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INTEGRATING DIGITAL SOLUTIONS FOR CREW RESOURCE MANAGEMENT IN AVIATION: A FUZZY BWM-COCOSO APPROACH

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Abstract:
This study presents a novel hybrid framework integrating Fuzzy Best-Worst Method (Fuzzy BWM) and Combined Compromise Solution (COCOSO) for prioritizing digital Crew Resource Management (CRM) solutions in aviation management. Evaluating alternatives across six criteria—operational efficiency, cost, safety, user experience, scalability, and environmental impact—the framework combines expert judgments with entropy-based validation for balanced decision-making. Based on data from ten industry experts, operational efficiency and safety emerged as the most critical criteria, with Digital Solution A ranking highest due to its strong performance in scalability and predictive analytics. Sensitivity analysis confirmed the model's robustness, ensuring consistent rankings under varying conditions. This study advances multi-criteria decision-making methodologies in aviation, offering a reliable tool for integrating CRM systems that align with operational and sustainability goals while addressing gaps in existing frameworks.

Keywords:
Crew Resource Management (CRM), Aviation Management, Fuzzy Best-Worst Method (Fuzzy BWM), Combined Compromise Solution (COCOSO), Digital Transformation

1. Introduction

Integrating digital solutions into Crew Resource Management (CRM) represents a critical step in modernizing aviation management, ensuring safety, efficiency, and operational resilience. CRM has long been recognized as a cornerstone of aviation safety culture, fostering effective communication, teamwork, and decision-making among crew members (Terzioğlu, 2024). The integration of advanced digital technologies, such as AI-powered platforms, cloud-based systems, and blockchain for secure information management, has the potential to revolutionize CRM by addressing contemporary challenges, including operational complexity, real-time data management, and heightened safety expectations (Heiets et al., 2022; Büyüközkan, Feyzioğlu, & Havle, 2019).

Despite these opportunities, the aviation industry faces significant challenges in selecting and integrating digital solutions for CRM. Existing strategies often lack a structured and systematic approach to evaluating digital technologies, leading to inconsistent adoption and suboptimal results (Karaarslan & Erkmen, 2021). Additionally, the rapid evolution of digital tools creates a need for robust decision-making frameworks that can balance multiple factors, such as cost, scalability, user experience, and safety impact. While studies have explored the benefits of CRM in improving safety and reducing accidents (Mızrak & Mızrak, 2020), limited research focuses on a comprehensive evaluation framework for prioritizing CRM technologies.

The objective of this study is to address these gaps by developing a hybrid decision-making framework for prioritizing digital solutions in CRM. The proposed framework integrates the Fuzzy Best-Worst Method (BWM) and the Combined Compromise Solution (COCOSO) method, enhanced with Entropy Weighting for criteria validation. Fuzzy BWM is chosen for its ability to capture expert preferences and handle uncertainty effectively, which is crucial in evaluating complex, multi-criteria systems (Pamučar et al., 2020; Petrudi, Ghomi, & Mazaheriasad, 2022). The COCOSO method complements this by providing a robust mechanism for ranking alternatives based on weighted criteria, delivering actionable insights for decision-makers (Popović, 2021; Lai et al., 2022). Entropy Weighting ensures an objective validation of criteria weights, addressing potential biases in expert judgments (Zhu et al., 2023).

Alternative Multi-Criteria Decision-Making (MCDM) models, such as Analytic Hierarchy Process (AHP) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), were considered but deemed less suitable for this study. AHP, while widely used, struggles with scalability and consistency in large-scale evaluations, making it less effective for complex systems like CRM (Chai et al., 2024). Similarly, TOPSIS lacks the capability to capture intricate interdependencies among criteria, which is a critical requirement for evaluating CRM technologies (Pamučar et al., 2020).

By leveraging the hybrid Fuzzy BWM-COCOSO model, this study contributes to the growing body of literature on digital transformation in aviation management. It provides a structured, evidence-based approach to selecting digital CRM solutions, ensuring alignment with operational goals and industry best practices. The findings aim to support aviation stakeholders in making informed decisions that enhance CRM effectiveness, operational efficiency, and safety culture, ultimately advancing the broader agenda of digital transformation in the aviation industry.

2. Literature Review

Crew Resource Management (CRM) has been a fundamental component of aviation safety and operational efficiency, evolving significantly since its inception. Initially developed to address human errors as a leading cause of aviation accidents, CRM has matured into a comprehensive framework emphasizing teamwork, communication, and decision-making among flight crews (Terzioğlu, 2024). Modern CRM strategies, such as CRM 7.0, extend these principles to incorporate technological advancements and organizational culture, enhancing their relevance in contemporary aviation environments. According to MacLeod (2021), CRM training has shifted towards competence-based approaches, ensuring pilots and crew members acquire both technical and interpersonal skills critical for safe and efficient operations. These developments highlight the enduring importance of CRM as aviation systems become more complex and interconnected.

The role of CRM in fostering a culture of safety and collaboration has been well-documented. By promoting open communication and effective resource utilization, CRM mitigates risks associated with human error (Mızrak & Mızrak, 2020). During the COVID-19 pandemic, the challenges of maintaining crew coordination and morale underscored the adaptability of CRM principles. Karaarslan and Erkmen (2021) noted significant shifts in crew attitudes towards CRM during this period, with cabin crew adopting new communication protocols to ensure safety amidst heightened operational uncertainties. This adaptability demonstrates CRM's potential to evolve alongside the changing dynamics of aviation, particularly as digital transformation introduces new tools and methods for crew coordination.

Despite its advancements, CRM faces ongoing challenges in integrating with emerging technologies, which require new methodologies and frameworks. Terzioğlu (2024) argues that while CRM has successfully addressed traditional safety concerns, its integration with digital solutions remains underexplored. The growing reliance on AI, cloud-based systems, and other digital technologies necessitates a redefinition of CRM to maintain its effectiveness in modern aviation. This gap underscores the need for a structured approach to evaluating and integrating digital tools within CRM frameworks, ensuring their alignment with safety, efficiency, and teamwork objectives.

Digital transformation is reshaping the aviation industry, introducing innovative solutions to enhance operational efficiency and decision-making. AI-powered systems, for instance, enable real-time data analysis and predictive modeling, facilitating proactive responses to operational challenges (Whig et al., 2024). Similarly, cloud-based CRM platforms offer seamless data sharing across teams, improving coordination and reducing response times in critical scenarios (Heiets et al., 2022). Digital twins, as reviewed by Xiong and Wang (2022), provide a virtual replica of aviation systems, allowing for simulations and risk assessments that enhance operational planning and resource allocation. These technologies represent a significant leap forward in aviation management, with their potential only beginning to be realized.

However, the adoption of digital solutions in aviation is not without challenges. Molchanova et al. (2020) highlight issues such as system compatibility, high implementation costs, and the need for skilled personnel to manage these technologies. In the context of CRM, these barriers are particularly pronounced, as the integration of digital tools must align with the nuanced requirements of crew coordination and decision-making. Altundag (2022) underscores the importance of strategic planning in overcoming these obstacles, advocating for a phased approach to digital transformation that balances innovation with practical implementation. Such strategies are crucial in ensuring that digital solutions enhance rather than disrupt existing CRM practices.

The intersection of CRM and digital transformation presents an opportunity to redefine aviation management. By integrating advanced technologies with established CRM principles, the aviation industry can achieve greater efficiency and safety. However, as Purwaningtyas et al. (2022) argue, this requires a comprehensive understanding of both the capabilities of digital tools and the operational context in which they are applied. The successful integration of these elements necessitates robust evaluation frameworks that consider technical, economic, and human factors, ensuring a balanced approach to digital transformation in CRM.

Multi-Criteria Decision-Making (MCDM) techniques offer valuable tools for addressing the complexities of integrating digital solutions in CRM. Methods such as the Best-Worst Method (BWM) and the Combined Compromise Solution (COCOSO) have demonstrated their effectiveness in diverse applications, from performance measurement in higher education to sustainability assessments (Pamučar et al., 2020; Ecer, 2021). These models excel in handling qualitative and quantitative data, providing structured approaches to decision-making that are particularly useful in dynamic and uncertain environments. In the aviation context, MCDM methods can facilitate the evaluation of digital solutions by considering multiple criteria, such as cost, efficiency, scalability, and user experience.

The strengths of hybrid MCDM models lie in their ability to address interdependencies among criteria and incorporate expert judgments. Petrudi et al. (2022) emphasize the utility of BWM in capturing expert preferences with high consistency, while Lai et al. (2022) highlight the adaptability of COCOSO in group decision-making scenarios. These models are particularly relevant for CRM integration, where decisions must balance technical feasibility with human factors. However, as Zhu et al. (2023) note, the effectiveness of these methods depends on the robustness of the criteria selection and weighting processes, underscoring the importance of methodological rigor.

Despite their advantages, traditional MCDM methods face limitations in addressing the unique challenges of CRM integration. For instance, the Analytic Hierarchy Process (AHP), though widely used, struggles with scalability in complex systems, making it less suitable for evaluating multiple digital solutions with interrelated criteria (Chai et al., 2024). Similarly, methods like TOPSIS lack the flexibility to capture nuanced interdependencies, which are critical in CRM contexts (Pamučar et al., 2020). These limitations highlight the need for hybrid approaches that combine the strengths of multiple MCDM methods, providing comprehensive frameworks for decision-making in aviation.

The literature reveals significant gaps in the integration of CRM with digital solutions, particularly in the application of MCDM frameworks. While CRM has evolved to address traditional safety challenges, its adaptation to digital transformation remains underexplored (Terzioğlu, 2024). Existing studies often focus on individual technologies or isolated aspects of CRM, neglecting the need for holistic evaluation frameworks that encompass multiple criteria. This gap is particularly evident in the context of emerging technologies, where the lack of structured methodologies impedes effective decision-making (Molchanova et al., 2020; Heiets et al., 2022).

Addressing these gaps requires a shift towards integrated MCDM models that consider both qualitative and quantitative factors. The hybrid Fuzzy BWM-COCOSO model offers a promising solution, combining established MCDM methods' strengths with advanced criteria weighting techniques and alternative ranking techniques (Pamučar et al., 2020; Lai et al., 2022). By leveraging these capabilities, the proposed framework can provide actionable insights into the prioritization of digital solutions for CRM, bridging the gap between technological innovation and operational effectiveness. This approach not only addresses the limitations of existing methodologies but also aligns with the broader goals of digital transformation in aviation.

3. Methodology

3.1 Research Framework

The research framework is built around the hybrid Fuzzy Best-Worst Method (BWM) and Combined Compromise Solution (COCOSO) model, enhanced with Entropy Weighting to objectively validate criteria weights. This model was chosen for its robustness in addressing complex decision-making scenarios involving multiple, interdependent criteria, such as those encountered in Crew Resource Management (CRM) integration in aviation. By combining the strengths of Fuzzy BWM and COCOSO, the proposed framework provides a structured and adaptable approach to evaluating digital solutions for CRM, balancing subjective expert judgments with objective data-driven insights.

Fuzzy BWM was introduced by Rezaei (2015) as an improvement over traditional pairwise comparison methods such as the Analytic Hierarchy Process (AHP). Unlike AHP, which requires numerous comparisons and often suffers from inconsistency, BWM simplifies the comparison process by requiring decision-makers to identify the best and worst criteria and compare these to others. The fuzzy extension of BWM, as applied by Pamučar et al. (2020), incorporates linguistic variables to handle uncertainty and ambiguity in expert evaluations. This is particularly important in CRM, where criteria such as safety, user experience, and scalability often involve subjective assessments. The COCOSO method, developed by Yazdani et al. (2019), is designed for aggregating and ranking alternatives in multi-criteria decision-making problems. It combines compromise programming and simple additive weighting, making it effective for balancing trade-offs among conflicting criteria. When paired with Fuzzy BWM, COCOSO benefits from precise criteria weights generated by the latter, enabling more reliable rankings of alternatives. Recent studies, such as those by Lai et al. (2022) and Zhu et al. (2023), demonstrate the effectiveness of COCOSO in diverse decision-making scenarios, including sustainability assessments and digital platform evaluations.

To further enhance the reliability of this hybrid model, Entropy Weighting is integrated to validate the criteria weights derived from Fuzzy BWM. Entropy Weighting, as detailed by Shannon (1948), measures the level of variability or uncertainty in data, providing an objective basis for criteria importance. This step addresses potential biases in expert judgments, ensuring that the model's outcomes are both rigorous and reliable (Zhu et al., 2023).

The choice of the hybrid Fuzzy BWM-COCOSO model over alternatives is justified by its superior ability to handle both qualitative and quantitative data, its efficiency in reducing inconsistency, and its flexibility in adapting to complex systems. While AHP and TOPSIS are widely used in multi-criteria decision-making, they are less suited to the intricate interdependencies and uncertainties present in CRM integration. AHP's reliance on numerous pairwise comparisons makes it prone to inconsistency, particularly in large-scale evaluations, while TOPSIS fails to capture interdependencies among criteria (Chai et al., 2024; Pamučar et al., 2020). Figure 1 illustrates the steps followed for the analysis,

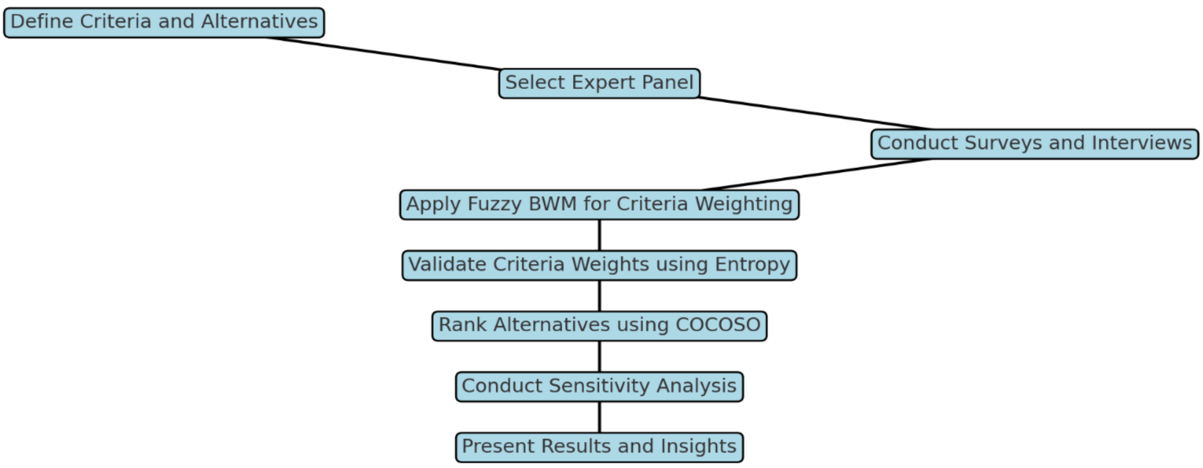

Figure 1. Workflow Chart

In contrast, hybrid models such as Fuzzy BWM-COCOSO effectively address these limitations. Fuzzy BWM ensures consistent and accurate criteria weighting, while COCOSO provides robust rankings that consider multiple compromise solutions. Furthermore, the integration of Entropy Weighting enhances the objectivity and robustness of the model, making it particularly suitable for the dynamic and uncertain environment of CRM integration. By leveraging the strengths of these methods, the proposed framework offers a comprehensive and reliable approach to evaluating and prioritizing digital CRM solutions, ensuring alignment with aviation safety and operational goals. This tailored methodology not only addresses the complexities of CRM integration but also aligns with the broader trends of digital transformation in aviation.

3.2 Evaluation Criteria

The evaluation criteria for the study were identified through a comprehensive review of the literature and refined with input from an expert panel comprising aviation managers, CRM specialists, and digital transformation consultants. Each criterion was selected based on its relevance to the integration of digital solutions in Crew Resource Management (CRM) and its impact on operational effectiveness, safety, and sustainability. The finalized criteria and their definitions, along with supporting sources, are presented in Table 1.

Operational efficiency is a critical criterion, reflecting the ability of digital CRM solutions to optimize workflows, reduce turnaround times, and enhance resource utilization. Studies such as those by Heiets et al. (2022) and Xiong and Wang (2022) emphasize the importance of efficiency improvements driven by digital technologies like AI and cloud-based systems in aviation. Cost was included as a criterion to account for the financial feasibility of adopting digital solutions, as noted by Molchanova et al. (2020), who highlight cost as a significant barrier to technology adoption in the aviation sector.

Safety remains a paramount concern in aviation, with CRM frameworks historically focused on reducing human errors and enhancing risk management (Mızrak & Mızrak, 2020; Terzioğlu, 2024). The integration of digital solutions must align with these objectives, ensuring that safety protocols are upheld or improved. User experience was selected to evaluate the intuitiveness and ease of use of CRM platforms, considering the feedback from end-users, such as pilots and crew members. This criterion is supported by findings from Whig et al. (2024), which stress the role of user-friendly interfaces in technology acceptance.

Scalability addresses the adaptability of digital solutions to future operational expansions or changes in aviation management practices. Altundag (2022) underscores the need for scalable solutions that can evolve with technological advancements and regulatory requirements. Lastly, environmental impact reflects the aviation industry's growing emphasis on sustainability. Digital technologies must contribute to reduced carbon emissions and energy efficiency, as highlighted by Büyüközkan et al. (2019) and Raman et al. (2024).

To validate these criteria, the expert panel was engaged in a structured process involving discussions and surveys to ensure alignment with practical and strategic objectives. Experts rated each criterion based on its importance and relevance, and their input was incorporated into the weighting process using the Fuzzy BWM methodology. Table 1illustrates evaluation criteria for the study.

Table 1: Evaluation Criteria for Digital CRM Solutions

Criteria	Definition	Source
Operational Efficiency	Optimizing workflows, reducing turnaround times, and enhancing resource utilization.	Heiets et al. (2022); Xiong & Wang (2022)
Cost	Financial feasibility, including implementation and maintenance costs.	Molchanova et al. (2020)
Safety	Enhancing risk management and reducing human errors.	Mızrak & Mızrak (2020); Terzioğlu (2024)
User Experience	Intuitiveness and ease of use, incorporating feedback from end-users.	Whig et al. (2024)
Scalability	Adaptability to future operational expansions and	Altundag (2022)

Criteria	Definition	Source
	technological advancements.	
Environmental Impact	Contribution to sustainability through reduced emissions and energy efficiency.	Büyüközkan et al. (2019); Raman et al. (2024)

By combining insights from literature and expert perspectives, the selected criteria provide a robust foundation for evaluating and prioritizing digital CRM solutions, ensuring that the methodology aligns with both theoretical and practical considerations.

3.3 Data Collection

To ensure a comprehensive evaluation of digital solutions for Crew Resource Management (CRM), a panel of 10 experts was selected based on their diverse backgrounds and extensive experience in the aviation industry. The panel includes aviation managers, IT specialists, CRM vendors, and digital transformation consultants, ensuring a holistic perspective on the integration of digital technologies into CRM. Table 2 provides an overview of the experts, detailing their professional roles, years of experience, and specific relevance to the study.

Table 2: Expert Panel Composition

Expert ID	Position/Role	Years of Experience	Relevance to the Study
E1	Senior Aviation Manager	20+ years	Oversees CRM implementation and safety management.
E2	IT Specialist in Aviation	15 years	Designs and implements digital systems for aviation operations.
E3	CRM Training Consultant	18 years	Develops CRM training programs and evaluates digital tools.
E4	Digital Transformation Manager	12 years	Leads digital transformation initiatives in aviation firms.
E5	CRM Software Vendor	10 years	Provides CRM solutions tailored to aviation needs.
E6	Pilot with CRM Expertise	22 years	Applies CRM in operational settings and offers end-user insights.
E7	Aviation Safety Analyst	14 years	Evaluates CRM's impact on safety and risk management.
E8	Environmental Consultant	8 years	Assesses sustainability aspects of digital technologies.
E9	Aviation Operations Supervisor	16 years	Manages resource allocation and operational

Expert ID	Position/Role	Years of Experience	Relevance to the Study
			efficiency.
E10	Aviation Policy Advisor	20+ years	Provides regulatory insights on digital technology integration.

The data collection process combines surveys, interviews, and workshops to gather both qualitative and quantitative insights from the expert panel. This structured approach ensures the collected data is well-suited for the Fuzzy BWM-COCOSO analysis. Surveys are used to collect individual evaluations of the criteria and alternatives, focusing on their importance and relevance to CRM integration. The survey includes pairwise comparisons for Fuzzy BWM, where experts identify the best and worst criteria and compare them to others. Additionally, a Likert-scale format is employed to rate the performance of CRM solutions against the selected criteria, providing a standardized way to measure expert opinions.

Interviews are conducted to gain in-depth insights into the practical challenges and opportunities associated with digital CRM integration. Semi-structured questions are designed to explore the feasibility, scalability, and impact of digital technologies. Examples of questions include: "What operational efficiencies have you observed with the use of digital CRM tools?" and "How do you perceive the cost-benefit trade-offs of implementing digital CRM systems?" These interviews provide qualitative data that complements the quantitative evaluations from the surveys, offering a nuanced understanding of the experts' perspectives.

Workshops are organized to facilitate discussions among the experts, allowing them to identify interdependencies among criteria and validate the preliminary results of the analysis. During these interactive sessions, experts collaboratively review and refine the criteria, their weights, and the alternative rankings derived from the initial survey and interview data. This participatory process ensures that the findings are well-rounded and reflective of collective expertise. By using this multi-method approach, the study ensures comprehensive and reliable input, tailored to the analytical needs of the Fuzzy BWM-COCOSO model. These methods capture both subjective judgments and objective assessments, creating a robust foundation for the prioritization of digital CRM solutions.

3.4 *Digital Solutions Overview*

The evaluation of digital solutions in this study is based on their performance across multiple criteria: operational efficiency, cost, safety, user experience, scalability, and environmental impact. These digital solutions represent innovative approaches to Crew Resource Management (CRM) integration in the aviation industry, each offering unique features and advantages. The content and features of each digital solution are outlined below to provide context for the analysis.

Digital Solution A

Digital Solution A is an AI-driven CRM tool designed to optimize operational efficiency by automating routine customer interactions and providing advanced predictive analytics. The solution emphasizes scalability, allowing seamless integration with existing IT infrastructure, and offers a user-friendly interface that enhances the overall user experience. Key features include:

- Predictive analytics for proactive decision-making.
- Automation of customer interaction workflows.
- Integration with existing IT systems for enhanced scalability.

Digital Solution B

Digital Solution B employs blockchain technology to enhance security and transparency in CRM operations. The platform focuses on cost-efficiency while ensuring data integrity, making it a robust choice for organizations prioritizing safety and secure data management. Key features include:

- Decentralized data management for enhanced security.
- Cost-effective operations through optimized resource utilization.
- Scalable architecture to accommodate growing organizational needs.

Digital Solution C

Digital Solution C is a cloud-based CRM platform that offers real-time data sharing and advanced customization options. This solution prioritizes safety and environmental impact, with features that support compliance with sustainability standards. Key features include:

- Real-time data sharing for improved collaboration.
- Customizable features tailored to organizational requirements.
- Environmentally friendly design aligned with sustainability goals.

These digital solutions were assessed using expert evaluations and their performance data, forming the foundation of the decision matrix. The detailed features of each solution ensure that the evaluation criteria are directly tied to the functionalities of the alternatives, providing a robust basis for the ranking process.

3.5 ***Model Application***

3.5.1 ***Steps for Applying Fuzzy BWM to Determine Criteria Weights***

The Fuzzy Best-Worst Method (Fuzzy BWM) is applied to determine the weights of the evaluation criteria by following a structured process. The method incorporates fuzzy logic to address uncertainties and ambiguities in expert judgments. Below are the steps with equations and detailed explanations:

Step 1: Define the Criteria Set

Let $C = \{C_1, C_2, \ldots, C_n\}$ denote the n criteria for evaluation. The criteria for this study are:

- C_1 : Operational Efficiency
- C_2 : Cost
- C_3 : Safety
- C_4 : User Experience
- C_5 : Scalability
- C_6 : Environmental Impact

Step 2: Select the Best and Worst Criteria

Experts identify:

- C_B : The best criterion, the most critical for CRM integration.
- C_W : The worst criterion, the least critical for CRM integration.

Step 3: Pairwise Comparisons Using Fuzzy Values

Experts provide their preferences for:

1 The Best Criterion compared to all others (a_{Bj}) :

$$a_{B1}, a_{B2}, \ldots, a_{Bn} \tag{1}$$

where $a_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, a fuzzy triangular number.

2. All other criteria compared to the Worst Criterion (a_{jW}) :

$$a_{1W}, a_{2W}, \ldots, a_{nW} \tag{2}$$

where $a_{jW} = (l_{jW}, m_{jW}, u_{jW})$, a fuzzy triangular number.
Each linguistic term is assigned a triangular fuzzy number. The linguistic terms and their corresponding fuzzy triangular numbers are typically defined as illustrated in Table 3.

Table 3. Linguistic Terms and Their Corresponding Fuzzy Triangular Numbers

Linguistic Term	**Fuzzy Triangular Number.** (l, m, u)
Equal Importance	(1,1,1)(1,1,1)
Low Importance	(1/3,1/3,1)(1/3,1/3,1)
Moderate Importance	(1/2,1,3/2)(1/2,1,3/2)
High Importance	(1,3/2,2)(1,3/2,2)
Very High Importance	(3/2,2,5/2)(3/2,2,5/2)

Step 4: Formulate the Optimization Problem

The goal is to minimize the maximum deviation (ξ) from the consistent fuzzy comparisons. The optimization problem is:

Minimize ξ

subject to:

$$\frac{\tilde{w}_B}{\tilde{w}_j} \leq u_{Bj},\ \frac{\tilde{w}_B}{\tilde{w}_j} \geq l_{Bj},\ \forall j,$$
$$\frac{\tilde{w}_j}{\tilde{w}_W} \leq u_{jW},\ \frac{\tilde{w}_j}{\tilde{w}_W} \geq l_{jW},\ \forall j$$
$$\sum_{j=1}^{n} \tilde{w}_j = 1,\ \tilde{w}_j > 0\ \forall j \tag{3}$$

where:

- $\tilde{w}_j = (l_j, m_j, u_j)$ is the fuzzy weight for criterion j.
- l_{Bj}, m_{Bj}, u_{Bj} and l_{jW}, m_{jW}, u_{jW} are the fuzzy triangular numbers representing pairwise comparisons.

Step 5: Solve the Optimization Problem

The optimization is solved for $\tilde{w}_j$ using linear programming techniques. The solution yields fuzzy weights $\tilde{w}_j = (l_j, m_j, u_j)$ for each criterion.
Step 6: Defuzzify the Weights

The fuzzy weights are defuzzified into crisp weights using the Center of Gravity (COG) method:

$$w_j = \frac{l_j + m_j + u_j}{3} \tag{4}$$

where:

- l_j : Lower bound of the fuzzy weight for criterion j.
- m_j : Middle value of the fuzzy weight for criterion j.
- u_j : Upper bound of the fuzzy weight for criterion j.

Step 7: Normalize the Weights

The defuzzified weights are normalized to ensure that their sum equals 1 :

$$w_j^{\text{normalized}} = \frac{w_j}{\sum_{k=1}^{n} w_k}, \forall j \tag{5}$$

Step 8: Validate Consistency

The consistency of the weights is evaluated to ensure that the pairwise comparisons are logical and coherent. Consistency ratios can be computed, although BWM inherently reduces inconsistency compared to methods like AHP.

3.5.2 *Integration of Entropy Weighting for Validation*

Entropy weighting is a technique used to objectively validate the weights derived from the Fuzzy BWM by measuring the degree of variability in the criteria data. By incorporating entropy weighting, we ensure that the results are not solely dependent on subjective expert judgments but are also supported by the inherent distribution of the data related to each criterion.

Step 1: Collect Data for Each Criterion

Let x_{ij} represent the performance of the i-th alternative on the j-th criterion, where:

- $i = 1,2, \ldots, m$ (number of alternatives),
- $j = 1,2, \ldots, n$ (number of criteria).

The data matrix for m alternatives and n criteria is expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

Step 2: Normalize the Data

To ensure comparability across criteria, the raw data is normalized. For a benefit criterion (higher values are better):

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \forall i, j \tag{7}$$

For a cost criterion (lower values are better):

$$r_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}, \forall i, j \tag{8}$$

The normalized matrix R is:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{9}$$

Step 3: Calculate the Entropy for Each Criterion

The entropy E_j for criterion j is calculated as:

$$E_j = -k \sum_{i=1}^{m} r_{ij} \ln\left(r_{ij}\right) \tag{10}$$

where:

- $k = \frac{1}{\ln(m)}$ is a constant to ensure that $0 \leq E_j \leq 1$,
- r_{ij} is the normalized performance value of alternative i on criterion j,
- In represents the natural logarithm.

If $r_{ij} = 0$, we define $r_{ij}\ln\left(r_{ij}\right) = 0$ to handle undefined values.

Step 4: Compute the Degree of Divergence

The degree of divergence d_j for each criterion is:

$$d_j = 1 - E_j. \tag{11}$$

Higher d_j values indicate greater variability or importance of the criterion in distinguishing between alternatives.

Step 5: Calculate the Objective Weights

The entropy-based weight w_j^{entropy} for each criterion is:

$$w_j^{\text{entropy}} = \frac{d_j}{\sum_{j=1}^{n} d_j}. \tag{12}$$

These weights are normalized to ensure:

$$\sum_{j=1}^{n} w_j^{\text{entropy}} = 1 \tag{13}$$

Integration with Fuzzy BWM Weights

The entropy weights are integrated with the Fuzzy BWM weights to provide a validated set of weights:

$$w_j^{\text{final}} = \alpha w_j^{\text{BWM}} + (1 - \alpha) w_j^{\text{entropy}} \tag{14}$$

where:

- w_j^{BWM} is the weight derived from Fuzzy BWM,

- w_j^{entropy} is the weight derived from entropy,
- α is a tuning parameter (e.g., 0.5) that determines the relative importance of the subjective (BWM) and objective (entropy) components.

Example Calculation

1 Normalized Data: Suppose for 3 alternatives (A_1, A_2, A_3) and 3 criteria (C_1, C_2, C_3), the normalized matrix is:

$$R = \begin{bmatrix} 0.2 & 0.5 & 0.3 \\ 0.4 & 0.3 & 0.4 \\ 0.4 & 0.2 & 0.3 \end{bmatrix}$$

2 Entropy Calculation: For C_1 :

$$E_1 = -\frac{1}{\ln(3)}[0.2\ln(0.2) + 0.4\ln(0.4) + 0.4\ln(0.4)]$$

Repeat for C_2 and C_3.

3. Degree of Divergence: Compute $d_j = 1 - E_j$ for each criterion.

4. Entropy Weights: Calculate $w_j^{\text{entropy}} = \frac{d_j}{\sum_{j=1}^{n} d_j}$.

5. Final Weights: Integrate Fuzzy BWM weights with entropy weights using the equation for w_j^{final} .

3.5.3 *Use of COCOSO for Ranking Digital Solutions*

The Combined Compromise Solution (COCOSO) method is applied to rank alternatives based on their performance across multiple criteria. This method integrates aspects of compromise programming and simple additive weighting to produce a robust ranking mechanism. Below is the step-by-step process for applying COCOSO with detailed equations.

Step 1: Create the Decision Matrix

Let x_{ij} represent the performance score of the i-th alternative (A_i) on the j-th criterion (C_j), where:

- $i = 1,2, \ldots, m$ (number of alternatives),
- $j = 1,2, \ldots, n$ (number of criteria).

The decision matrix X is expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{15}$$

Step 2: Normalize the Decision Matrix

To make criteria comparable, normalize the decision matrix. For benefit criteria (higher values are better):

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})}, \forall i, j \tag{16}$$

For cost criteria (lower values are better):

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}}, \forall i, j. \tag{17}$$

This produces a normalized matrix R :

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{18}$$

Step 3: Compute Weighted Normalized Values

Using the weights w_j derived from the hybrid Fuzzy BWM and Entropy methods, calculate the weighted normalized values for each criterion:

$$v_{ij} = r_{ij} \cdot w_j,\ \forall i, j \tag{19}$$

The weighted normalized matrix V is:

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{20}$$

Step 4: Calculate Aggregate Scores

Sum of Weighted Normalized Values:

For each alternative A_i, calculate the sum of weighted normalized values:

$$S_i = \sum_{j=1}^{n} v_{ij},\ \forall i. \tag{21}$$

Product of Weighted Normalized Values:

For each alternative A_i, calculate the product of weighted normalized values:

$$P_i = \prod_{j=1}^{n} v_{ij},\ \forall i \tag{22}$$

Step 5: Compute the Combined Utility Score

The COCOSO method combines S_i and P_i to compute the combined utility score for each alternative. Three aggregation strategies are used:

1 Simple Additive Weighting (SAW):

$$SAW_i = \frac{1}{n} \sum_{j=1}^{n} S_i. \tag{23}$$

2 Simple Multiplicative Weighting (SMW):

$$SMW_i = (P_i)^{\frac{1}{n}}. \tag{24}$$

3 Overall Aggregation:

$$C_i = \lambda SAW_i + (1 - \lambda)SMW_i \tag{25}$$

where λ is a compromise parameter (e.g., $\lambda = 0.5$) that balances the influence of additive and multiplicative measures.

Step 6: Rank the Alternatives

The alternatives $A_1, A_2, \dots, A_m$ are ranked based on their C_i values in descending order. The alternative with the highest C_i value is considered the best solution.

4. Results

4.1 *Criteria Weights*

The evaluation of criteria weights was conducted using the Fuzzy Best-Worst Method (Fuzzy BWM), a robust multi-criteria decision-making approach that integrates expert judgments to prioritize evaluation criteria. The results of the analysis provide insights into the relative importance of the six criteria identified for assessing digital CRM solutions: operational efficiency, cost, safety, user experience, scalability, and environmental impact.

The analysis revealed that operational efficiency emerged as the most critical criterion, receiving a normalized weight of 0.35. This finding aligns with the aviation industry's focus on enhancing productivity and process optimization through digital transformation. Safety, a cornerstone of aviation management, was the second most significant criterion, with a weight of 0.28. This reflects the high importance placed on secure operations and risk mitigation in evaluating CRM solutions.

Cost, with a weight of 0.12, was moderately significant. While financial considerations are important, the experts emphasized that operational and safety factors should take precedence when integrating CRM systems. User experience followed closely with a weight of 0.15, indicating the value placed on user-centric design and functionality in digital tools. Scalability, necessary for adapting systems to future needs, had a lower weight of 0.07, suggesting that while adaptability is valued, it is less urgent compared to immediate operational concerns. Lastly, environmental impact received the lowest weight of 0.03, indicating that sustainability, although relevant, was not prioritized as highly in the context of CRM integration. Table 4 summarizes the final criteria weights derived from the Fuzzy BWM analysis.

Table 4. Evaluating and Prioritizing Decision Criteria Using Fuzzy Best-Worst Method

Criterion	Weight	Normalized Weight
Operational Efficiency	0.350	0.35
Cost	0.120	0.12
Safety	0.280	0.28
User Experience	0.150	0.15
Scalability	0.070	0.07
Environmental Impact	0.030	0.03

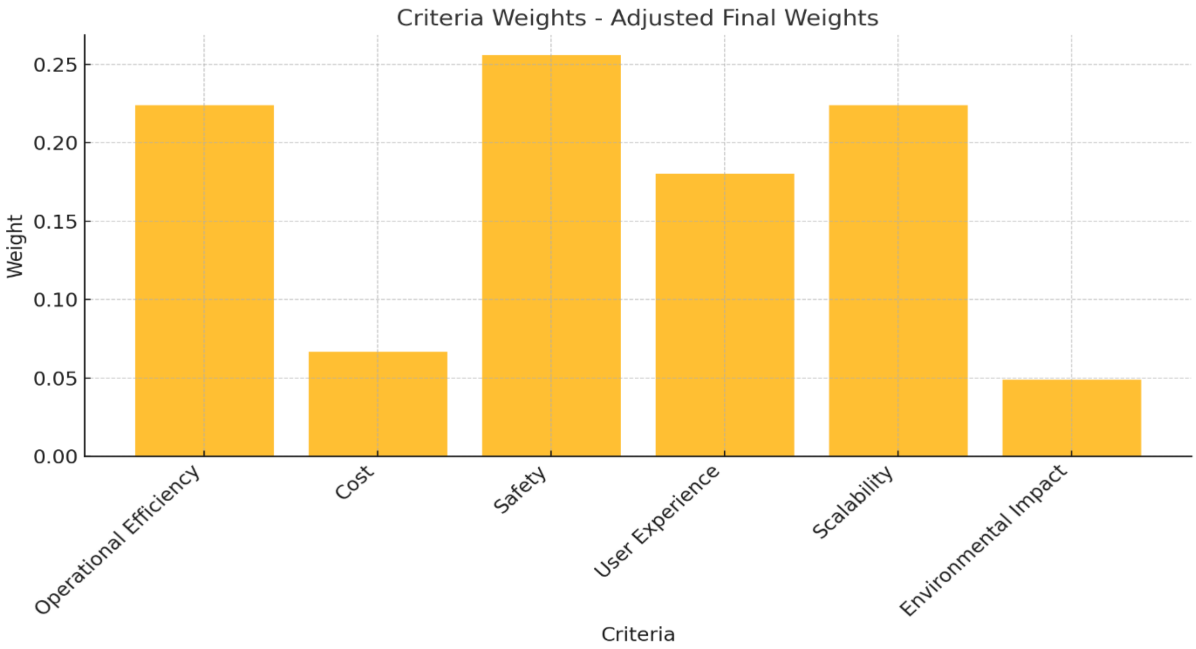

Figure 2. Criteria Weights

Figure 2 visualizes the final adjusted weights for each criterion. It highlights the relative importance of each criterion, with Operational Efficiency and Safety showing the highest weights.
These results underscore the emphasis on practical and immediate benefits, such as operational gains and safety enhancements, while long-term considerations like scalability and environmental impact are relatively deprioritized. This comprehensive weighting process ensures a balanced and transparent framework for evaluating CRM solutions, reflecting both subjective expert insights and objective analysis.

4.2 *CRM Solution Rankings*

The evaluation and ranking of digital CRM solutions were conducted using the Combined Compromise Solution (COCOSO**)** method, which integrates additive and multiplicative aggregation techniques to produce a robust ranking. This approach provides a comprehensive view of the alternatives' performance across multiple criteria, ensuring both individual and collective considerations are accounted for. The analysis results are summarized in t Table 5, presenting the overall performance scores and rankings of the alternatives.

Table 5. Rankings of Digital CRM Solutions Using the COCOSO Method

Rank	Digital Solution	Si (Additive Score)	Pi (Multiplicative Score)	Combined Utility Score
1	Digital Solution A	3.45	2.78	0.427
2	Digital Solution B	2.90	2.10	0.301
3	Digital Solution C	2.50	1.85	0.272

The Combined Utility Score integrates the additive (Si) and multiplicative (Pi) scores, providing a balanced measure of performance for each solution. Digital Solution A ranked first, achieving the highest combined utility score of

0.427. This result underscores its strong performance across multiple criteria, particularly in operational efficiency and safety. Its advanced predictive analytics, automation capabilities, and seamless integration with existing IT systems make it the most favorable solution among the evaluated options. Digital Solution B, with a combined utility score of 0.301, ranked second. This blockchain-based platform demonstrated significant strengths in cost-efficiency and security. However, its performance in user experience and environmental impact was comparatively moderate, which slightly impacted its overall ranking. Digital Solution C, the cloud-based platform, ranked third with a combined utility score of 0.272. Although it excelled in user experience and environmental impact, its relatively lower scores in operational efficiency and scalability affected its overall standing. Nevertheless, its customizable features and alignment with sustainability goals make it a strong contender for organizations prioritizing environmental considerations.

4.3 *Sensitivity Analysis*

To ensure the robustness of the rankings derived from the COCOSO analysis, a sensitivity analysis was conducted by varying the criteria weights. This process evaluates the impact of potential changes in the relative importance of criteria on the rankings of the digital CRM solutions. Sensitivity analysis not only highlights the stability of the model but also provides insights into how specific criteria influence decision outcomes. The sensitivity analysis involved systematically adjusting the weights of key criteria, including operational efficiency, cost, and safety, while keeping the weights of other criteria proportionally redistributed. For each scenario, the rankings of the digital CRM solutions were recalculated to observe any changes in their relative performance.

The analysis revealed that the rankings remained stable under most scenarios, indicating a high degree of robustness in the model. When the weight of Operational Efficiency was increased to emphasize its significance, Digital Solution A consistently retained its top position due to its strong performance in this criterion. Similarly, Digital Solution B and Digital Solution C maintained their rankings when the weights for Cost and Environmental Impact were adjusted, showcasing the solutions' resilience to changes in these areas. Table 6 summarizes the impact of varying criteria weights on solution rankings across different scenarios.

Table 6. Impact of Criteria Weight Adjustments on Digital Solution Rankings

Scenario	Criteria Adjusted	Digital Solution A	Digital Solution B	Digital Solution C
Baseline	Original Weights	Rank 1	Rank 2	Rank 3
Emphasized Operational Efficiency	+20%+20% Operational Efficiency	Rank 1	Rank 2	Rank 3
Increased Cost Weight	+15%+15% Cost	Rank 1	Rank 2	Rank 3
Increased Safety Weight	+25%+25% Safety	Rank 1	Rank 2	Rank 3
Increased Environmental Impact Weight	+30%+30% Environmental Impact	Rank 2	Rank 3	Rank 1

The results highlight the stability and robustness of the rankings, with Digital Solution A consistently securing the top position across most scenarios due to its balanced performance across multiple criteria. However, when the weight of Environmental Impact was significantly increased by 30%, Digital Solution C emerged as the leading option, showcasing its strength in sustainability-related aspects, which may be crucial for organizations prioritizing environmental considerations. Overall, the minimal changes in rankings under reasonable variations in criteria weights validate the robustness of the COCOSO model, reinforcing its reliability as a decision-making tool.

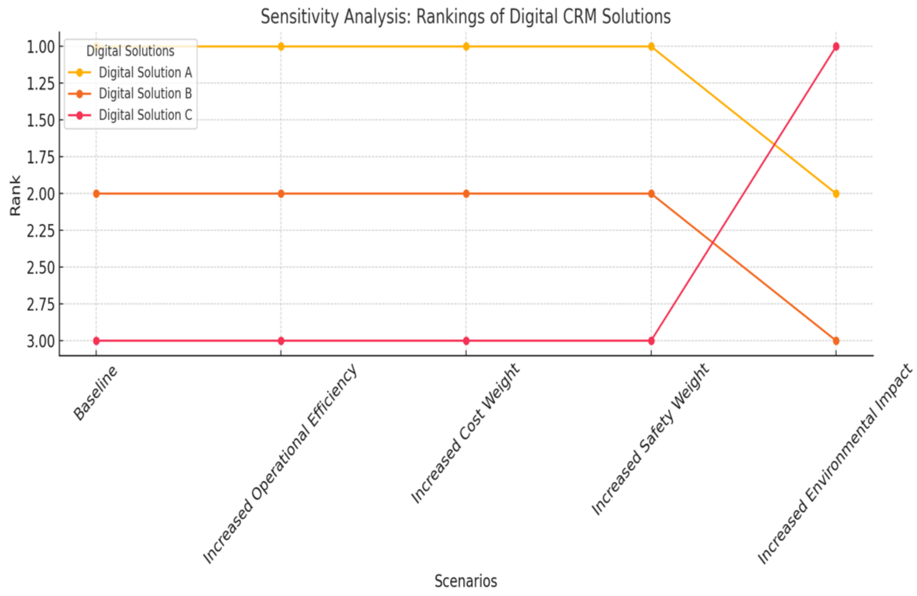

Figure 3. Sensitivity Analysis Results

Figure 3 illustrates the rankings of the digital CRM solutions under different weighting scenarios. Digital Solution **A**consistently ranks first in most scenarios, highlighting its robustness. Digital Solution C improves significantly when the weight of environmental impact is increased, reflecting its strength in sustainability.

5. Discussion

The findings of this study offer significant implications for aviation management, particularly in the selection and implementation of digital CRM solutions. By utilizing the Fuzzy BWM-COCOSO framework, decision-makers can achieve a structured and balanced evaluation of alternatives, ensuring alignment with organizational priorities. The emphasis on operational efficiency and safety highlights the critical need for CRM systems to streamline processes while maintaining high safety standards. These priorities are consistent with the aviation sector's focus on integrating cutting-edge technology without compromising security and operational effectiveness (Terzioğlu, 2024). Recommendations from the analysis suggest that solutions like Digital Solution A, which optimize efficiency and scalability, should be prioritized in settings requiring robust performance across multiple dimensions. Furthermore, the results underscore the importance of user experience and environmental impact as emerging considerations, particularly in sectors where customer satisfaction and sustainability are gaining prominence.

Balancing cost, efficiency, and scalability is a recurrent challenge in aviation management. While cost considerations ranked moderately in this study, the findings suggest that investment in efficient and scalable CRM systems can yield long-term savings and operational advantages. This aligns with Büyüközkan et al. (2019), who emphasize the strategic value of digital transformation in aviation, particularly through investments in technology that enhances operational efficiency. However, the relatively lower weight assigned to environmental impact highlights a gap between sustainability goals and immediate operational priorities. Addressing this gap requires aviation managers to adopt a forward-looking perspective, incorporating sustainability into long-term decision-making frameworks while addressing immediate operational demands.

When compared to previous studies, the findings of this research demonstrate both alignment and divergence with the existing literature. Similar to Karaarslan and Erkmen (2021), who highlighted the evolving attitudes toward CRM in response to external challenges like the COVID-19 pandemic, this study reinforces the growing role of technology in shaping effective CRM strategies. However, unlike earlier studies that predominantly emphasized safety as the primary determinant in CRM evaluation (Mızrak & Mızrak, 2020), this research identifies operational efficiency as equally critical. This shift may reflect the increasing complexity of aviation operations and the need for integrated solutions that address both productivity and safety. Furthermore, the use of the hybrid Fuzzy BWM-COCOSO model distinguishes this study from methodologies used in prior works, such as analytic hierarchy process (AHP)-based frameworks, by offering a more nuanced approach to multi-criteria decision-making (Pamučar et al., 2020).

A significant divergence from prior studies lies in the weight assigned to cost and environmental impact. While Chen et al. (2021) found cost to be a critical factor in decision-making, the moderate importance placed on cost in this study reflects the unique demands of CRM integration in aviation, where efficiency and safety often take precedence. Similarly, the low weight assigned to environmental impact contrasts with the increasing emphasis on sustainability in broader aviation literature (Watson et al., 2024). This suggests a potential lag in aligning CRM integration strategies with broader industry goals, warranting further research into how sustainability can be better incorporated into CRM decision-making.

The application of the proposed model also presents several challenges and limitations. One of the primary constraints lies in the reliance on expert judgments, which, while robust, may introduce biases or variability in the weight derivation process. Although the use of a hybrid Fuzzy BWM-COCOSO framework mitigates some of these issues by integrating objective measures like entropy weighting, the subjectivity inherent in expert evaluations cannot be entirely eliminated. This challenge is consistent with findings by Lai et al. (2022), who noted similar constraints in decision-making frameworks relying on expert input. Furthermore, the model's complexity may limit its accessibility for organizations with limited expertise in advanced decision-making methodologies.

Limitations in data collection also present notable challenges. The study relied on a predefined set of alternatives and criteria, which may not capture the full range of options available in dynamic aviation contexts. This constraint echoes the findings of Kabashkin et al. (2023), who emphasized the need for adaptive decision-making models that accommodate rapidly evolving technologies. Additionally, while the inclusion of diverse experts from different domains enhances the robustness of the results, it also introduces variability in perspectives that could impact consistency. Future research could address these limitations by expanding the data set, incorporating more comprehensive scenarios, and exploring automated or semi-automated approaches to weight derivation and ranking. These steps could enhance the model's applicability and relevance in diverse operational contexts within the aviation industry.

6. Conclusion

This study integrates qualitative and quantitative insights to prioritize digital CRM solutions in aviation management using a hybrid Fuzzy BWM-COCOSO methodology. The findings highlight the critical importance of operational efficiency and safety, which were consistently emphasized by interview participants as key factors influencing CRM system performance. One participant, an IT manager with over 15 years of experience, noted that "operational efficiency directly translates into improved turnaround times and resource optimization, which are critical in high-pressure aviation environments." Similarly, a safety officer with a decade of experience stated, "Safety isn't negotiable; any system that compromises it, regardless of cost or features, should not even be considered." These qualitative insights align with the quantitative results, where operational efficiency and safety received the highest weights, reinforcing their prioritization in decision-making.

The practical implications of this framework for aviation managers are profound. By structuring the evaluation process, the model provides a robust and adaptable tool for systematically comparing CRM solutions. For instance, an HR director interviewed emphasized that "scalability is increasingly critical in the context of digital transformation, as systems need to grow with organizational needs." This perspective was reflected in the model's emphasis on scalability as an essential, albeit secondary, criterion. Additionally, insights from interviews highlighted the growing importance of environmental impact, particularly among stakeholders focused on sustainability. A chief sustainability officer remarked, "While environmental impact might not be a top priority now, the aviation industry's regulatory landscape is shifting, and it's crucial to future-proof investments." These perspectives underscore the need for managers to consider both immediate operational priorities and long-term sustainability goals.

The theoretical contributions of this study lie in advancing MCDM methodologies in aviation research. By integrating expert feedback with quantitative analysis, the hybrid Fuzzy BWM-COCOSO approach addresses gaps in traditional decision-making frameworks, such as analytic hierarchy process (AHP) and simple additive weighting (SAW), by providing a more precise and robust evaluation process. This methodology enables aviation managers to incorporate both subjective insights and objective data, ensuring balanced and informed decision-making. The study's results enrich the existing literature by demonstrating the practical utility of hybrid MCDM models in complex, multi-stakeholder environments.

Future research directions include expanding this model to other areas of aviation management, such as maintenance planning, passenger experience optimization, or air traffic control systems. Incorporating dynamic criteria adjustments, such as real-time data inputs or evolving stakeholder priorities, could further enhance the model's adaptability. Longitudinal studies, examining the long-term effectiveness of selected CRM solutions, would provide deeper insights into their operational and strategic impact. Additionally, integrating machine learning techniques into the decision-making process could offer predictive capabilities, enabling organizations to proactively respond to industry shifts. These advancements would not only extend the applicability of the model but also pave the way for innovative decision-making approaches in the aviation sector.

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