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Research article

Alternative prioritization for mitigating competition-related issues in Tanzania sugar industry using an integrated multi-criteria decision-making approach

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ABSTRACT

Professionals and policymakers often encounter challenges in selecting and ranking effective solutions to address competition-related issues in various industries including sugar industry. Despite extensive research in this area, the Tanzanian context, significantly impacted by these challenges, has not received sufficient attention. Thus, this study aims to fill this gap by identifying and prioritizing these issues. It proposes four strategies and establishes five criteria for prioritization. To achieve this, the study introduces an integrated methodology to assess criteria weights and rank strategies based on these weighted criteria. The FullEX technique is applied to assess the criteria weights, while the AROMAN (Alternative Ranking Order Method Accounting for Two-Step Normalization) method is used to rank the alternatives. The study validates this methodology through a sensitivity and comparative analyses, which identifies the *amendment of the law to accommodate the leniency program (S1)* as the most appropriate strategy for mitigating competition-related issues in the sugar industry.

1. Introduction

Sugar stands as an essential commodity within modern societies, with the sugar industry holding a pivotal role in the economic landscape of numerous African nations [1,2]. In Tanzania specifically, the sugar industry reigns as the largest agro-based industry, exerting significant influence on the nation's economy. This vital industry not only bolsters food security but also serves as a cornerstone for the tax base and poverty alleviation efforts through substantial job creation, providing livelihoods for over 30,000 individuals [3]. Despite its critical role, domestic sugar production has consistently fallen short of meeting national demand. To address this gap, various initiatives have been set in motion to enhance industry productivity, notably the national development program known as Big Results Now (BRN). Aligned with the goal of elevating Tanzania to a middle-income economy by 2025, BRN prioritizes investments in key sectors, with agriculture, particularly sugarcane cultivation, taking center stage. Additionally, the Southern Agriculture Growth Corridor of Tanzania (SAGCOT), a formidable public-private partnership initiative, aims to mobilize

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private sector involvement and investments across central to southern regions of Tanzania, advancing the nation's aspirations for a green industrial revolution [4]. These concerted efforts are anticipated to spur investments and foster growth within Tanzania's sugar industry.

The anticipated escalation of sugar production in Tanzania is likely to face sustainability issues, which can be examined from two viewpoints. Firstly, there is a rising concern regarding habitat destruction for plantation expansion, extensive water consumption for irrigation, and environmental pollution stemming from the widespread use of agrochemicals [5]. Secondly, there is a potential susceptibility of this predominantly unchangeable subsector to fluctuations in commodity prices driven by speculation [6].

At the beginning of 2024, Tanzania witnessed a surge in public outcry due to the steep rise in sugar prices. The nation has been grappling with a prolonged sugar shortage, initially attributed to exaggerated rainfall in the preceding year. However, allegations have surfaced regarding industry cartels involved in hoarding and manipulating prices [7]. These accusations pose significant concerns for consumer welfare and demand immediate attention. Responding to the crisis, President Dr. Samia Suluhu Hassan publicly announced the government's strategy to tackle the issue, emphasizing its adverse effects on both consumer well-being and the broader Tanzanian economy.

Numerous studies have been undertaken to evaluate the obstacles encountered by the sugar industry in Tanzania. For instance, Odek et al. [8] organized a workshop to pinpoint issues in the sugar industry and propose suggestions for the way forward. Martin and Sharp [9] studied contract farming in Tanzania, particularly analyzing challenges within the Mtibwa sugarcane outgrower frame. Sulle et al. [10] discussed the challenges in Tanzania's sugar industry, drawing from experiences with SAGCOT and the new alliance. Previous studies on Tanzania's sugar industry haven't evaluated or ranked competition-related issues, nor have they prioritized alternative solutions. A comprehensive managerial perspective is necessary to fill these gaps and effectively prioritize alternatives. Such an approach should include different criteria to enhance the results in the decision-making procedure. Multi-criteria decision-making (MCDM) techniques, renowned for managing intricate issues and various criteria, offer a suitable solution for this endeavor [11–14].

1.1. Objectives

The primary goal of the study is to assess and prioritize competition-related issues within Tanzania's sugar industry from a managerial viewpoint and propose alternative solutions to tackle them. To achieve this objective, a hybrid model that combines the FullEX and AROMAN approaches, along with a two-step normalization process, will be employed. This hybrid model aims to identify alternative solutions by assigning varying weights to different criteria, thus addressing the competition-related issues in the Tanzania sugar industry.

1.2. Motivation of FullEX-AROMAN approach

The FullEX method provides distinct advantages. (i) Unlike other subjective methods such as best worst method (BWM), stepwise weight assessment ratio analysis (SWARA), full consistency method (FUCOM), and analytic hierarchy process (AHP) which involve comparing criteria through pairwise comparisons (PCs), the FullEX method integrates an expert's reputation, considering both their years of experience and educational background. This is essential for decision-making, as experts evaluate and prioritize criteria based on their importance. Decision accuracy increases with greater expert experience, and a higher level of education signifies the theoretical knowledge necessary for precise decision-making. Furthermore, (ii) The AHP method relies on expert input to perform PCs, converting their assessments into numerical values on a one-to-nine scale to establish the significance of each criterion. In contrast, the SWARA method dismisses less important criteria, focusing on ranking only the most crucial ones. The BWM method is particularly effective when objective data is lacking, using PCs between the Best and Worst options to help minimize anchoring bias [15]. FUCOM, on the other hand, involves n-1 pairwise comparisons using integer or decimal scales to evaluate the criteria [16]. The FullEX method adopts a Fuller's triangle approach for PCs, also based on expert judgments, but it differs by factoring in the experts' education level and years of experience [17]. Moreover, the FullEX method features a unique consistency ratio (CR) calculation, which sets it apart from other subjective methods. It also involves a second round of interviews with experts, without revealing the outcomes of the first round, where they assign a percentage value to each criterion on a scale from 0 to 100 %. During this subsequent round, experts allocate a percentage of significance to each criterion on a scale ranging from 0 to 100 %.

Data normalization is the process of converting the input data of a decision-making matrix into a scale ranging from 0 to 1. This transformation allows decision-makers to create a consistent structure for the data, facilitating easier and more relevant calculations in subsequent steps. Normalization is particularly important when comparing alternatives that involve different types of numerical values for criteria [18]. The normalized value indicates each criterion's relative position within its overall range, making the choice of normalization technique crucial, as it can significantly affect the decision-making outcome. Many MCDM methods utilize a single normalization approach, but relying solely on one can result in misleading information due to its overly simplistic and subjective nature [19]. In the AROMAN method, two normalization techniques are applied, and the resulting normalized values are aggregated into an averaged normalized decision-making matrix. The first technique employed is linear normalization, which calculates the normalized value based on the distance from either the worst alternative (max-type criterion) or the best alternative (min-type criterion). The second technique is vector normalization, which is symmetric and computationally efficient [20]; this method is also used in the TOPSIS technique. A study comparing several normalization methods—such as min-max, vector, linear, and logarithmic—found that the rankings of alternatives varied significantly depending on the normalization approach used [20]. Following this finding, the AROMAN approach is introduced by Bošković et al. [21] combining linear and vector normalization through arithmetic means to achieve more precise normalized data, as this combination offers a more accurate representation of empirical data. Additionally, when comparing the final rankings produced by the AROMAN method with those generated by other MCDM techniques like TOPSIS, ARAS, WASPAS, and EDAS, distinct differences emerged among these approaches. Most of these methods depend on a single type of normalization (such as min-max or vector normalization) and primarily vary in how they calculate their final rankings. In contrast, AROMAN offers several advantages: (i) it evaluates alternatives using both quantitative and qualitative measures, (ii) it employs dual normalization methods to boost precision and sensitivity analysis, (iii) it adopts a user-friendly ranking system that simplifies calculations, and (iv) it clearly distinguishes between criteria that are benefits versus those that are costs.

1.3. Study contributions

This paper makes several valuable contributions to the scientific community, Tanzania, and society, including.

- The application of integrated MCDM methodology, enriching the academic literature on the competition-related issues mitigation in sugar industry at a national scale.
- The raise of awareness among practitioners and decision-makers in Tanzania regarding the critical challenges that hinder the competition-related issues mitigation in the sugar industry, along with appropriate strategy.
- The introduction of a user-friendly, step-by-step process for addressing complex MCDM challenges.
- The wide applicability of this integrated approach, which offers opportunities for other researchers to solve complex MCDM problems in various sectors beyond the competition-related issues mitigation in the sugar industry.
- The provision of decision-making technique, assisting both academics and practitioners in making more informed choices concerning the sustainability of Tanzania's sugar sector.

The rest of the paper is organized as follows: Section 2 Literature review, 3 Methodology, 4 Application, 5 Sensitivity analysis, 6 Comparative analysis, 7 Findings and discussion, 8 Managerial implications, 9 Conclusion and future directions.

2. Literature review

Two sub-sections are included in section 2.

2.1. Overview of approaches related to sugar industry studies

Studies investigating the sugar industry have been conducted in numerous countries across the globe. For instance, Mbua and Atta-Aidoo [22] investigated how sugarcane out-growers' response to changes in price and non-price factors affected acreage supply over a 30-year time span using time-series data. Rweyendela and Mwegoha [23] studied industrial symbiosis at Tanzania's largest sugar refinery, identifying underlying factors through interviews, site visits, and document reviews. Kangile et al. [24] assessed trade governance's influence on the sugar trade in Tanzania using cross-sectional survey data from various actors in the supply chain. Mwinuka and Mlay [25] studied Tanzania's sugar export performance and estimated the sugar export supply function over three decades. Kalume and Kongolo [26] studied how Kagera Sugar Limited (KSL) has boosted sugar production in Tanzania through descriptive analysis, finding significant contributions to national output. Murali et al. [27] studied the spatial integration of sugar markets in India and the relationship between Indian white sugar export prices and the global market. Their findings suggested that while only four out of eleven sugar markets are connected, supply plays a crucial role in shaping long-term price behavior in India. Dubb [28] examined how capital accumulation shapes the dynamics of the sugar sector in southern Africa, with a particular focus on analyzing value relationships. Mendieta et al. [29] explored the environmental advantages of deploying inexpensive digesters to repurpose agro-industrial waste in the non-centrifugal cane sugar (NCS) sector. Khalifa et al. [30] analyzed the impact of subsidy reforms on the Tunisian sugar industry using a storage model. They employed econometric simulation to explore how different scenarios of price increases due to subsidy removal affected sugar imports and production. Xie et al. [31] investigated the performance of seven publicly traded sugar firms in China, employing two distinct models. They found that in 2012, the Chinese sugar industry showed generally low performance, with five out of seven companies falling short of optimal efficiency. Mazwi and Chambati [32] studied how land redistribution in Zimbabwe twenty years ago affected wealth accumulation among sugar outgrowers by diversifying sugar production. They found increased participation in sugar production following extensive land reforms, leading to noticeable wealth accumulation through farm mechanization.

2.2. MCDM related studies to the sugar sector

MCDM methods are effective decision-making approaches widely utilized across diverse domains [33–36]. For instance, Iskanderani et al. [37] presented strategies for enhancing truck loading efficiency and overall operations at a leading sugar manufacturing plant in the Middle East. Their aim was to minimize waiting times for trucks at loading stations while also boosting capacity. Asrol and Yani [38] assessed the sustainability of the sugarcane agro-industry supply chain and proposed improvement strategies. Salehib et al. [39] recognized and ranked information technology obstacles within the sugarcane supply chain in Khuzestan province. Manzini Poli et al. [40] utilized an integrated multicriteria approach to evaluate the sustainable utilization of agro-industrial residues (AIR) as solid biofuels. Singh et al. [41] utilized AHP to outline energy-efficient attributes in Indian sugar mills. Mursiti et al. [42] introduced a framework for developing competency maps for human resources engaged in the cane sugar production process. Anojkumar et al. [43] illustrated the use of a MCDM technique to select appropriate pipe materials for minimizing corrosive wear in the sugar industry. Kumar and Kansara [44] pinpointed barriers to IT adoption in India's sugar industry supply chain. Anojkumar et al. [45] utilize different MCDM methods for effective material selection within the sugar industry. Gani and Hantoro [46] assessed electricity sales potential in alternate development plans for three sugarcane industries. Jiménez Borges et al. [47] explored a range of biomass options suitable for the sugar industry, considering factors related to sustainability. Hussain et al. [48] selected the optimal material for induction cookware in the sugar industry, focusing on maximum performance at minimal cost. Beeram et al. [49] offered guidance on selecting a sustainable juice extraction technology through different decision-making methods. Anojkumar and Ilangkumaran [50] identified the ideal material for pipes to reduce corrosion-related wear in sugar production. Darji and Rao [51] presented the use of various intelligent MCDM techniques for material selection of pipes in the sugar industry. Khorramrouz and Galankashi [52] developed a fuzzy-based model to prioritize faults in the sugar industry. Rajkumar and Malliga [53] ranked the buyers for selling a sugar plant's by-products. Ummi et al. [54] created a risk priority framework and mitigation strategies for reverse supply chain risk management in the palm sugar industry. Kittiyankajon and Chetchotsak [55] presented an aggregation algorithm for group decision-making to prioritize strategies in the sugar industry. Arslan and Çunkaş [56] conducted a performance evaluation of sugar plants utilizing the TOPSIS method in an uncertain environment. Deepa et al. [57] introduced a framework for ranking sugarcane farms based on sustainability. The MCDM related studies to the sugar industry is indicated in Table 1.

2.3. Research gaps

The research identifies the following gaps: a) The Tanzania sugar industry's challenges in prioritizing alternatives to mitigate competition-related issues lack exploration and resolution from the perspective of MCDM. This groundbreaking study aims to uncover these challenges and recommend efficient strategies through a systematic ranking process. b) There is currently no extensive framework available that integrates the FullEX and AROMAN methods to address challenges and propose effective strategies for mitigating competition-related issues in the industry.

Table 1
MCDM used for sugar industry related studies.

Authors	Focus	Method	CA	SA	Location
Iskanderani et al. [37]	Sugar manufacturing optimization	AHP, TOPSIS	No	No	Middle East
Asrol and Yani [38]	Sugarcane agro-industry supply chain assessment	ANFIS, FCM	No	Yes	–
Salehib et al. [39]	Barriers assessment in sugarcane supply chain	ANP, DEMATEL	No	No	Iran
Manzini Poli et al. [40]	Sugarcane sustainability evaluation instrument	PROMETHEE	No	No	Mexico
Singh et al. [41]	Equipment effectiveness evaluation in İndia sugar mill enterprise	AHP	No	No	India
Mursiti et al. [42]	Human resource development in sugarcane enterprise	MEMCDM	No	No	Indonesia
Anojkumar et al. [43]	Material choice in sugar sector	F-AHP, VIKOR	No	No	–
Kumar and Kansara [44]	IT barriers evaluation in sugar supply chain	AHP, F-AHP	No	No	India
Anojkumar et al. [45]	Material choice in sugar sector	PROMETHEE, AHP, F-AHP	No	No	–
Gani and Hantoro [46]	Sugar-cane industry development choice	ANP	No	No	–
Jiménez Borges et al. [47]	Biomass sustainable assessment in sugar industry	Delphi/AHP	No	No	–
Hussain et al. [48]	Material selection in sugar industry	Cross-Entropy	No	No	–
Beeram et al. [49]	Sustainable juice extraction approach selection	AHP	No	No	–
Anojkumar and Ilangkumaran [50]	Material selection in sugar manufacturing industry	FAHP, GRA, TOPSIS	No	No	–
Darji and Rao [51]	Material selection in sugar industry	TODIM, ARAS, OCRA, EVAMIX	No	No	–
Khorramrouz and Galankashi [52]	Fault diagnosis and prioritization in sugar industry	FAHP	No	No	–
Rajkumar and Malliga [53]	Buyers in selling by-product prioritization	FAHP	No	No	–
Ummi et al. [54]	Risk prioritization and risk mitigation approach for palm sugar reverse supply chain	ISM, DEMATEL	No	No	–
Kittiyankajon and Chetchotsak [55]	Strategy prioritization in sugar industry	Aggregation algorithm	No	No	Thailand
Arslan and Çunkaş [56]	Performance evaluation of sugar plants	TOPSIS	No	No	–
Deepa et al. [57]	Sustainable Sugarcane Farms assessment	VTOPES	No	No	–
Our study	*Alternative Prioritization for Mitigating Competition-Related Issues in Tanzania Sugar Industry*	*FullEX-AROMAN*	*Yes*	*Yes*	*Tanzania*

Note: **AHP**- Analytic Hierarchy Process, **ANP**- Analytic Network Process, **ANFIS**- Adaptive neuro-fuzzy inference system, **DEMATEL**- Decision Making Trial and Evaluation Laboratory Model, EVAMIX- EVAluation of MIXed data, **FCM**- Fuzzy Cognitive Map, **ISM**- Interpretive Structural Modeling, **MEMCDM**- Multi-Expert Multi-Criteria Decision Making, **OCRA**- Operational Competitiveness Rating Analysis, **PROMETHEE**- Preference Ranking Organization Method for Enrichment Evaluation, **TOPSIS**- Technique for Order Preference by Similarity to Ideal Solution, **TODIM**-an acronym in Portuguese of Interactive and Multicriteria Decision Making, **VIKOR**- Vlsekriterijumska Optimizacija I KOmpromisno Resenje; **VTOPES**- VIKOR TOPSIS entropy, and standard deviation.

3. The FullEX-AROMAN methodology

The FullEX method introduces a new angle by emphasizing the significance of criteria selection in the decision-making process, incorporating expert opinions and their impact on the ultimate decision [58]. A graphical depiction of this process is presented in Fig. 1.

Central to the FullEX method is the recognition of experts' credentials, including their educational background and experience. Since its introduction, this approach has predominantly found application in the fields like propulsion technology [59], mining sector sustainability [60], and net-zero emissions [61].

The AROMAN method presents an innovative approach aimed at refining decision-making within multi-criteria environments. It employs a dual-step normalization process to ensure fair comparisons between alternatives [21]. By considering both the significance of criteria and their corresponding weights, AROMAN generates a comprehensive ranking order [62]. Despite being relatively recent, this methodology has attracted significant attention and has been applied in various contexts. These include effective supply chain management practice implementation [63], postal networks selection [64], healthcare system devolution strategy [65], professional drivers' selection [66], cargo bike delivery concepts [67], levels of durable competitiveness [68], waste treatment technologies [69],

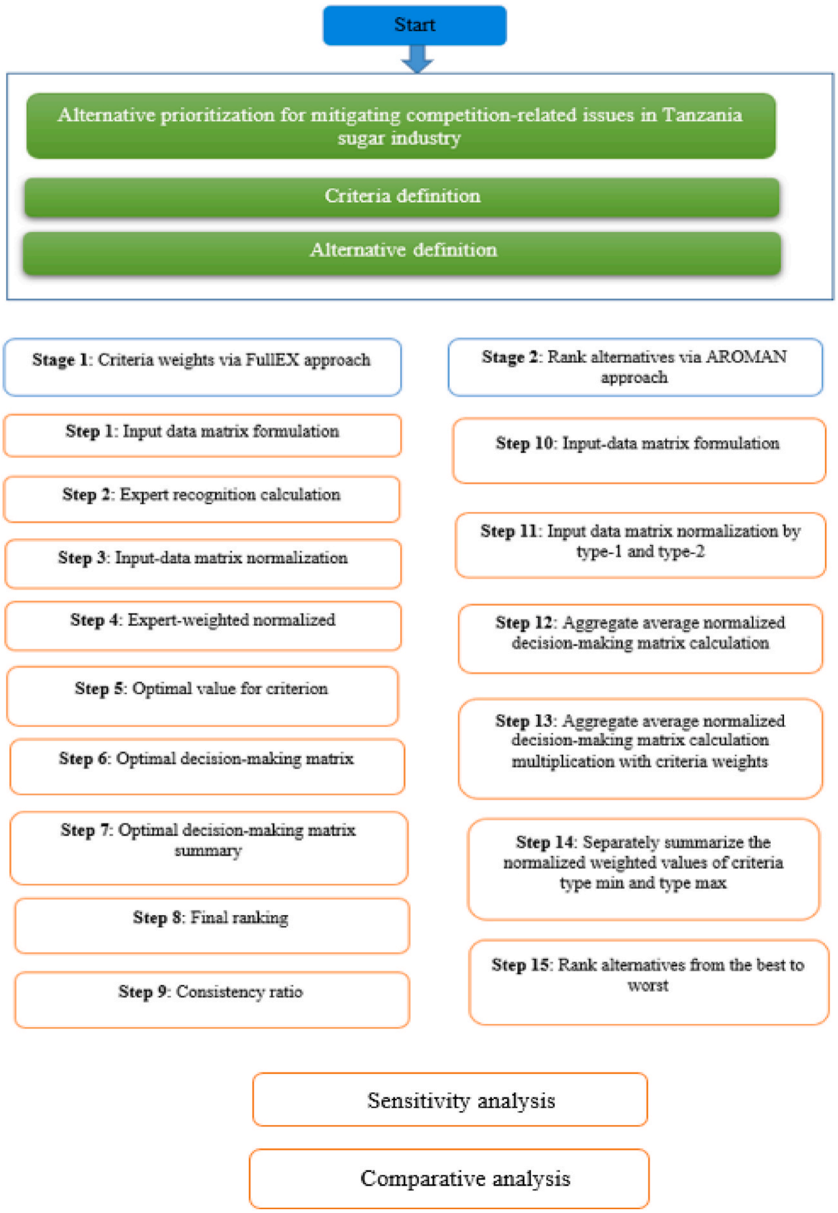

Fig. 1. Flowchart of our proposed methodology.

electric vehicles comparison [70], European investment sector prioritization [71], and autonomous vehicle acceptance by public [72].

The FullEX-AROMAN method is a systematic approach for evaluating alternative options by pinpointing the significance of decision-making criteria through expert assessments. It consists of two phases, comprising a total of 15 steps. The first phase involves utilizing the nine steps of the FullEX method to establish criteria weights, while the second phase employs the six steps of the AROMAN method to prioritize the alternatives. The process of applying this method sequentially is outlined as follows.

First phase: The FullEX method entails nine sequential steps for execution.

Step 1. Input data matrix formulation is shown in Table A1 in appendix.

Fuller's method, a recognized approach for evaluating criteria importance [58], involves paired comparisons. Experts assess two criteria at a time, determining the more significant one in each pair by expressing their preference.

Step 2. Expert's recognition calculation. The triangular shape emerges because of a step-by-step comparison of criteria, with each successive step excluding the previously compared criterion. In assessing expert reputations, the initial phase involves using Eq. (1) to establish the competence level (L_i), which considers both years of experience and educational qualifications

$$L_i = \frac{YE_i + ED_i}{2}, i = 1, 2, \ldots, q, \tag{1}$$

Here, YE_i represents the years of experience for the i-th expert, and ED_i indicates the educational degree of the i-th expert. Regarding educational degrees, a scale ranging from one to three points is adopted, with BSc for 1, Master for 2, and Ph.D. for 3. Following the assessment of each expert's competence level, the reputation of the i-th expert is calculated applying Eq. (2) below.

$$W^{Ei} = \frac{L_i}{\sum_{i=1}^{q} E_i}, i = 1, 2, \ldots, q. \tag{2}$$

Step 3. Input-data matrix normalization. After creating the input data matrix, the normalization process begins. This involves applying the technique described in Eq. (3), as shown in Table A2 in appendix.

$$v_{ij} = \frac{x_{ij}}{\sum\limits_{i=1}^{q} x_{ij}}, i = 1, 2, \ldots, q, j = 1, 2, \ldots, p. \tag{3}$$

Step 4. Expert-weighted normalized input-data matrix obtention. During this stage, the normalized input data is multiplied by the experts' significance, as defined by Eq. (4), and illustrated in Table A3 in appendix.

$$r_{ij} = v_{ij} \cdot W^{Ei}, i = 1, 2, \ldots, q, j = 1, 2, \ldots, p. \tag{4}$$

Step 5. Optimal value identification for each criterion. The primary aim of this stage is to ascertain the optimal value ($V_{j\ max}$) for each criterion within the columns. This is calculated using Eq. (5) and presented in Table A4 in appendix.

$$V_{j\ max} = \max_{i=1,2,\ldots,q} r_{ij}, j = 1, 2, \ldots, p. \tag{5}$$

Step 6. Optimal decision-making matrix obtention. During this phase, every element in the expert-weighted normalized matrix is divided by its respective optimal value ($V_{j\ max}$), which is calculated using Eq. (6) and shown in Table A5 in appendix.

$$y_{ij} = \frac{r_{ij}}{V_{j\ max}}, i = 1, 2, \ldots, q, j = 1, 2, \ldots, p. \tag{6}$$

Step 7. Combine the values from each column in the optimal decision-making matrix using Eq. (7).

$$K_j = \sum_{i=1}^{q} y_{ij}, i = 1, 2, \ldots q, j = 1, 2, \ldots, p. \tag{7}$$

Step 8. Final ranking application. In this stage, the significance of criteria (F_j) is computed as follows:

$$F_j = \frac{K_j}{\sum_{j=1}^{p} K_j}, i = 1, 2, \ldots q, j = 1, 2, \ldots, p. \tag{8}$$

Step 9. Consistency index calculation. In subjective methods such as the FullEX approach, guaranteeing the trustworthiness of expert input is pivotal. Unlike the AHP method, which gauges inconsistency rates using a standardized approach, the FullEX method demands a distinct strategy. It entails computing the consistency index (CI), which involves conducting a second interview round with experts who are uninformed of the original round's outcomes for the evaluated criteria. During this phase, experts assign percentage-based importance scores to each criterion, ensuring a collective sum of 100 % for all "n" criteria. By juxtaposing the findings from both rounds, decision-makers can gauge the reliability of the results. If the responses from the second round are designated as P_j and the previously derived FullEX weights as (F_j), the consistency index (CI) can be computed applying Eq. (9).

$$CI = \frac{\sum_{j=1}^{n} \left| F_j * 100 - P_j \right|}{100} \tag{9}$$

If CI ⟨0.1, the results are reliable; otherwise, experts should reconsider the assessment process. In essence, a CI ⟨ 0.1 shows acceptable consistency.

Second stage: Six steps have characterized the AROMAN technique as follows.

Step 10. A formulation of Ymxn (decision-making matrix) is made with $y_{11}, \ldots, y_{2j}, \ldots, y_{mn}$ as input data via Eq. (10).

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1j} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{21} & \cdots & y_{2j} & \cdots & y_{2n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mj} & \cdots & y_{mn} \end{bmatrix}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, \mathrm{n}. \tag{10}$$

Step 11. Normalization of data is done after the matrix is established. This includes linear (Eq. (11)) and vector (Eq. (12)) ones to generate aggregate normalized matrix (Eq. (13)).

$$P_{ij} = \frac{y_{ij} - \min_i y_{ij}}{\max_i y_{ij} - \min_i y_{ij}}, i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{11}$$

$$P_{ij}^{*} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^{2}}};\ i = 1, 2, \ldots, m, j = 1, 2, \ldots, n. \tag{12}$$

$$P_{ij}^{norm} = \frac{\mu P_{ij} + \left(1 - \mu\right) P_{ij}^{*}}{2};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{13}$$

where P_{ij}^{norm}- Aggregated averaged normalization; μ- Weighting factor changing from 0 to 1. In our case, μ = 0.5.

Step 12. This stage is computed via Eq. (14).

$$\widehat{P_{ij}} = W_{ij} \cdot P_{ij}^{norm};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{14}$$

Step 13. The sum of the normalized weighted data is obtained via Eq. (15) and Eq. (16), respectively:

$$D_i = \sum_{j=1}^{n} \widehat{P_{ij}}^{(min)};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n; \tag{15}$$

$$U_i = \sum_{j=1}^{n} \widehat{P_{ij}}^{(max)};\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{16}$$

Step 14. δ and 1-δ level are obtained for the sum values of D_i and U_i *using* Eq. (17) and Eq. (18), respectively.

$$\hat{D_i} = D_i^{\delta} = \left(\sum_{j=1}^{n} \widehat{P_{ij}}^{(min)} \right)^{\delta}; \tag{17}$$

$$\hat{U_i} = U_i^{1-\delta} = \left(\sum_{j=1}^{n} \widehat{P_{ij}}^{(max)}\right)^{1-\delta} \tag{18}$$

where: δ- coefficient level framed in [0,1]

Step 15. The computation of $\hat{U_i}$ and $\hat{D_i}$ *values* differences is done followed by the application of S_i as the last rank equation (Eq. (19)).

$$S_i = e^{(\hat{U_i} - \hat{D_i})} \tag{19}$$

4. Application case study

This section applies the proposed model to prioritize solutions for competition issues in the Tanzanian sugar industry, covering criteria and alternatives definition, and results of alternatives classification.

4.1. Criteria and alternative definition

In our study, five criteria defining the challenges related to competition related issues in the Tanzanian sugar industry, along with four associated alternatives for addressing them, are presented in Table A6. While some of the challenges and alternatives were derived from existing studies, others were identified through expert consultations. Engaging experts in this process is crucial for evaluating decision-making issues, analyzing current challenges, and finding concrete solutions. Experts can vary in terms of education, experience, skills, and age. However, it is important to carefully consider the number of experts involved in the evaluation process, as having more than seven experts can result in variations in the overall assessment outcomes [73]. In some cases, studies have utilized evaluations from as few as three experts [74]. To ensure a logical and reliable evaluation, this study consulted competition authority experts in Tanzania's sugar industry. Specific criteria were established to select these experts, which included being senior executives in the industry with at least five years of relevant experience. Out of ten experts who were invited, six responded positively. The researchers conducted individual online meetings with these highly qualified professionals and chose to work with them. All the experts in our study are practitioners, each holding a minimum of a bachelor's degree and having at least nine years of experience in the field.

4.2. Results of alternatives rank for competition issues mitigation

This study sought to prioritize measures aimed at alleviating competition issues within Tanzania's sugar industry by utilizing an integrated methodology called FullEX-AROMAN. The approach involved assessing five key criteria and considering four potential alternatives [75–80], outlined in Table A6 in appendix. Six competition authority experts participated in data collection; their backgrounds detailed in Table A7 in appendix. Notably, the FullEX approach underscored the importance of two parameters: experience and educational level (1-Ph.D., 2-Master, 3-Bachelor). The ranking of alternatives proceeded in two stages: initially assigning weights to the five criteria, followed by ranking the four alternatives.

Step 1. In the initial stage, experts utilize Fuller's triangle principle to compare pairs of criteria and indicate which they consider to be superior. This process forms the input data matrix, a critical prerequisite for determining the importance of the criteria in subsequent calculations. Following the experts' evaluation, the input data matrix is constructed and shown in Table 2.

Step 2. Once the initial input data matrix is formulated, the expert assessment follows.

Step 3 and step 4. The input data is normalized using the expert weighted matrix through Eq. (3) and Eq. (4), with results displayed in Tables 3 and 4.

Step 5 and step 6. The optimal decision-making matrix (Table 5) is derived by dividing each element of the expert-weighted normalized input data matrix by its corresponding optimal value (V_{jmax}).

Step 7 and step 8. The optimal decision-making matrix combines all values to compute the final criteria weights (F_j) using Eq. (8), shown in Fig. 2.

Table 2
Input-data matrix.

Experts/criteria	C1	C2	C3	C4	C5
E_1	3	3	1	1	2
E_2	1	2	4	0	3
E_3	1	2	4	0	3
E_4	2	3	2	0	3
E_5	2	3	2	0	3
E_6	0	3	2	1	4
Sum	9	16	15	2	18

Table 3
Normalized input-data matrix.

Experts/criteria	C1	C2	C3	C4	C5
E_1	0.3333	0.1875	0.0667	0.5000	0.1111
E_2	0.1111	0.1250	0.2667	0.0000	01667
E_3	0.1111	0.1500	0.2667	0.0000	01667
E_4	0.2222	0.1875	0.1333	0.0000	01667
E_5	0.2222	0.1875	0.1333	0.0000	01667
E_6	0.0000	0.1875	0.1333	0.5000	0.2222

Table 4
Expert-weighted normalized input-data matrix.

Experts/criteria	C1	C2	C3	C4	C5
E_1	0.0712	0.0400	0.0142	0.1068	0.0237
E_2	0.0187	0.0211	0.0449	0.0000	0.0281
E_3	0.0212	0.0239	0.0509	0.0000	0.0318
E_4	1.2359	1.0428	0.7416	0.0000	0.9270
E_5	0.0400	0.0337	0.0240	0.0000	0.0300
E_6	0.0000	0.0232	0.0165	0.0618	0.0275
V_{jmax}	1.2359	1.0428	0.7416	0.1068	0.9270

According to the findings presented in Fig. 2, using the FullEX approach, the most significant barriers to addressing competition-related issues in Tanzania's sugar industry are as follows: The highest market concentration within the sector, (C4: 0.3709), and the practice of price fixing (C2: 0.2669), stand out as the top two critical challenges. Other challenges are ranked in the following order: C1: 0.2636⟩ C3: 0.0553 > C5: 0.0433.

Step 9. To validate the results, a further round of expert interviews was conducted as the concluding step in the FullEX technique to gather data on the importance of criteria, expressed as percentage distributions from 0 to 100 %. As outlined in Table 6, the findings demonstrate a consistency rate below 0.1 (**CI = 0.086**), suggesting an acceptable level of reliability.

In the second stage, alternatives are rated on a 1–7 scale based on set criteria. Expert opinions are in Table 7, forming the input data matrix in Table 8**.**

After forming the initial decision matrix, the input data is normalized, as shown in Tables 9–11.

Next, the aggregated averaged normalized decision matrix was multiplied by the criteria weights (refer to Table 12).

With $\lambda = 0.2$, the calculations for L_i and A_i values are carried out. The ultimate ranking is then computed, and the findings are depicted in Fig. 3 and Table 13. The obtained rank is S1 > S4 > S3 > S2. The first *"S1-Amendment of the law to accommodate the leniency program" and* the fourth *"S4- Competition Authority should do conduct public awareness campaigns"* are the top two appropriate alternatives for mitigating the competition related issues in Tanzania sugar industry, because they both have relatively higher values compared to others.

5. Sensitivity analysis

The sensitivity analysis, which is essential for evaluating the reliability of the utilized method [81], comprises two initial stages aimed at assessing the stability of the FullEX approach. Furthermore, a third stage is devoted to examining the stability of the AROMAN approach. At last, a fourth stage is conducted including the sensitivity analysis with respect to variations of criteria weights. In the first stage, the challenges encountered by the competition authority of Tanzanian in addressing competition-related issues in sugar industry are ranked based on variations in expert reputation. The second stage involves assessing the consequences of excluding the most experienced expert. In the third stage, the threshold value (λ) is adjusted incrementally by 0.1 units, ranging from 0 to 1, to analyze its impact. Lastly, the impact of criteria weights variation is done.

Table 5
Optimal decision-making matrix.

Experts/criteria	C1	C2	C3	C4	C5
E_1	0.0576	0.0384	0.0192	1.0000	0.0256
E_2	0.0151	0.0202	0.0606	0.0000	0.0303
E_3	0.0172	0.0229	0.0687	0.0000	0.0343
E_4	1.0000	1.0000	0.0323	0.0000	0.0323
E_5	0.0323	0.0323	0.0323	0.0000	0.0323
E_6	0.0000	0.0222	0.0222	0.5789	0.0296
F_j	0.2636	0.2669	0.0553	0.3709	0.0433

Fig. 2. Criteria weights ranking.

Table 6
CI calculation.

	L_j	E_1	E_2	E_3	E_4	E_5	E_6	Average $\mathbf{P_j}$	$\lvert \mathbf{F_J*100} - \mathbf{P_j} \rvert$	CI
C1	0.264	25	25	20	20	25	25	23.30	3.02	0.030
C2	0.267	20	25	30	35	25	25	26.60	0.02	0.002
C3	0.055	15	10	5	5	10	10	9.16	3.64	0.036
C4	0.370	35	35	40	35	35	35	35.83	1.25	0.012
C5	0.043	5	5	5	5	5	5	5.00	0.67	0.067
										0.086

Note: The values from third to eighth columns are given in percentage (%).

Table 7
Alternative assessment.

S1	C1	C2	C3	C4	C5	S2	C1	C2	C3	C4	C5
E_1	9	8	7	1	8		9	9	8	2	7
E_2	3	3	3	3	3		5	5	5	5	5
E_3	5	3	3	2	3		7	7	8	8	6
E_4	8	7	9	2	7		8	7	9	5	8
E_5	8	5	9	2	7		6	8	9	5	6
E_6	8	9	6	3	9		8	9	9	7	8
Average	6.8	5.8	6.2	2.2	6.2	*Average*	7.2	7.5	8.0	5.3	6.7
S3	C1	C2	C3	C4	C5	**S4**	C1	C2	C3	C4	C5
E_1	8	8	8	2	8		8	7	8	1	7
E_2	5	5	5	5	2		3	3	3	2	2
E_3	8	7	7	5	8		4	5	4	4	5
E_4	7	8	9	5	9		9	9	5	2	6
E_5	9	9	9	5	9		7	6	6	3	6
E_6	9	9	9	6	9		7	6	5	2	6
Average	7.7	7.7	7.8	4.7	7.5	*Average*	6.3	6.0	5.2	2.3	5.3

Table 8
Input data matrix.

	C1	C2	C3	C4	C5
S1	6.800	5.800	6.200	2.200	6.200
S2	7.200	7.500	8.000	5.300	6.700
S3	7.700	7.700	7.800	4.700	7.500
S4	6.300	6.000	5.200	2.300	5.300

Table 9
Linear normalization of the initial decision-making matrix.

	C1	C2	C3	C4	C5
S1	0.357	0.000	0.357	0.000	0.409
S2	0.642	0.894	1.000	1.000	0.636
S3	1.000	1.000	0.928	0.806	1.000
S4	0.000	0.105	0.000	0.032	0.000

Table 10
Vector normalization of the initial decision-making matrix.

	C1	C2	C3	C4	C5
S1	0.484	0.426	0.449	0.283	0.478
S2	0.512	0.551	0.579	0.682	0.517
S3	0.548	0.565	0.565	0.605	0.579
S4	0.448	0.440	0.376	0.296	0.409

Table 11
Aggregate average normalization (β = 0.5).

	C1	C2	C3	C4	C5
S1	0.210	0.106	0.201	0.071	0.222
S2	0.288	0.361	0.395	0.421	0.288
S3	0.387	0.391	0.373	0.353	0.394
S4	0.112	0.136	0.094	0.082	0.102

Table 12
Aggregated average weighted normalized matrix with summarized criterion types.

	C1	C2	C3	C4	C5
S1	0.056	0.028	0.011	0.026	0.009
S2	0.076	0.097	0.022	0.156	0.012
S3	0.102	0.104	0.021	0.131	0.017
S4	0.029	0.036	0.005	0.031	0.004

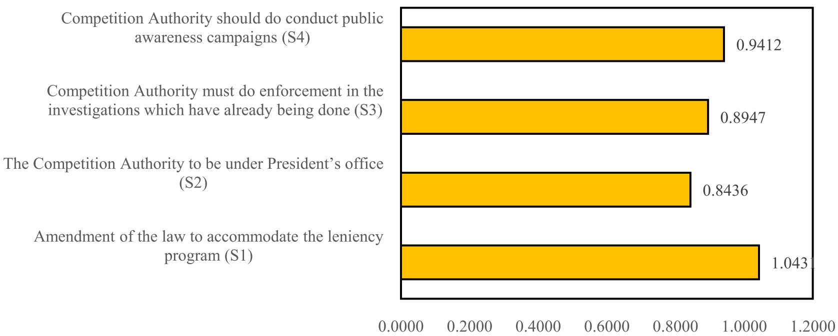

Fig. 3. Final rank of alternatives.

Table 13
L_i and A_i values, differences, and final rank.

	L_i	A_i	$A_i - L_i$	Rank
S1	0.234	0.276	0.042	1.043
S2	0.503	0.332	−0.170	0.843
S3	0.485	0.374	−0.111	0.894
S4	0.259	0.198	−0.060	0.941

5.1. Rank of criteria while varying the reputation of experts

In this segment, the model analyzes the variations in experts' reputations to compare the weights assigned to criteria across three options. The first option, termed as "original," incorporates both years of experience (YE) and educational degree (ED). The second option focuses solely on YE, while the third option solely considers ED. The results are visualized in Fig. 4.

Fig. 4 provides compelling evidence that incorporating both variables into the calculation of experts' reputation substantially enhances the model's stability, as indicated by the trajectory of the blue line. This robust performance suggests that a dual-variable approach leads to more consistent and dependable outcomes, effectively capturing the multifaceted nature of expert contributions. When only one variable is considered, the model risks oversimplifying the complexities involved, which can result in a significant decrease in the initial criteria values. Such a reduction not only undermines the accuracy of the assessment but also introduces

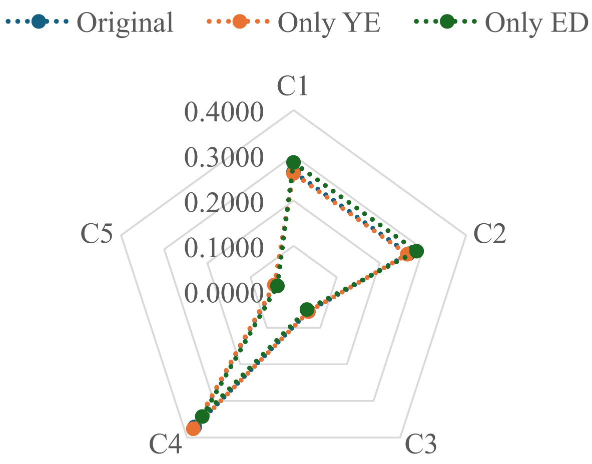

Fig. 4. First sensitivity analysis outcomes.

potential biases that may distort the evaluation of expert performance. This observation emphasizes the critical importance of adopting a holistic perspective that accounts for various dimensions of expertise, ensuring that evaluations are both fair and comprehensive. Furthermore, the findings advocate strongly for the implementation of the FullEX method, a recently established technique for criterion weighting.

5.2. Omitting the most experienced expert during the procedure

The next phase involves evaluating the stability of the FullEX method by excluding two experts: the most experienced expert (E1), who possesses 16 years of experience and a high degree level (Ph.D.-3), and one randomly chosen expert (E5) with the least experience (9 years) and an educational level of Master (2). The results of this assessment are presented in Fig. 5.

A close examination of the results in Fig. 5 reveals a notable shift in the criteria ranking when the most experienced expert, E1, is excluded from the decision-making process. This shift suggests that E1's extensive experience and advanced qualifications significantly contributed to the overall evaluation, indicating a strong correlation between an expert's reputation and the influence they wield in shaping criteria priorities. Conversely, the removal of the randomly chosen expert, E5, whose contributions were comparatively less impactful, results in minimal changes to the criteria ranking. This stark contrast emphasizes the pivotal role that expertise and reputation play in the decision-making framework. The findings illustrate that while every expert brings value to the process, the most experienced individuals can disproportionately influence outcomes, potentially skewing the overall results if their input is not considered. Such insights highlight the necessity for decision-makers to carefully evaluate the composition of their expert panels and recognize the varying degrees of influence that different experts may exert.

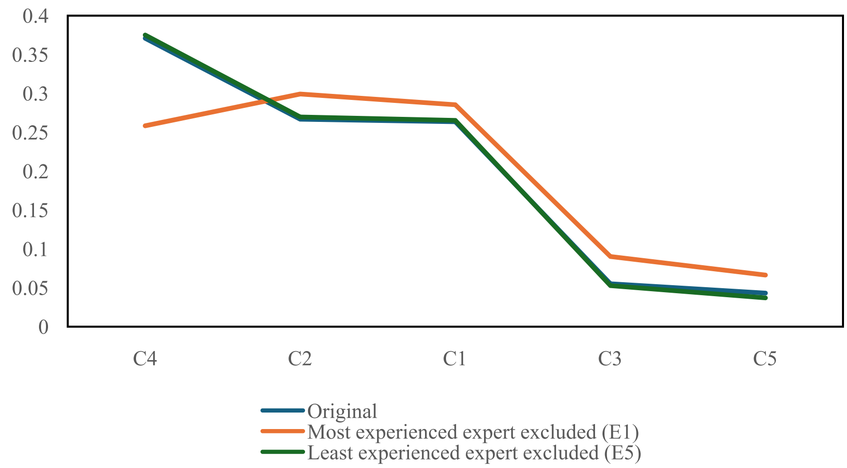

Fig. 5. Second sensitivity analysis outcome.

5.3. Sensitivity analysis with respect to threshold value variation

A sensitivity analysis was conducted by progressively adjusting the threshold value in intervals of 0.1, ranging from 0 to 1. The resultant ranking outcomes are presented comprehensively in Table 14**.**

The findings reveal that, irrespective of the value of λ, the overall ranking of alternatives exhibits remarkable consistency. This stability across different λ values suggests that the ranking process is resilient and not overly sensitive to fluctuations in the weighting parameter. Such robustness is crucial for ensuring that the decision-making framework remains reliable, allowing stakeholders to confidently identify the best alternatives without being unduly influenced by variations in the parameter. Fig. 6 provides a clear graphical representation of these alternative rankings, visually illustrating how the order of preference remains largely unchanged across the different λ values tested. This visual aid enhances our understanding of the ranking stability, enabling a more intuitive grasp of how the alternatives compare against one another. The consistent rankings not only affirm the validity of the evaluation method but also indicate that the underlying criteria used for assessment are effectively capturing the relevant dimensions of performance. Moreover, the implications of this consistency are significant for practitioners who rely on these rankings for informed decision-making. It underscores the reliability of the model, suggesting that even with adjustments in parameter values, stakeholders can maintain confidence in the outcomes produced.

According to the results presented in Table 14, the Weighted Spearman correlation coefficient (r_w) and the Weighted Similarity rank coefficient (WS) were computed, with their ranking similarities detailed in Table 15. These metrics provide crucial insights into how adjusting the threshold in 0.1 increments from 0 to 1 affects the alignment of alternative rankings. Notably, the Weighted Spearman correlation coefficients in Table 15 reveal that at a threshold of 0.1, there was a shift in rankings where S3 and S4 exchanged positions, while other comparisons remained largely stable. In contrast, the Weighted Similarity rank coefficient demonstrated that a value of 1.0 signifies identical rankings.

5.4. Sensitivity analysis with respect to variations of criteria weights

In MCDM approach, the weight assigned to each criterion significantly influences the final ranking or decision outcome. However, uncertainties or hesitations in the assessment of these criteria often arise, particularly when there is subjectivity in determining their relative importance. Sensitivity analysis provides a means to evaluate the robustness of the results when the criteria weights are altered. By exploring various scenarios with adjusted weights, we can examine how these changes affect the decision-making outcomes, thereby assessing the stability and reliability of the initial model.

In this section, we apply a sensitivity analysis using the **pysensmcda** package [82], which generated 10 different scenarios of criteria weights based on initial weights of [0.2636, 0.2669, 0.0553, 0.3709, 0.0433] for the five criteria (C1 to C5). Each scenario represents a different set of weights, simulating potential variations in decision-makers' perspectives. The generated scenarios of weights are shown in Table 16.

The objective is to assess how sensitive the final decision is to these variations in criteria weights, and to evaluate the robustness of the outcomes. A robust decision would remain consistent despite changes in the weights, while significant variations in results may indicate a need for further refinement of the weight assessment process.

The AROMAN method was applied to evaluate the performance of the examined alternatives under the 10 generated weight scenarios. Table 17 presents the evaluation scores of the four alternatives (S1, S2, S3, S4) across the 10 different scenarios. These scores reflect how well each alternative performed under different weight configurations, providing insight into the robustness of each alternative's ranking when the criteria weights are adjusted.

The sensitivity analysis using the AROMAN method reveals that Alternative S1 consistently performs the best across all generated weight scenarios, showing strong robustness in the decision-making process. Its scores range from 1.0038 to 1.0926, with the highest performance observed in scenario 6, where criteria C1 and C4 are more heavily weighted. This indicates that S1 is particularly well-suited when these criteria are given greater importance. The relatively small variation in S1's scores across scenarios suggests that its ranking remains stable, even when different weight configurations are applied, reinforcing its reliability as the top alternative.

In contrast, alternative S2 shows greater sensitivity to changes in the weight distribution, with its scores varying more significantly, from 0.7951 to 0.9084. This suggests that S2's performance is more dependent on the specific weightings of criteria, and it generally performs less favourably when higher weights are assigned to C3 and C5. Alternatives S3 and S4 show moderate performance, with scores closely following each other, but they consistently rank below S1. Both S3 and S4 show their best results in scenario 6 as well, benefiting from increased emphasis on C1 and C4. Overall, the analysis highlights S1 as the most robust alternative, while S2 is more sensitive to changes in criteria weightings.

Table 18 presented below confirms that the results are highly stable across all generated scenarios, as alternative S1 consistently

Table 14
Sensitivity analysis outcomes.

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
S1	0.423	0.522	0.649	0.776	0.905	1.043	1.200	1.393	1.648	2.014	2.574
S2	0.383	0.480	0.556	0.639	0.734	0.844	0.977	1.144	1.365	1.670	2.112
S3	0.397	0.499	0.582	0.673	0.776	0.895	1.036	1.210	1.434	1.732	2.148
S4	0.411	0.492	0.602	0.711	0.822	0.941	1.079	1.256	1.504	1.888	2.542

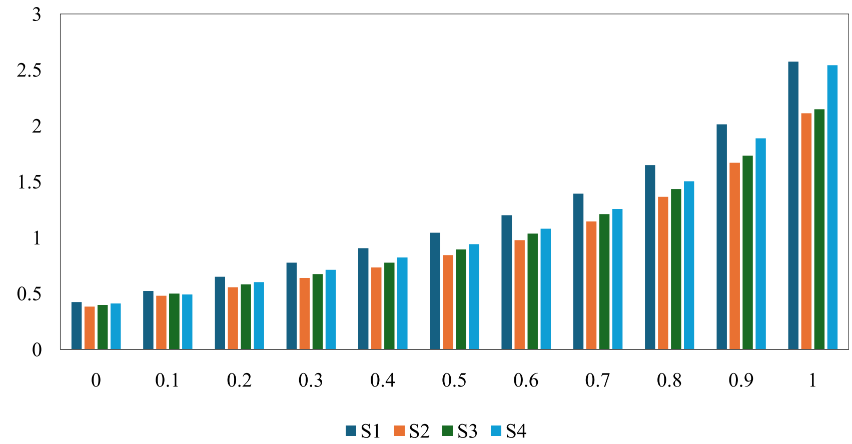

Fig. 6. Sensitivity analysis outcomes based on alternatives.

Table 15
Comparison of rankings similarity with respect to sensitivity analysis.

r_w	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.1	0.8	1.0	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
0.2	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.3	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.4	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.5	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.6	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.7	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.8	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
0.9	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
1	1.0	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
WS	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
0	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.1	0.8125	1.0000	0.8125	0.8125	0.8125	0.8125	0.8125	0.8125	0.8125	0.8125	0.8125
0.2	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.3	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.4	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.5	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.6	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.7	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.8	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.9	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
1	1.0000	0.8125	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table 16
Scenarios generated based on the initial criteria weights.

Scenarios	C1	C2	C3	C4	C5
S1	0.2489	0.2581	0.0254	0.4170	0.0506
S2	0.2255	0.2763	0.0488	0.4293	0.0201
S3	0.2895	0.2951	0.0409	0.3479	0.0266
S4	0.2667	0.3025	0.0462	0.3386	0.0460
S5	0.2929	0.2722	0.0346	0.3500	0.0503
S6	0.3029	0.2373	0.0823	0.3155	0.0621
S7	0.2150	0.2536	0.0864	0.3753	0.0697
S8	0.2642	0.2579	0.0698	0.3711	0.0369
S9	0.2678	0.302	0.0709	0.3469	0.0124
S10	0.2432	0.2475	0.0775	0.3424	0.0894

holds the first position, followed by S4, S3, and S2 in second, third, and fourth places, respectively, in every case. Despite the variations in criteria weights across the 10 scenarios, the rankings do not shift, indicating that the proposed recommendations are robust.

This stability demonstrates that the decision-making outcomes are not excessively sensitive to changes in criteria importance,

Table 17
Resulting scores from the AROMAN method with changed criteria weights according to scenario number.

Scenarios	S1	S2	S3	S4
S1	1.0236	0.8125	0.8664	0.9276
S2	1.0038	0.7951	0.8413	0.9126
S3	1.0378	0.8393	0.8897	0.9373
S4	1.0387	0.8418	0.8910	0.9367
S5	1.0518	0.8524	0.9073	0.9478
S6	1.0926	0.9084	0.9641	0.9781
S7	1.0491	0.8535	0.9019	0.9443
S8	1.0483	0.8514	0.9017	0.9453
S9	1.0332	0.8395	0.8842	0.9332
S10	1.0718	0.8805	0.9337	0.9611

Table 18
Ranking of alternatives according to evaluation scores.

Scenarios	S1	S2	S3	S4
S1	1	4	3	2
S2	1	4	3	2
S3	1	4	3	2
S4	1	4	3	2
S5	1	4	3	2
S6	1	4	3	2
S7	1	4	3	2
S8	1	4	3	2
S9	1	4	3	2
S10	1	4	3	2

reinforcing confidence in the reliability of the chosen alternatives.

6. Comparative analysis

To evaluate the outcomes of the FullEX-AROMAN method, alternative strategies for addressing competition-related issues in the Tanzanian sugar industry were assessed using several recently developed MCDM methods, including the measurement of alternatives and ranking according to compromise solution (MARCOS) [83] and the additive ratio assessment (ARAS) [84]. Both methods yielded the same ranking for the alternatives aimed at mitigating competition-related issues (Fig. 7): *amendment of the law to accommodate the leniency program (**S1**) > competition authority should conduct public awareness campaigns (**S4**) > competition authority must do enforcement in the investigations which have already being done* (**S3**) > *the competition authority to be under President's office (S2)*. It can be concluded that the approach presented is extremely reliable.

According to the results presented in Fig. 7, the comparison of correlations values was computed, with their ranking similarities detailed in Table 19. All rankings from the compared methods are the same, thus the correlation values are 1, indicating the same order of alternatives.

Fig. 7. Comparative analysis with the MARCOS and ARAS approaches.

Table 19
Comparison of correlations values with respect to different applied methods.

r_w	FullEX-AROMAN	MARCOS	ARAS
FullEX-AROMAN	1	1	1
MARCOS	1	1	1
ARAS	1	1	1
WS	FullEX-AROMAN	MARCOS	ARAS
FullEX-AROMAN	1	1	1
MARCOS	1	1	1
ARAS	1	1	1

7. Findings and discussion

Based on prior research and expert insights, it is apparent that the competition authority of Tanzania with regard to sugar sector has encountered significant challenges in addressing competition-related issues. To identify the most pressing challenges, we employed a FullEX methodology to assess their severity. Our study underscores the paramount concern of high market concentration within the industry, a sentiment echoed by Grullon et al. [85], who highlighted the correlation between high market concentration, elevated industry margins, and weakened competition. Indeed, in Tanzania, the prevalence of high market concentration in the sugar industry is attributable to a range of factors. These include barriers to entry such as prohibitive initial costs and economies of scale, which discourage new entrants and solidify the positions of incumbents. Additionally, government policies tend to favor established sugar producers, providing them with advantages and erecting barriers to competition. Vertical integration, where companies control various stages of the supply chain, enhances efficiencies and cost advantages, presenting challenges for smaller competitors. Historical factors, such as early market dominance and the consolidation of smaller entities, further entrench this concentration. Addressing this issue necessitates a multifaceted approach involving regulatory reforms, competition promotion, and strategic interventions. This entails implementing policies to prevent monopolistic practices and promote competition through stricter enforcement of antitrust laws and transparency measures. Diversification of ownership should be encouraged, with incentives provided for new entrants, including small-scale farmers and cooperatives. Improving infrastructure, such as transportation networks and processing facilities, can reduce barriers to entry and enable smaller producers to compete more effectively. Supporting small-scale producers through capacity-building initiatives and access to credit fosters a more inclusive industry. Gradual market liberalization, coupled with support for innovation and technology adoption, can enhance competitiveness and consumer choice. Strengthening producer associations empowers them to negotiate better terms and reduce production costs. Moreover, robust monitoring and enforcement mechanisms ensure compliance with regulations and promote fair competition.

Identified as the second most significant challenge in addressing competition-related issues within the Tanzania sugar industry, price fixing casts a shadow over various aspects of the market. Through the artificial establishment of prices at predetermined levels, it severely limits consumer choice, depriving them of the advantages of competitive pricing dynamics and reducing their options. Furthermore, this practice acts as a deterrent for potential new entrants, impeding competition and stifling innovation within the sector. Price fixing also serves to erect barriers to entry, making it arduous for aspiring competitors to gain traction and challenge the dominance of established players. Ultimately, consumers bear the brunt with inflated prices, resulting in diminished purchasing power and potential welfare losses, particularly affecting vulnerable demographics. Additionally, price fixing breaches antitrust laws, potentially exposing involved entities to legal consequences and tarnishing their reputations, thereby undermining trust and competitive integrity in the marketplace. Tackling this challenge necessitates robust enforcement of antitrust regulations, the promotion of pricing transparency, and the cultivation of a truly competitive market environment.

The results obtained from the integrated methodology indicated that "*the amendment of the law to incorporate a leniency program (S1)*" is considered the most appropriate strategy for mitigating competition-related issues in the sugar industry in Tanzania. This finding aligns with the study of Wanyande [86] who indicates the potential of this program to enhance market transparency and encourage compliance with competition laws. According to his study [86], a leniency program offers reduced penalties or immunity to firms that voluntarily disclose anti-competitive behaviors, such as collusion or price-fixing, which have been prevalent in the sugar sector. By incentivizing companies to come forward with information about their own or others' wrongdoings, this approach can uncover hidden practices that harm market competition, ultimately leading to a more equitable marketplace. Moreover, the program fosters a culture of compliance by promoting self-regulation among industry players, thereby diminishing the likelihood of future anti-competitive conduct. This proactive stance not only protects consumers through fair pricing and improved product availability but also strengthens the overall integrity of the sugar industry, encouraging healthier competition and fostering innovation. In a market where regulatory enforcement may be challenging, the leniency program serves as a practical tool to facilitate cooperation between businesses and regulators, paving the way for a more robust and competitive sugar sector in Tanzania.

8. Managerial implications

The study uncovers two significant challenges to addressing competition issues within Tanzania's sugar sector: high market concentration and price fixing. These findings provide crucial insights for policymakers tasked with resolving existing challenges in the industry. The research offers practical recommendations, emphasizing the necessity of adopting a comprehensive strategy that includes regulatory reforms, promotion of competition, and targeted interventions. Furthermore, it highlights the pivotal role of stringent enforcement of antitrust regulations, promotion of pricing transparency, and the establishment of a genuinely competitive market environment. These recommendations aim to guide policymakers in formulating effective strategies to enhance the competitiveness and sustainability of Tanzania's sugar industry.

8. Conclusion and future recommendations

This paper examines alternative for addressing competition-related issues in Tanzania's sugar industry. It identifies key issues and proposes four potential solutions to help policymakers make informed decisions. Employing the FullEX-AROMAN methodology, this study moves beyond traditional qualitative approaches often seen in prior research by integrating insights from industry professionals based on their experience and educational backgrounds. The FullEX method assigns weights to various criteria, while the AROMAN approach is utilized to rank the alternatives. A notable aspect of this methodology is its dual normalization techniques for standardizing data sets, coupled with the creation of specific strategies to address competition-related problems in the sugar sector. Additionally, this methodology supports sensitivity and comparative analyses, enabling robust result generation and comparisons. Among the significant challenges identified—such as high market concentration and price fixing—the most viable strategy for overcoming these obstacles is to amend the law to incorporate a leniency program (S1).

This paper makes several valuable contributions to the scientific community, Tanzania, and society, including.

- The application of integrated MCDM methodology, enriching the academic literature on the competition-related issues mitigation in sugar industry at a national scale.
- The raise of awareness among practitioners and decision-makers in Tanzania regarding the critical challenges that hinder the competition-related issues mitigation in the sugar industry, along with appropriate strategy.
- The introduction of a user-friendly, step-by-step process for addressing complex MCDM challenges.
- The wide applicability of this integrated approach, which offers opportunities for other researchers to solve complex MCDM problems in various sectors beyond the competition-related issues mitigation in sugar industry.
- The provision of decision-making technique, assisting both academics and practitioners in making more informed choices concerning the sustainability of Tanzania's sugar sector.

Although significant contributions are made through this study, some limitations have been noticed. Firstly, the study does not address or incorporate any established group decision-making techniques, group decision support systems, or group decision processes. Future research should consider integrating such methods to facilitate structured group interactions, ensuring more transparency in the results. This would better reflect collective expert judgment, providing more comprehensive and balanced insights. Second, there is a lack of systematic literature review or detailed justification process to identify the criteria and alternatives in this study. Future study should consider focusing on a research procedure that entailed conducted searches in the Google Scholar database or web of science or Scopus employing specific terms such as "factors OR indicators OR criteria OR challenges" AND "sugar industry OR sugar sector" AND "Tanzania" AND "competition-related issues" AND "mitigation strategies", with the following inclusion criteria: (1) the search includes references published within the years 2001–2024, given that the compilation of the criteria and gathering of relevant data happened in 2024 and (2) the reference articles are published in scientific peer-reviewed journals. Thirdly, the expert weighting process is simple. Therefore, future study should consider make it more sophisticated and developed a consensus-based model for all experts that incorporates a consensus coefficient. Fourthly, the findings of this study may lack generalizability to other African countries, as conditions and circumstances vary across the continent. Thus, it is important to replicate the research framework in different African nations, especially other highly competitive sugar producers in Africa such as Uganda, Malawi, Zambia, Swaziland, and Egypt and compare the resulting outcomes. Another limitation is that the methods applied are ineffective when dealing with uncertainty. For decision-making in such contexts, it would be advantageous for future research to explore the FullEX-AROMAN method within a fuzzy environment. As a future direction, the study could develop a fuzzy-FullEX-AROMAN approach to address uncertainty, not only in prioritizing alternatives to mitigate competition-related issues in Tanzania's sugar industry but also in other complex competition-related issues.

CRediT authorship contribution statement

Tafuteni Nicholaus Chusi: Writing – review & editing, Writing – original draft, Validation, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yu Zuo:** Writing – review & editing, Visualization, Validation, Resources, Formal analysis. **Azam Shehbaz:** Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis. **Mouhamed Bayane Bouraima:** Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation.

Ethics declaration

This study does not involve any human or animal subjects, and it is in accordance with research ethical standards.

Data availability

Data will be made available on request.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e41521.

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