where higher values indicate more favorable customer characteristics, while CR-4 (Installment Ratio) is treated as a cost criterion because a lower installment ratio represents a more favorable condition. These characteristics provide sufficient variation among alternatives and enable the dataset to be used for evaluating the ability of MCDM methods to handle differences in scale, data variation, and criterion characteristics in customer selection problems.

4.2. Comparative Weighting Methods

To evaluate the effectiveness of the proposed A-Entropy weighting method, a comparative analysis was conducted against several established

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objective weighting methods. The selected methods represent different principles for determining criterion importance, including information-based, correlation-based, and criterion-removal-based approaches. The comparison focuses on the resulting weight distributions, the degree of criterion weight imbalance, and the consistency of the weights generated across different criteria. This analysis is intended to determine whether A-Entropy can provide a more balanced weighting structure while preserving the discriminative information contained in the original decision data. The selected weighting methods therefore serve as benchmarks for assessing the methodological characteristics and practical effectiveness of the proposed approach.

The weight comparison is done to evaluate how Entropy, and A-Entropy distribute the level of importance for each criterion based on the characteristics of the data used. Each method has a different mechanism for capturing information in the dataset, so they can produce different weights even when applied to the same decision matrix. Entropy sets weights based on the level of information diversity. Meanwhile, A-Entropy is used as an adaptive approach to produce a more balanced weight distribution while still preserving the information contained in data variations. A comparison of weighting results in the lecturer selection case is presented in Table 3.

Table 3. Comparison of Weights in Lecturer Selection

Method	C1	C2	C3	C4	C5
Entropy	0.4368	0.2834	0.0042	0.0603	0.0051
A-Entropy	0.3333	0.2387	0.0665	0.1011	0.0670

The comparison of weights in the vendor selection case is presented in Table 3.

Table 4. Comparison of Weights in Leasing Customer Selection

Method	CR-1	CR-2	CR-3	CR-4	CR-5	CR-6	CR-7
Entropy	0.0614	0.2849	0.1435	0.0693	0.1363	0.0743	0.2303
A-Entropy	0.0749	0.2614	0.1434	0.0814	0.1374	0.0856	0.2159

Overall, the comparison in the leasing customer selection case shows that A-Entropy provides a more balanced distribution of criterion weights than the conventional Entropy method. Entropy assigns the highest weights to CR-2 (0.2849) and CR-7 (0.2303), while relatively lower weights are assigned to CR-1 (0.0614), CR-4 (0.0693), and CR-6 (0.0743). In contrast, A-Entropy slightly reduces the dominance of CR-2 and CR-7 to 0.2614 and 0.2159, respectively, while increasing the weights of CR-1, CR-4, CR-5, and CR-6 to 0.0749, 0.0814, 0.1374, and 0.0856, respectively. Meanwhile, CR-3 remains almost unchanged, with weights of 0.1435 and 0.1434 under Entropy and A-Entropy, respectively. These results indicate that A-Entropy redistributes the criterion importance by reducing the concentration on highly weighted criteria and increasing the contribution of relatively lower-weighted criteria, thereby providing a more balanced representation of criterion importance for the leasing customer selection problem.

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4.3. Comparative Ranking Alternative

The Comparative Ranking of Alternatives is conducted to evaluate the differences in ranking outcomes produced by each weighting method when applied to the same decision matrix. This analysis compares the rankings generated using Entropy and A-Entropy to identify how changes in criterion weights affect the relative positions of the alternatives. By examining the resulting rankings, the analysis can determine whether the proposed A-Entropy weighting produces consistent ranking patterns while reducing the influence of excessively dominant criteria. The comparison is performed for both the lecturer selection and vendor selection cases, providing an empirical basis for assessing the impact of the weighting approach on the final decision-making results.

A comparative ranking of alternatives was carried out using the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method to examine the impact of different weighting approaches on the final ranking of alternatives. In this analysis, MOORA was applied using weights generated by the Entropy and A-Entropy methods, while keeping the same decision matrix and evaluation criteria to ensure a consistent comparison. The rankings obtained were then compared to identify changes in the relative positions of the alternatives and to assess whether the more balanced weight distribution from the A-Entropy method affected the final decision outcomes. The results of the comparative ranking for the lecturer selection case are presented in Figure 2.

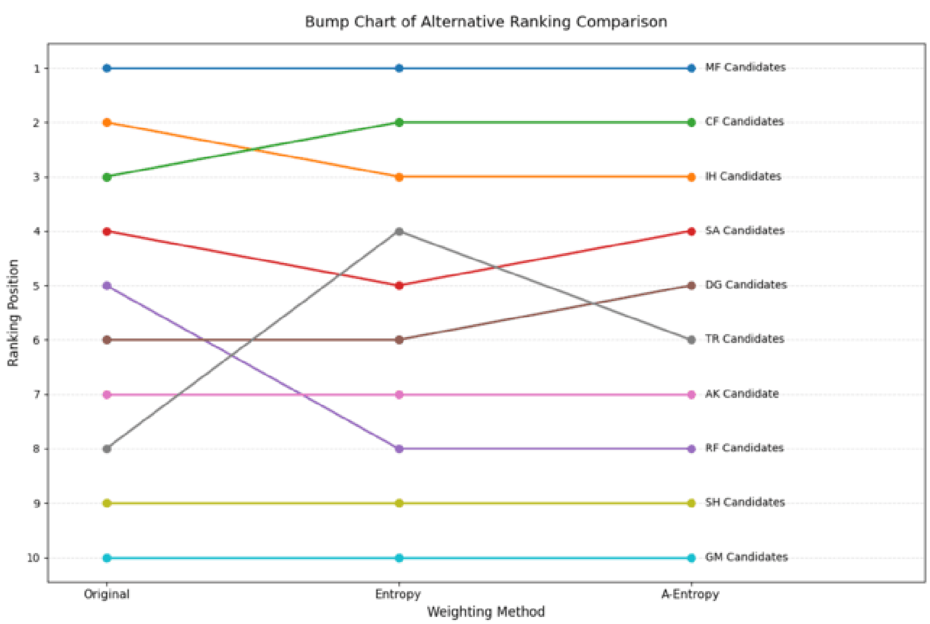

Figure 2. Comparison Results of Rankings in the Lecturer Selection

The chart in Figure 3 shows the changes in the ranking of alternatives based on the Original, Entropy, and A-Entropy weighting approaches. Candidate MF kept the first position across all three approaches, which shows absolute rank stability, while Candidates SH and

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GM also remained at ranks 9 and 10. Some alternatives experienced moderate changes, particularly Candidate IH (2 → 3 → 3), Candidate CF (3 → 2 → 2), and Candidate SA (4 → 5 → 4), where the *A-Entropy* method restored Candidate SA's original position. The most noticeable changes happened with Candidate RF (5 → 8 → 8) and Candidate TR (8 → 4 → 6), indicating higher sensitivity to these weighting methods. Meanwhile, Candidate DG rank improved from 6 to 5 with the A-Entropy method, while Candidate AK remained stable at rank 7. Overall, the A-Entropy method produces ranking patterns that generally stay close to the initial rankings for most alternatives, while also reducing or stabilizing some ranking shifts that appear due to conventional Entropy weighting.

The Comparative Ranking of Alternatives for the leasing customer selection case is performed using the Proximity Indexed Value (PIV) method to examine how different weighting approaches influence the final ranking of customer alternatives. In this analysis, PIV is applied using the weights generated by the Entropy and A-Entropy methods while maintaining the same decision matrix and evaluation criteria to ensure a consistent comparison. The analysis focuses on changes in the relative positions of customer alternatives and evaluates the extent to which the more balanced weight distribution produced by A-Entropy affects the resulting preference order. The comparative ranking results for the leasing customer selection case using PIV are presented in Figure 3.

Figure 3. Comparison Results of Rankings in the Customer Selection

The comparison results show that Customer Candidates 11 to 8 have completely stable rankings at positions 1–4 across all three approaches, while Customer Candidates 3 to 1 also maintain their positions at ranks 5–7. Ranking changes start to appear with Customer Candidate 9 (8 → 9 → 9) and Customer Candidate 6 (9 → 8 → 8), indicating a position swap due to the application of Entropy. Interestingly, A-Entropy keeps the results the same as Entropy for these two alternatives. At the lower end,

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Customer Candidate 4 moves from rank 13 to 14 with Entropy, but goes back to rank 13 using A-Entropy, while Customer Candidate 7 shifts from rank 14 to 13 with Entropy and back to rank 14 with A-Entropy. Other alternatives, namely Customer Candidate 12, 2, 15, and 10, maintain the same position across all methods. Overall, A-Entropy produces a ranking very close to the ORI ranking and is able to restore the initial positions for Customer Candidate 4 and Customer Candidate 7, while most of the alternatives still show ranking stability.

V. Result and Discussion

The Results and Discussion section evaluates the proposed A-Entropy method from both the weighting and decision-ranking perspectives. The analysis first examines the initial weight distribution generated by conventional Entropy Weighting to identify the extent of criterion weight imbalance, followed by an evaluation of the adaptive balancing mechanism in regulating these disparities. The resulting weights are then compared with those obtained from alternative weighting approaches to assess the characteristics of the proposed method. Subsequently, the influence of different weighting schemes on alternative rankings is analyzed, including changes in ranking positions and their consistency with the original ranking. Finally, ranking robustness is assessed to determine the stability of the decision results under different weighting conditions, while the overall findings are discussed in relation to the effectiveness of A-Entropy for producing a more balanced and reliable weighting structure.

5.1. Initial Entropy Weight Distribution

The initial Entropy Weighting results for the lecturer selection problem show a highly uneven distribution of criterion weights, indicating that the information content of the criteria differs substantially across the evaluated alternatives. As presented in Table 1, C1 receives the highest weight of 0.4368, followed by C2 with 0.2834, while the remaining criteria obtain considerably smaller weights, namely C4 with 0.0603, C5 with 0.0051, and C3 with only 0.0042. The weight assigned to C1 is particularly dominant, accounting for nearly half of the total criterion importance, whereas C3 and C5 contribute only marginally to the overall decision structure. The difference between the largest and smallest weights is substantial, with C1 being more than one hundred times larger than C3. This distribution indicates that the conventional Entropy method strongly emphasizes the criterion with the greatest discriminatory information while substantially reducing the contribution of criteria whose performance values are relatively homogeneous across alternatives. Although such a distribution is mathematically consistent with the information-based principle of Entropy Weighting, the resulting concentration of importance may cause the subsequent decision-making process to be strongly influenced by C1 and, to a lesser extent, C2. Consequently, the initial weighting

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structure provides a clear example of criterion weight imbalance that motivates the application of the proposed adaptive balancing mechanism.

A similar but less extreme pattern can be observed in the leasing customer selection problem. The Entropy weights presented in Table 1 demonstrate that CR-2 obtains the highest weight of 0.2849, followed by CR-7 with 0.2303, while CR-3 and CR-5 receive weights of 0.1435 and 0.1363, respectively. The remaining criteria have relatively lower contributions, including CR-1 at 0.0614, CR-4 at 0.0693, and CR-6 at 0.0743. Compared with the lecturer selection case, the weight distribution in the leasing customer selection dataset is more dispersed across several criteria, as no single criterion approaches the dominance observed for C1. Nevertheless, CR-2 and CR-7 together account for more than half of the total weighting structure, demonstrating that the Entropy method still places substantially greater emphasis on a limited number of criteria. In particular, the weight of CR-2 is more than four times that of CR-1, while CR-7 is approximately three times larger than CR-1. This indicates that the degree of imbalance is dataset-dependent and is determined by the information distribution contained in each criterion. Therefore, the results demonstrate that Entropy Weighting can produce different levels of weight concentration depending on the characteristics of the decision matrix, reinforcing the need for a balancing mechanism that can adapt to the specific degree of imbalance rather than applying a fixed correction to every dataset.

Overall, the two datasets demonstrate an important characteristic of the conventional Entropy Weighting approach: the resulting weights are strongly dependent on the relative information and variation contained in the criteria. The lecturer selection dataset exhibits a particularly severe imbalance, where C1 and C2 dominate the weighting structure and C3 and C5 receive almost negligible contributions. In contrast, the leasing customer selection dataset presents a more distributed structure, although CR-2 and CR-7 remain considerably more influential than the other criteria. These differences are important because they show that criterion weight imbalance cannot be characterized using a single fixed level across different decision problems. A weighting distribution that may appear moderately concentrated in one dataset can become highly concentrated in another, potentially producing different effects on the aggregation and ranking of alternatives. The initial Entropy results therefore serve as the baseline for evaluating the proposed A-Entropy mechanism, particularly in terms of whether adaptive adjustment can reduce excessive weight concentration while preserving the relative information captured by the original entropy-based weights. This comparison provides the basis for the subsequent analysis of the Performance of the Adaptive Balancing Mechanism, where the extent to which the proposed approach modifies these initial distributions is examined.

5.2. Performance of the Adaptive Balancing Mechanism

The A-Entropy results demonstrate a clear balancing effect on the initial Entropy weight distributions. For the lecturer selection

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problem, the weight of C1 decreases from 0.4368 to 0.3333, while C2 decreases from 0.2834 to 0.2387. In contrast, the criteria with very low initial weights experience substantial increases, with C3 rising from 0.0042 to 0.0665, C4 from 0.0603 to 0.1011, and C5 from 0.0051 to 0.0670. These changes indicate that A-Entropy successfully reduces the dominance of C1 and C2 while increasing the contribution of criteria that were previously assigned very small weights. Importantly, C1 remains the criterion with the highest weight, indicating that the information captured by the original Entropy method is not eliminated. Instead, its dominance is moderated, resulting in a more proportionate distribution of criterion importance. Thus, the adaptive mechanism effectively reduces the substantial disparity observed in the initial Entropy weights while preserving the relative importance of the criteria.

For the leasing customer selection problem, the weight adjustment also demonstrates a balancing pattern, although the magnitude of the adjustment is more moderate. CR-2, which initially has the highest weight of 0.2849, decreases to 0.2614, while CR-7 decreases from 0.2303 to 0.2159. Meanwhile, several criteria with relatively low initial weights increase, including CR-1 from 0.0614 to 0.0749, CR-4 from 0.0693 to 0.0814, and CR-6 from 0.0743 to 0.0856. CR-5 shows a small increase from 0.1363 to 0.1374, whereas CR-3 remains almost unchanged, decreasing slightly from 0.1435 to 0.1434. This pattern demonstrates that the adaptive balancing mechanism does not apply an identical adjustment to all criteria. Instead, dominant criteria are moderately reduced, while criteria with relatively lower contributions are increased, and criteria with intermediate weights are largely preserved. This behavior indicates that A-Entropy can adapt the magnitude of weight adjustment according to the characteristics of the initial weight distribution.

Overall, the comparison between Entropy and A-Entropy demonstrates that the balancing mechanism produces a stronger adjustment for datasets with greater initial weight imbalance. In the lecturer selection problem, the weight range changes from 0.4368–0.0042 under Entropy to 0.3333–0.0665 under A-Entropy, representing a substantial reduction in the disparity between the highest and lowest weights. In the leasing customer selection problem, the range changes from 0.2849–0.0614 to 0.2614–0.0749, indicating a more moderate adjustment. These results support the adaptive characteristic of A-Entropy, as the method does not simply force all criterion weights toward an equal distribution but instead regulates the degree of correction according to the observed imbalance. By reducing excessive dominance while increasing the contribution of underweighted criteria, A-Entropy produces a more balanced weighting structure while maintaining meaningful differences among criteria. This provides the basis for the subsequent Comparative Analysis of Weighting Methods to further examine how the proposed method differs from conventional weighting approaches.

5.3. Comparative Analysis of Weighting Methods

The comparison between Entropy and A-Entropy in the lecturer selection problem demonstrates that the proposed method produces a

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substantially more balanced criterion-weight distribution while retaining the relative importance identified by the conventional approach. Under Entropy Weighting, C1 has the highest weight at 0.4368, followed by C2 at 0.2834, whereas C3 and C5 receive extremely small weights of 0.0042 and 0.0051, respectively. After applying A-Entropy, the weight of C1 decreases to 0.3333 and C2 decreases to 0.2387, while C3 increases considerably to 0.0665 and C5 to 0.0670. C4 also increases from 0.0603 to 0.1011. This change indicates that A-Entropy reduces the excessive concentration of importance on C1 and C2 and provides greater representation to the remaining criteria. Importantly, the ranking of the criteria by weight is not completely reversed: C1 and C2 remain the two most influential criteria, demonstrating that the proposed method does not simply equalize the weights. Instead, A-Entropy modifies the magnitude of the differences while preserving the general information structure generated by Entropy. The comparison therefore indicates that the proposed method is particularly effective when the conventional Entropy method generates highly concentrated weights.

A different pattern is observed in the leasing customer selection problem, where the initial Entropy weights are already more evenly distributed than those of the lecturer selection dataset. CR-2 obtains the largest Entropy weight at 0.2849, followed by CR-7 at 0.2303, while CR-3 and CR-5 receive 0.1435 and 0.1363, respectively. The A-Entropy results reduce the weights of the two dominant criteria, with CR-2 decreasing to 0.2614 and CR-7 to 0.2159. At the same time, the lower-weighted criteria generally receive moderate increases, including CR-1 from 0.0614 to 0.0749, CR-4 from 0.0693 to 0.0814, and CR-6 from 0.0743 to 0.0856. CR-5 changes only slightly from 0.1363 to 0.1374, while CR-3 remains almost identical at 0.1434. This relatively small adjustment is consistent with the less severe imbalance in the initial distribution. Rather than introducing a strong redistribution, A-Entropy applies a more controlled correction, reducing the dominance of CR-2 and CR-7 while maintaining the weights of criteria that already occupy intermediate positions. The results therefore demonstrate that the proposed method can produce different adjustment magnitudes according to the initial structure of the weighting distribution.

From a comparative perspective, the two datasets provide evidence that A-Entropy behaves differently from conventional Entropy according to the severity of weight imbalance. The lecturer selection dataset experiences a stronger redistribution because its initial weights contain an extreme disparity, whereas the leasing customer selection dataset undergoes a more moderate adjustment because its initial distribution is comparatively less concentrated. This distinction is an important characteristic of the proposed method because an effective balancing mechanism should not apply an identical correction regardless of the underlying data characteristics. The comparison also shows that A-Entropy does not eliminate the discriminatory information captured by Entropy; instead, it reduces excessive dominance and strengthens the representation of criteria with very low contributions. In the lecturer selection case, the gap between the highest and lowest weights is

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substantially reduced, while in the leasing customer selection case the changes remain relatively limited. Therefore, the comparative results suggest that A-Entropy provides a more controlled weighting structure by combining the data-driven characteristics of Entropy with an adaptive balancing mechanism. These differences in weight distribution are subsequently important for understanding the Impact on Alternative Ranking, since changes in criterion importance can directly influence the aggregation results and the final positions of the alternatives.

5.4. Impact on Alternative Ranking

The impact of the weighting methods on alternative ranking can be evaluated by comparing the original ranking with the rankings generated using Entropy and A-Entropy for both decision problems. In the lecturer selection dataset, several alternatives maintain their original positions across the three approaches, particularly MF Candidates at rank 1, AK Candidate at rank 7, SH Candidates at rank 9, and GM Candidates at rank 10, indicating strong ranking stability for these alternatives. However, noticeable changes occur for several middle-ranked candidates. IH Candidates move from rank 2 to 3 under Entropy and remain at rank 3 with A-Entropy, while CF Candidates improve from rank 3 to 2 under both weighting approaches. SA Candidates move from rank 4 to 5 with Entropy but return to rank 4 under A-Entropy, indicating that the adaptive balancing mechanism restores its original position. RF Candidates experience a larger change from rank 5 to 8 under both methods, whereas DG Candidates remain at rank 6 with Entropy and improve to rank 5 with A-Entropy. The most substantial variation is observed for TR Candidates, which move from rank 8 to rank 4 under Entropy and then to rank 6 under A-Entropy. These results indicate that changes in criterion weights can affect the relative position of alternatives, particularly those whose performance is strongly influenced by criteria experiencing substantial weight adjustments.

For the leasing customer selection dataset, the ranking results demonstrate considerably greater stability across the three approaches. Customer Candidate 11, 5, 14, 8, 3, 13, and 1 maintain exactly the same positions under Original, Entropy, and A-Entropy, occupying ranks 1 through 7. The only changes occur among a small number of lower-ranked alternatives. Customer Candidate 9 moves from rank 8 to rank 9 under Entropy and remains at rank 9 with A-Entropy, while Customer Candidate 6 moves from rank 9 to rank 8 and retains this position under A-Entropy. At ranks 13 and 14, Customer Candidate 4 changes from rank 13 to 14 under Entropy but returns to rank 13 with A-Entropy, whereas Customer Candidate 7 changes from rank 14 to 13 under Entropy and returns to rank 14 under A-Entropy. The remaining alternatives, including Customer Candidate 12, 2, 15, and 10, maintain their original positions throughout the comparison. This relatively stable ranking pattern is consistent with the more moderate changes in criterion weights observed in the leasing customer selection problem, suggesting that the smaller adjustments introduced by A-Entropy have limited effects on the final ordering of alternatives.

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Overall, the ranking comparison indicates that the effect of A-Entropy on alternative positions is dataset-dependent and closely related to the magnitude of weight redistribution. The lecturer selection problem exhibits greater ranking changes, particularly for alternatives such as RF Candidates and TR Candidates, because the initial Entropy weights contain a pronounced imbalance that is substantially modified by A-Entropy. In contrast, the leasing customer selection problem shows considerably higher ranking stability, with most alternatives retaining their original positions despite the adjustment of criterion weights. Importantly, A-Entropy does not uniformly force the ranking to match the original ranking; rather, its influence depends on how the modified criterion weights interact with the performance values of each alternative. Nevertheless, A-Entropy restores the original positions of SA Candidates in the lecturer selection problem and Customer Candidate 4 and Customer Candidate 7 in the leasing customer selection problem, demonstrating that balancing the criterion weights can alter ranking outcomes in a direction closer to the original decision structure. These findings provide an initial indication of the ranking behavior of A-Entropy and motivate the subsequent Ranking Robustness Analysis to quantitatively assess the consistency and stability of the resulting rankings.

5.5. Ranking Robustness Analysis

Ranking robustness analysis is conducted to quantitatively evaluate the stability of the alternative rankings produced by Entropy and A-Entropy in comparison with the original ranking. While the previous analysis identifies individual changes in alternative positions, robustness analysis provides an overall measure of ranking consistency by examining the degree of agreement among the ranking structures. This analysis is particularly important for determining whether the adaptive balancing mechanism produces ranking results that remain stable despite changes in criterion weights. A higher level of ranking correlation indicates that the ordering of alternatives is largely preserved, whereas a lower correlation reflects greater sensitivity to the weighting scheme[34], [35]. Therefore, the robustness analysis provides additional evidence for assessing whether A-Entropy can reduce the potential instability caused by imbalanced criterion weights and maintain a consistent decision structure across different datasets.

The Ranking Robustness Analysis for the lecturer selection case evaluates the consistency between the original ranking and the rankings generated using Entropy and A-Entropy through the Spearman rank correlation coefficient. This analysis is used to determine the extent to which the ordering of alternatives is preserved after applying different weighting approaches. A higher Spearman correlation indicates stronger agreement with the original ranking, while a lower value indicates greater changes in the relative positions of alternatives. The comparison focuses on the correlation patterns between the original ranking and each weighting method to assess whether the adaptive balancing mechanism can maintain ranking consistency while modifying the

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criterion weight distribution. The resulting comparison of Spearman correlation values is presented in Figure 4.

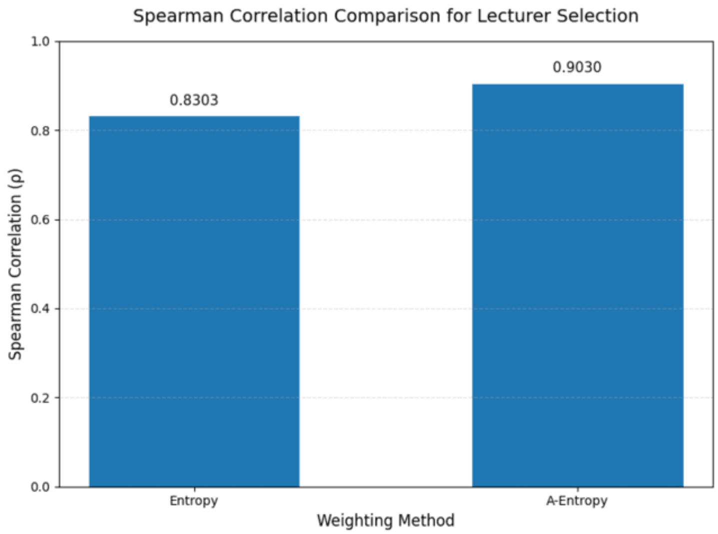

Figure 4. Comparison Correlation Values in the Lecturer Selection

Figure 4 presents the comparison of Spearman rank correlation values between the original lecturer selection ranking and the rankings generated using Entropy and A-Entropy. The Entropy method produces a Spearman correlation coefficient of 0.8303, while A-Entropy achieves a higher correlation of 0.9030. These values indicate the degree of agreement between each resulting ranking and the original ranking, with the higher correlation obtained by A-Entropy showing a closer correspondence to the original alternative ordering. Overall, the comparison demonstrates the relative ranking consistency of the two weighting approaches in the lecturer selection case.

The Ranking Robustness Analysis for the customer selection case evaluates the consistency between the original ranking and the rankings generated using Entropy and A-Entropy through the Spearman rank correlation coefficient. This analysis is used to determine the extent to which the ordering of alternatives is preserved after applying different weighting approaches. A higher Spearman correlation indicates stronger agreement with the original ranking, while a lower value indicates greater changes in the relative positions of alternatives. The comparison focuses on the correlation patterns between the original ranking and each weighting method to assess whether the adaptive balancing mechanism can maintain ranking consistency while modifying the criterion weight distribution. The resulting comparison of Spearman correlation values for the customer selection case is presented in Figure 5.

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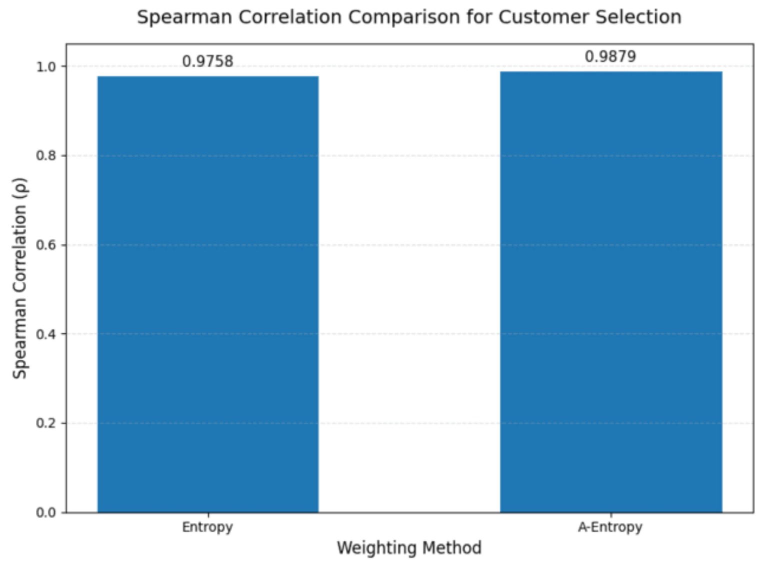

Figure 5. Comparison Correlation Values in the Customer Selection

Figure 5 presents the comparison of Spearman rank correlation values between the original customer selection ranking and the rankings generated using Entropy and A-Entropy. The Entropy method obtains a Spearman correlation coefficient of 0.9758, while A-Entropy achieves a higher correlation of 0.9879. These results indicate that both weighting methods produce rankings that are highly consistent with the original ranking, with A-Entropy showing a slightly stronger correspondence. The higher correlation obtained by A-Entropy indicates that the adaptive balancing mechanism maintains the overall ranking structure while adjusting the criterion weight distribution.

Overall, the ranking robustness analysis demonstrates that both Entropy and A-Entropy maintain a high level of consistency with the original rankings across the lecturer and customer selection cases. However, A-Entropy achieves higher Spearman correlation values than Entropy in both cases, indicating that the adaptive balancing mechanism can adjust the criterion weights while preserving the relative ordering of alternatives. These findings support the ability of A-Entropy to provide a more balanced weighting structure without substantially altering the established ranking pattern, thereby enhancing the stability and robustness of the resulting decision outcomes.

5.6. Discussion

The experimental results demonstrate that the effectiveness of an objective weighting method is not determined only by its ability to extract information from the decision matrix, but also by how the resulting weight distribution influences the overall decision structure. The conventional Entropy method assigns criterion importance according to the degree of information diversity contained in each criterion, which can lead to substantial differences in weight magnitude when the variability among criteria is heterogeneous. This characteristic is

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clearly reflected in the lecturer selection case, where the weighting structure becomes highly concentrated on C1 and C2, while C3 and C5 receive very limited contributions. Although such a distribution is consistent with the underlying information-based principle of Entropy, an extremely concentrated weighting structure may cause the final decision to depend disproportionately on a small number of criteria. The proposed A-Entropy method addresses this issue by introducing an adaptive balancing mechanism that regulates the distance between the entropy-derived weights and a more balanced distribution. The adjustment is not designed to eliminate the information differences among criteria, but rather to prevent criteria with relatively low information variation from becoming almost irrelevant to the decision process. This distinction is important because the objective of the proposed method is not to replace data-driven weighting with equal weighting, but to establish a controlled compromise between information discrimination and weight balance. Consequently, the resulting weighting structure remains data-dependent while reducing excessive concentration, which provides a more flexible basis for subsequent MCDM aggregation.

The comparison between the two case studies further indicates that the behavior of A-Entropy is strongly influenced by the characteristics of the underlying decision matrix. The lecturer selection dataset contains a much more pronounced disparity in the initial entropy weights, resulting in a stronger redistribution after the adaptive mechanism is applied. In contrast, the leasing customer selection dataset already exhibits a comparatively more distributed weighting structure, and therefore the adjustment introduced by A-Entropy is more moderate. This difference supports the adaptive nature of the proposed approach because the magnitude of adjustment changes according to the observed level of weight imbalance rather than being imposed uniformly across all datasets. Such behavior is particularly relevant in practical MCDM applications, where different decision problems can exhibit substantially different distributions of criterion information. A fixed balancing strategy could potentially over-correct datasets with moderate imbalance or fail to adequately address datasets with severe concentration. A-Entropy instead provides a mechanism through which dominant criteria can be moderated while criteria with very small contributions receive additional representation. At the same time, criteria occupying intermediate positions are largely preserved, indicating that the method does not arbitrarily redistribute importance. This characteristic suggests that A-Entropy can function as a preprocessing weighting mechanism that improves the structural balance of criterion importance before the weights are incorporated into the ranking stage.

The ranking results provide further insight into the practical consequences of the proposed weighting mechanism. The changes observed in the lecturer selection case show that alternatives can respond differently to weight redistribution depending on their performance profiles across the criteria. Alternatives whose strengths or weaknesses are closely associated with criteria receiving substantial weight adjustments are more likely to experience changes in their relative

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positions. Therefore, ranking variation should not necessarily be interpreted as an undesirable consequence of A-Entropy, because changes in criterion importance are expected to modify the aggregation of alternative performance. More importantly, the results show that A-Entropy does not systematically disrupt the ranking structure. Several alternatives retain their positions, while some alternatives that changed under conventional Entropy return closer to their original positions after adaptive balancing. A similar pattern is observed in the customer selection case, but with substantially greater ranking stability because the initial weighting structure is less concentrated and the corresponding adjustments are smaller. The fact that most customer alternatives preserve their positions suggests that moderate balancing can modify criterion importance without producing substantial changes in the final decision order. These findings indicate that the relationship between weighting balance and ranking stability is not linear or uniform; it depends on the interaction between the magnitude of weight changes and the performance differences among alternatives. Thus, A-Entropy should be viewed not as a method that guarantees identical rankings, but as an approach intended to reduce the potential influence of excessive criterion dominance while maintaining the underlying decision structure.

The Spearman correlation analysis provides additional evidence regarding the robustness of the ranking outcomes and strengthens the interpretation of the preceding analyses. In the lecturer selection case, the correlation increases from 0.8303 under Entropy to 0.9030 under A-Entropy, while in the customer selection case it increases from 0.9758 to 0.9879. The higher correlations obtained by A-Entropy indicate that the adaptive balancing mechanism can modify the criterion-weight distribution without causing substantial divergence from the original ranking structure. The improvement is particularly meaningful in the lecturer selection case, where the initial entropy weights exhibit a much stronger imbalance and the adaptive adjustment is consequently more pronounced. In the customer selection case, the improvement is smaller because both weighting structures already generate highly consistent rankings. These observations suggest that the contribution of A-Entropy is most evident when the conventional weighting process produces excessive concentration of criterion importance. From a methodological perspective, the results indicate that balancing the weight distribution can improve ranking consistency while retaining the discriminative characteristics of objective weighting. However, the findings should be interpreted within the scope of the two case studies and the corresponding ranking methods, rather than as evidence of universal superiority across all MCDM problems. Overall, the experimental evidence supports A-Entropy as a controlled adaptive weighting approach that combines the information sensitivity of Entropy Weighting with a mechanism for reducing excessive weight imbalance, thereby providing a more balanced weighting structure and maintaining strong ranking robustness across different decision environments.

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VI. Conclusion

This study proposed the Adaptive Entropy (A-Entropy) weighting method as an extension of conventional Entropy Weighting to address excessive imbalance in objective criterion weights. The proposed approach introduces an adaptive balancing mechanism based on the deviation of entropy-derived weights from an equal-weight distribution, allowing the degree of adjustment to respond to the initial imbalance of the weighting structure. The experimental results from lecturer selection and leasing customer selection demonstrate that A-Entropy effectively reduces the dominance of highly weighted criteria while increasing the contribution of criteria with relatively small weights. In the lecturer selection case, the substantial initial imbalance was reduced more strongly, whereas the customer selection case exhibited a more moderate adjustment because its initial weight distribution was comparatively balanced. The resulting alternative rankings also remained highly consistent with the original rankings, with A-Entropy achieving higher Spearman correlation values than conventional Entropy in both cases. These findings indicate that A-Entropy can provide a more balanced objective weighting structure while preserving the general ordering of alternatives. Overall, the proposed method offers an adaptive weighting mechanism that combines the information sensitivity of Entropy Weighting with controlled weight balancing, making it a potential alternative for MCDM-based Decision Support Systems where criterion dominance and ranking stability are important considerations.

6.1. Implication

The findings of this study indicate that A-Entropy provides a practical approach for improving the balance of objective criterion weights while retaining the information-driven characteristics of conventional Entropy Weighting. The adaptive mechanism reduces excessive concentration on highly dominant criteria and increases the contribution of criteria with relatively low entropy-based weights. The results demonstrate that the degree of adjustment depends on the initial level of weight imbalance, allowing stronger correction for highly concentrated weighting structures and more moderate adjustment when the weights are already relatively distributed. Furthermore, the higher Spearman correlation values obtained by A-Entropy indicate that the balancing process can be performed without substantially changing the overall alternative ranking structure. From a decision-support perspective, A-Entropy can therefore serve as a complementary objective weighting approach for MCDM applications in which excessive criterion dominance may affect the balance of the subsequent ranking process.

6.2. Limitation

Despite these findings, this study has two main limitations. First, the proposed A-Entropy method has not yet been extensively evaluated using large-scale datasets with a substantially greater number

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of alternatives and criteria. Consequently, its computational efficiency, processing time, memory requirements, and scalability under increasing data dimensions remain to be systematically examined. Second, the comparative evaluation is mainly conducted against conventional Entropy Weighting, while other objective weighting methods are not included as comparative benchmarks. Therefore, the relative performance of A-Entropy in terms of weight distribution, computational efficiency, and ranking consistency compared with alternative weighting approaches remains insufficiently explored. These limitations indicate the need for further experiments using large-scale datasets and comprehensive comparisons with various objective weighting methods to provide a more complete assessment of the scalability and effectiveness of A-Entropy.

6.3. Future Research Directions

Future research can extend the evaluation of A-Entropy using a broader range of datasets, application domains, numbers of alternatives, and criterion structures to examine its performance under diverse decision-making conditions. Comparative studies can also incorporate other objective weighting methods, such as CRITIC, MEREC, LOPCOW, CILOS, and standard deviation-based weighting, to provide a more comprehensive evaluation of the adaptive balancing mechanism. In addition, future studies may integrate A-Entropy with various MCDM ranking methods and employ additional robustness measures, including Kendall's tau, rank reversal analysis, sensitivity analysis, and perturbation-based testing. The proposed mechanism could also be extended to uncertain, fuzzy, interval, or dynamic decision matrices. These directions would provide further insight into the flexibility, stability, and applicability of A-Entropy for more complex Decision Support System environments.

CRediT Authorship Contribution Statement

Hetty Rohayani: Conceptualization, Validation, Writing – Original Draft Preparation, Writing – Review & Editing. **Kevin Kurniawansyah:** Data curation, Formal analysis, Writing – Original Draft Preparation. **Rahmi Handayani:** Investigation, Writing – Original Draft Preparation. **Mohamad Nizam Yusof:** Methodology, Validation, Writing – Original Draft Preparation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

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