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A comparative fuzzy strategic assessment framework for space mission selection at NASA

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ABSTRACT

Strategic decision-making in space mission selection is inherently complex, requiring a balance of multiple, often conflicting, quantitative and qualitative factors under uncertainty. This paper introduces a novel fuzzy analytical framework that extends the Strategic Assessment Model (SAM) by incorporating trapezoidal fuzzy numbers to evaluate mission alternatives systematically. By addressing the uncertainty inherent in space exploration planning, this model provides a structured approach to assessing internal, transactional, and contextual factors—marking the first application of such techniques in NASA's mission selection process. The framework's application to Mars, lunar, and solar system exploration missions demonstrates its ability to provide robust and data-driven insights. The findings reveal that solar system exploration consistently emerges as the most resilient option, achieving a superior Mission Selection Score across diverse scenarios. Comprehensive sensitivity analysis further underscores the framework's reliability, showing that solar system exploration remains the optimal choice in approximately 90 % of cases despite variations in uncertainty levels. This research significantly advances the field of strategic space mission assessment by offering a rigorous, adaptable decision-support tool for decision-makers. It enhances NASA's capability to navigate the complexities of mission planning, ensuring optimal allocation of resources in an era of increasing privatization and international collaboration in space exploration. The proposed fuzzy SAM approach establishes a new benchmark for multi-criteria decision-making under uncertainty, paving the way for future applications in space policy, mission prioritization, and beyond.

1. Introduction

Strategic decision-making has become a focal point of contemporary management research, with an extensive body of literature highlighting its significance. A search on the Web of Science for "strategic decision-making" yields >10,000 papers, revealing a growing volume of scholarly work and underscoring the increasing recognition of this area. This interest is driven by the need to understand how decision-maker perceptions shape the interactions between environmental factors, strategic decision-making, and organizational structure. This is particularly pertinent in space mission planning, where decisions have profound and far-reaching economic, (geo)political, and social implications. Despite its critical importance, the influence of management factors, contextual elements, and decision-specific characteristics on strategic decision-making processes in this fascinating area remains underexplored in research.

In various sectors, including portfolio management, infrastructure project investments, and supplier or location selection in production and logistics, strategic decision-making is commonly supported by multi-criteria decision-making (MCDM) techniques such as the Analytical Hierarchy Process (AHP), Best Worst Method (BWM), and Strategic Assessment Model (SAM); for examples, see Dhumras and Bajaj [1], Kermani et al. [2], and Wang et al. [3]. The most critical influential factors in space mission planning are related to the environment. The Strategic Assessment Model (SAM) developed by Tavana and Banerjee [4] has been applied to decompose complex strategic problems into manageable components, separating the decision-making environment into three categories:

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- *Internal Environment:* Factors influencing the organization's internal operations.
- *Transactional Environment:* Factors involving direct organizational interactions with reciprocal influences.
- *Contextual Environment:* External factors impacting the organization over which it has minimal control.

This categorization aligns well with the complex and multi-faceted nature of space mission planning, where objectives must be formulated and resources assessed in environments characterized by high uncertainty. SAM relies on objective data and expert judgments, providing a structured framework that supports consistent decision-making while preserving critical human insight. As space exploration transitions into the for-profit sector and becomes increasingly privatized, the complexity of strategic decision-making intensifies, requiring advanced methodologies to address inherent uncertainties and conflicting criteria. Factors influencing space mission planning span a broad spectrum, including technological feasibility, budgetary constraints, geopolitical considerations, and public interest.

Space mission planning often involves semi-structured or unstructured problems, where decision-makers face incomplete, imprecise, or ambiguous information due to rapidly changing conditions and external uncertainties. Traditional decision-making approaches often struggle to address these challenges, particularly the vagueness and imprecision of subjective judgments. Fuzzy set theory, introduced by Zadeh [5], offers a robust mathematical framework for handling such complexities. By utilizing linguistic variables and trapezoidal fuzzy numbers, decision-makers can systematically incorporate qualitative assessments alongside quantitative data, enabling robust evaluations even in the face of incomplete or ambiguous information.

The technical innovation of this study lies in developing a fuzzy analytical framework that enhances SAM to evaluate mission alternatives. This framework employs a seven-step process, integrating environmental scanning with fuzzy weights to calculate composite scores that measure the risks and benefits of each mission alternative. By introducing fuzzification into SAM, the model offers a robust tool for comparing strategic alternatives under uncertain conditions. The proposed model is applied to a real-world case study at NASA, focusing on evaluating Mars, lunar, and solar system exploration missions. This application highlights the framework's effectiveness in addressing the intricate complexities of space mission planning.

Additionally, a sensitivity analysis investigates the impact of varying degrees of vagueness in the weighting schemes of environmental factors, further demonstrating the robustness of the model across a wide range of scenarios. This study represents the first application of fuzzy theory to strategic space mission selection, providing a novel and valuable tool for decision-makers navigating the complexities of uncertain environments. By addressing gaps in existing methodologies, the study contributes to the broader field of strategic decision-making and offers actionable insights for future research and practical applications in space exploration.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature, emphasizing the novelty of this study. Section 3 introduces the preliminaries of fuzzy set theory and operations for trapezoidal fuzzy numbers. Section 4 details the proposed step-by-step procedure for evaluating space mission alternatives. Section 5 examines the model's application in a NASA mission selection case study. Section 6 concludes the paper and outlines directions for future research.

2. Related work

Our study touches upon strategic decision-making with definable alternatives in conjunction with relevant MCDM techniques and, most importantly, the context of space mission selection. Focusing on the application context and conducting a literature search in the "space mission" area reveals an overwhelming volume of existing research; for example, the Web of Science provides 1369 sources with this keyword. However, almost all the articles do not address the problem of space mission selection but rather deal with ethical or medical aspects, especially human-related social or psychological risks, or technological (technology selection, etc.), environmental, or political and public aspects of space missions; see, for example, Maharik and Fischhoff [6], Bertrand et al. [7], Szocik [8], Bursch et al. [9], Marquez et al. [10], and Tokudome et al. [11]. Fig. 1 illustrates the top twenty Web of Science categories in which the articles are primarily located and may reflect the abovementioned impression.

Several studies have applied MCDM techniques in space mission planning, including Tavana and Hatami-Marbini [12], Tavana et al. [13], and Tavana et al. [14]. Thousands of papers have explored MCDM methods in various domains (see Mardani et al. [15] and Sitorus et al.

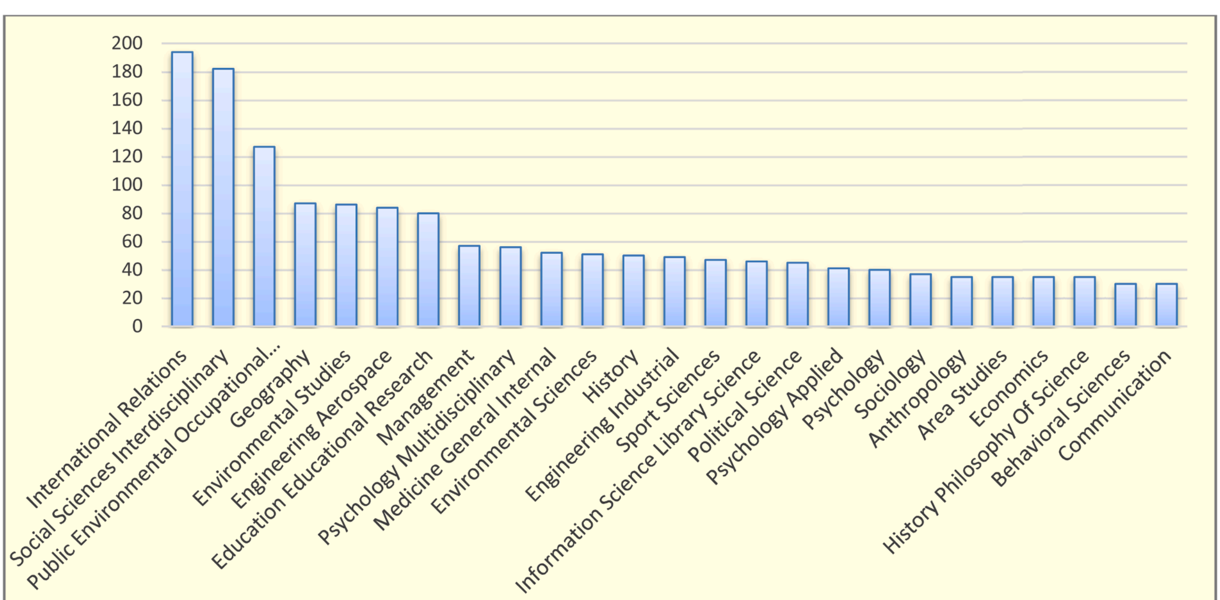

Fig. 1. Top twenty web of science categories.

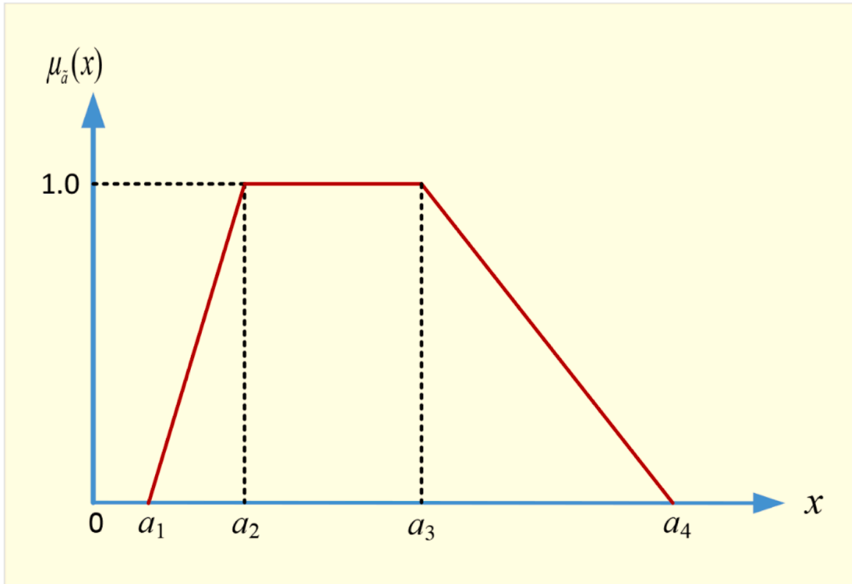

Fig. 2. Trapezoidal fuzzy numbers.

Table 1
Trapezoidal fuzzy numbers basic operations.

Opposite	$-(a_1, a_2, a_3, a_4) = (-b_4, -b_3, -b_2, -b_1)$	(2)
Inverse	$(a_1, a_2, a_3, a_4)^{-1} = (1/a_4, 1/a_3, 1/a_2, 1/a_1)$	(3)
Addition	$\tilde{a} \oplus \tilde{b} = (a_1, a_2, a_3, a_4) + (b_1, b_2, b_3, b_4) = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4)$	(4)
Subtraction	$\tilde{a} \ominus \tilde{b} = (a_1, a_2, a_3, a_4) - (b_1, b_2, b_3, b_4) = (a_1 - b_4, a_2 - b_3, a_3 - b_2, a_4 - b_1)$	(5)
Multiplication by scalar or non-fuzzy	$r \otimes \tilde{a} = r \otimes (a_1, a_2, a_3, a_4) = \begin{cases} (r \times a_1, r \times a_2, r \times a_3, r \times a_4), & r \geq 0 \\ (r \times a_4, r \times a_3, r \times a_2, r \times a_1), & r < 0 \end{cases}$	(6)
Multiplication by fuzzy	$\tilde{a} \otimes \tilde{b} = (a_1, a_2, a_3, a_4) \otimes (b_1, b_2, b_3, b_4) = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3, a_4 \times b_4)$	(7)
Division by fuzzy	$\tilde{a} \oslash \tilde{b} = (a_1, a_2, a_3, a_4) \oslash (b_1, b_2, b_3, b_4) = (a_1/b_4, a_2/b_3, a_3/b_2, a_4/b_1)$	(8)
Square root	$\sqrt{\tilde{a}} = (\sqrt{a_1}, \sqrt{a_2}, \sqrt{a_3}, \sqrt{a_4})$	(9)

[16] for an overview), but none have specifically addressed space mission selection under uncertainty. A study closely related to our work, Sawik [17], develops a deterministic multi-objective optimization model based on a weighted sum approach, integrating risk assessment, sustainability considerations, and supply chain dependencies in space mission planning. While this study offers a systematic optimization framework, it does not explicitly account for uncertainty or provide a real-world application, making it fundamentally different from our fuzzy SAM approach. In contrast, our model explicitly incorporates linguistic uncertainty and expert-driven assessments, ensuring a more adaptable and robust decision-making process for space mission selection at NASA.

Recent computational advancements have further enhanced decision-support models for space exploration. For instance, Wong et al. [18] explore how cybernetic intelligence systems are increasingly integrated into space exploration, enhancing decision-making through real-time data processing and adaptive learning in spacecraft operations. Geda and Tang [19] propose a hybrid quantum-classical computing framework, demonstrating how quantum computing can optimize mission scheduling, trajectory planning, and space system autonomy. Their research highlights the potential of quantum-enhanced decision-making for complex space missions. Other recent works have focused on specific mission applications:

- Rollock and Klaus [20] highlight how emergent technologies enable autonomous decision-making in deep-space missions, reducing Earth-based dependence.
- Sokol et al. [21] introduce the DIANA underwater analog mission, demonstrating the role of analog missions in refining crew selection and operations.
- Impresario et al. [22] present LICIACube, showcasing how small-scale autonomous systems contribute to planetary defense and deep-space exploration.
- Tokudome et al. [11] outline long-term strategies for space transportation, emphasizing system-level decision-making and multi-criteria evaluation.

Despite these advancements, strategic space mission selection remains largely unexplored. Recent studies have focused on AI-driven automation, quantum computing optimizations, and analog mission simulations; however, these approaches primarily enhance individual mission operations rather than providing a structured framework for selecting missions under uncertainty. The fuzzy SAM approach proposed in this study uniquely integrates expert-driven assessments, environmental scanning, and fuzzy logic, filling this critical gap in strategic space exploration decision-making. To address this gap, we extend the Strategic Assessment Model (SAM) developed by Tavana [4] by integrating fuzzy set theory, marking its first application in space mission selection.

Unlike previous studies applying MCDA methods such as AHP, TOPSIS, or hybrid frameworks to broader mission planning, the fuzzy SAM approach systematically integrates environmental scanning with fuzzy logic, allowing for the structured decomposition of internal, transactional, and contextual mission factors. This makes it uniquely suited for strategic space mission selection—an essential yet underexplored domain where uncertainty, conflicting criteria, and long-term planning constraints must be carefully managed. By integrating SAM with fuzzy logic, we introduce a powerful decision-support tool for evaluating competing space exploration alternatives while effectively managing high uncertainty and complex trade-offs. The following section outlines the essential principles of fuzzy theory, forming the foundation for our framework.

3. Fuzzy numbers and linguistic variables

As mentioned, space missions are subject to a high level of uncertainty that is often beyond the grasp of statistics. Zadeh [5] introduced fuzzy sets to depict and manage data and information characterized by non-statistical vagueness and uncertainties. They are designed to mathematically model ambiguities, providing formal tools to address the imprecision inherent in many problems. Fuzzy set theory utilizes linguistic terms to capture decision-makers' preferences, with fuzzy sets representing the subjectivity and imprecision involved in evaluation processes. Readers can refer to Zimmermann [23] for a comprehensive discussion.

While fuzzy literature often emphasizes triangular functions, which are a special case of trapezoidal ones, we adopt trapezoidal functions for their superior ability to capture the variability and ambiguity inherent in factors influencing space mission selection—such as internal, transactional, and contextual factors—that frequently overlap or lack sharp boundaries. Trapezoidal functions effectively address these complexities, avoiding the limitations of triangular functions' restrictive peak and offering greater tolerance for variations in expert judgments, a crucial aspect of multi-criteria decision-making. This section focuses on the fundamental definitions of fuzzy sets, fuzzy numbers, and linguistic variables, with an emphasis on trapezoidal functions, as outlined by Buckley [24], Kaufmann and Gupta [25], Negi [26], and Zadeh [27]. These fundamentals are provided in Definitions 1 through 5 and form the basis for our evaluation in the application section.

Definition 1. A fuzzy subset $\widetilde{a}$ in a universe of discourse X, is characterized by a membership function $\mu_{\widetilde{a}}(x)$ that maps each element x in X to a real number in the interval [0,1]. The function value $\mu_{\widetilde{a}}(x)$ is termed the grade of x membership in $\widetilde{a}$ [25].

Definition 2. The height of a fuzzy set refers to the maximum membership grade achieved by any element within that set. A fuzzy subset $\widetilde{a}$ in the universe of discourse X is normalized if its height is equal to 1 [28].

Definition 3. A positive trapezoidal fuzzy number (PTFN) $\widetilde{a}$ can be defined by the four-tuple $\widetilde{a} = (a_1, a_2, a_3, a_4)$. The membership function $\mu_{\widetilde{a}}(x)$, as shown in Fig. 2, is defined by Eq. (1) [25]:

$$\mu_{\widetilde{a}}(x) = \begin{cases} 0, \ x \le a_1 \\ \dfrac{(x - a_1)}{(a_2 - a_1)}, \ x \in (a_1, \ a_2) \\ 1, \ x \in (a_2, \ a_3) \\ \dfrac{(a_4 - x)}{(a_4 - a_3)}, \ x \in (a_3, \ a_4) \\ 0, \ x \ge a_4 \end{cases} \tag{1}$$

For a trapezoidal fuzzy number $\widetilde{a} = (a_1,a_2,a_3,a_4)$, if $a_2 = a_3$, then $\widetilde{a}$ is referred to as a triangular fuzzy number. A non-fuzzy number r can be expressed as $(a_1 = r, a_2 = r, a_3 = r, a_4 = r)$ using the notation introduced. According to the extension principle of Dubois and Prade [29], the fuzzy sum $\oplus$ and fuzzy subtraction $\ominus$ of any two trapezoidal fuzzy numbers result in trapezoidal fuzzy numbers. However, fuzzy multiplication $\otimes$ only yields approximately a trapezoidal fuzzy number.

For any two trapezoidal fuzzy numbers, $\widetilde{a} = (a_1, a_2, a_3, a_4)$ and $\widetilde{b} = (b_1, b_2, b_3, b_4)$, with $a_1, a_2, a_3, a_4, \ b_1, b_2, b_3, b_4 > 0$, and a positive real number r, key operations involving the fuzzy numbers $\widetilde{a}$ and $\widetilde{b}$ are summarized in Table 1.

Definition 4. If a matrix $\widetilde{A}$ contains at least one component, which is a fuzzy number. It is called a fuzzy matrix [24].

Definition 5. The assignment of a real value to a fuzzy number is called defuzzification.

The process of defuzzification, as roughly indicated by Definition 5, can take various forms; however, the most commonly used defuzzification technique is based on computing the centroid. Defuzzifying a trapezoidal fuzzy number using the centroid method involves calculating the weighted average of the fuzzy number's membership function using integration. The centroid provides a crisp value that represents the center of gravity of the fuzzy number's membership function. For trapezoidal fuzzy numbers $\widetilde{a} = (a_1,a_2,a_3,a_4)$, the centroid value is [30]:

$$G(\widetilde{a}) = \frac{\int_{-\infty}^{\infty} x \cdot \mu_{\widetilde{a}}(x) dx}{\int_{-\infty}^{\infty} \mu_{\widetilde{a}}(x) dx} = \frac{1}{4}(a_1, a_2, a_3, a_4) \tag{10}$$

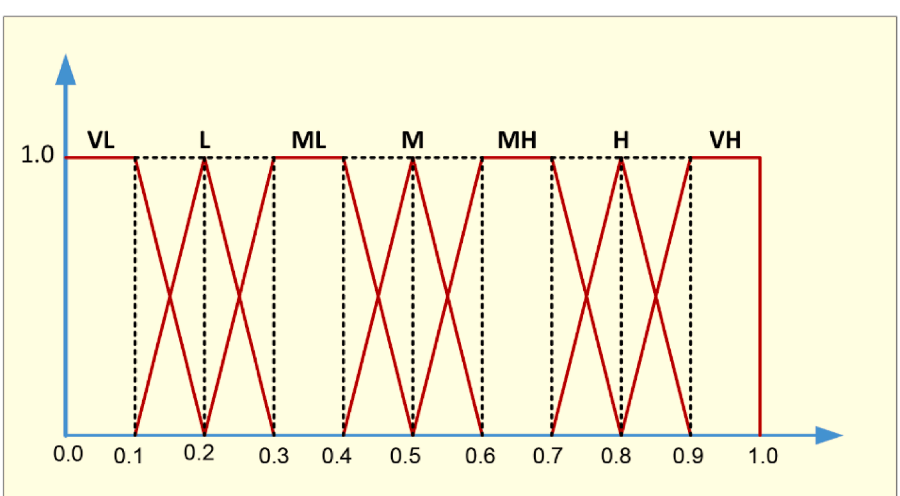

Fig. 3. The membership function of the importance weights.

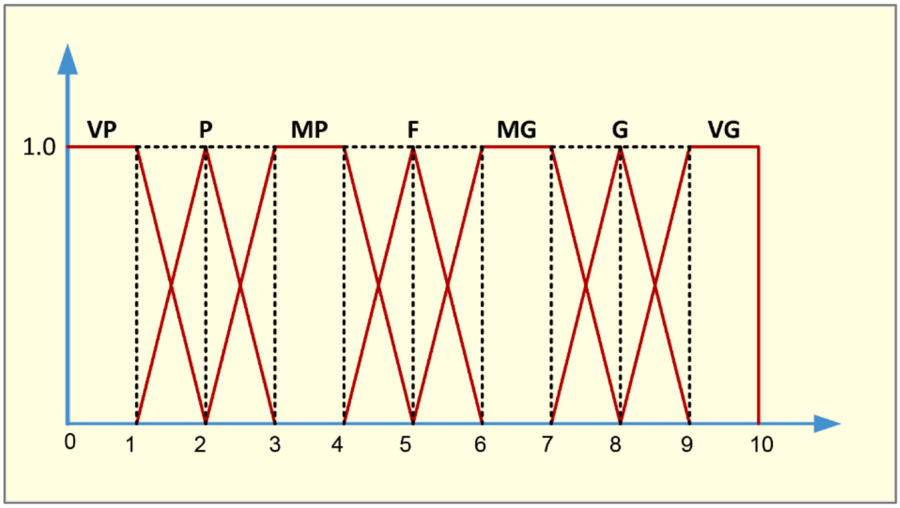

Fig. 4. The membership function of the performance scores.

Table 2
Symbolic representation in the fuzzy model.

	Mission selection score per unit of risk $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{V}_m$	Total mission selection score of mission alternative m $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{S}_m$	The standard deviation of mission alternative m $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{U}_m$	Total opportunity value of mission alternative m $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{T}_m$	Total threat value of mission alternative m $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{V}^u_m$	Variance of mission alternative m for opportunities $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{V}^t_m$	Variance of mission alternative m for threats $(m = 1,\ 2,\ \ldots,q)$
$\widetilde{W}^u_i$	Importance weight of the environmental layer i $(i = 1,\ 2,\ 3)$ for opportunities
$\widetilde{W}^t_i$	Importance weight of the environmental layer i $(i = 1,\ 2,\ 3)$ for threats
$\widetilde{R}^u_{ij}$	Importance weight of opportunity j in the environment i $(i = 1,\ 2,\ 3;\ j = 1,2,\ldots,N^u_i)$
$\widetilde{R}^t_{ij}$	Importance weight of threat j in the environment i $(i = 1,\ 2,\ 3;\ j = 1,2,\cdots,N^t_i)$
$\widetilde{P}^{u,m}_{ij}$	Performance score of mission alternative m for opportunity j in the environment i $(m = 1,\ 2,\ \ldots,q;\ i = 1,\ 2,\ 3;\ j = 1,2,\ldots,N^u_i)$
$\widetilde{P}^{t,m}_{ij}$	Performance score of mission alternative m for threat j in the environment i $(m = 1,\ 2,\ \cdots,q;\ i = 1,\ 2,\ 3;\ j = 1,2,\cdots,N^t_i)$
N^u_i	Number of opportunities in the environment i $(i = 1,\ 2,\ 3)$
N^t_i	Number of threats in the environment i $(i = 1,\ 2,\ 3)$

This allows for the following inference: Let $\widetilde{a} = (a_1, a_2, a_3, a_4)$ and $\widetilde{b} = (b_1, b_2, b_3, b_4)$ be two trapezoidal fuzzy numbers, then it holds: If we have $\widetilde{a} \geq \widetilde{b}$ $(component - wise)$, then $G(\widetilde{a}) \geq G(\widetilde{b})$.

4. The fuzzy SAM approach

The strategic decision-making environment includes all critical factors, both internal and external to an organization, that need to be considered throughout the strategic planning process. Environmental scanning is used to gather relevant information to understand this environment better. As mentioned in the introduction and as proposed in SAM, we categorize the environment into three main classes, which are then assessed using fuzzy theory: (1) Internal Environment, which consists of controllable factors within the organization; (2) Transactional Environment; which involves factors that interact with the organization and are partially controllable; and (3) Contextual Environment, which encompasses factors that indirectly affect the organization and are uncontrollable. The following section elaborates on the stages of our seven-step procedure in greater detail.

4.1. The seven stages of fuzzy SAM

Our seven-step approach methodically assesses various space mission strategies by quantifying their value and associated space mission risk. The space mission value indicates how favorable an option is, while the space mission risk assesses the likelihood of failing to achieve the anticipated benefits. Further details on calculating these elements will be provided in the subsequent section. The seven stages following the identification of strategic options at NASA, which consist of three different exploration strategies—Mars, lunar, or solar system exploration—are:

(1) Identify options, opportunities, and threats within each environment
(2) Define environment-related fuzzy weights.
(3) Define fuzzy weights related to opportunities and threats.
(4) Specify fuzzy scores associated with the opportunities and threats
(5) Calculate the fuzzy space mission value for each mission alternative
(6) Calculate the fuzzy space mission risk for each mission alternative
(7) Evaluate potential strategy

Each of these steps is described below.

(1) Identify options, opportunities, and threats within each environment

Once we have defined our options, it is essential to identify all opportunities and threats related to the problem within each of the three environments. These opportunities and threats establish a framework for evaluating the potential outcomes of the mission alternatives, or more precisely, the strategies, by focusing on problem-specific opportunities and threats rather than general possibilities. The internal environment includes controllable factors that present internal opportunities and threats. Stevenson [31] provides an extensive list of possible opportunities and threats applicable to any organization. Here, the transactional environment encompasses opportunities and threats related to competitors, customers, regulatory bodies, labor markets, creditors, and suppliers, which are primarily semi-controllable. Finally, the contextual environment comprises uncontrollable factors, including international, economic, political, legal, social, cultural, and demographic influences.

(2) Define environment-related fuzzy weights.

In the second step, we need to specify the subjective weights that reflect the relative significance of the internal, transactional, and contextual environments relevant to our strategic decision problem. This paper treats these importance weights as linguistic variables. Since linguistic evaluations are approximations of the decision-makers' subjective judgments, linear trapezoidal membership functions can effectively capture the ambiguity inherent in these assessments [32–34]. The trapezoidal fuzzy numbers corresponding to linguistic variables are displayed in Fig. 3, where, for example, the trapezoidal fuzzy number for the linguistic term "moderately high (MH)" is specified by the boundaries (0.5, 0.6, 0.7, 0.8).

(3) Define fuzzy weights related to opportunities and threats.

Once we identify the opportunities and threats within each environment and specify the environment-related fuzzy weights, we assign fuzzy weights to each opportunity and threat using the same linguistic variables as in Step (1) (see Fig. 3).

(4) Specify fuzzy scores associated with the opportunities and threats

Linguistic variables provide a flexible and intuitive way to capture human perceptions and assessments. The linguistic variables we employ to determine the performance scores for each opportunity and threat in our evaluation include: "Very Poor (VP)," "Poor (P)," "Moderately Poor (MP)," "Fair (F)," "Moderately Good (MG)," "Good (G)," and "Very Good (VG)." These variables represent a spectrum of evaluation, ranging from the lowest level of satisfaction or performance (Very Poor) to the highest (Very Good). To effectively utilize these linguistic variables, we convert them into trapezoidal fuzzy numbers, depicted in Fig. 4.

(5) Calculate the fuzzy space mission value for each mission alternative

To determine each mission alternative's fuzzy space mission value, we employ a fuzzy algebraic model provided in the next section. A mission alternative's value reflects its overall attractiveness, calculated by subtracting its fuzzy threat value from its fuzzy opportunity value. These values are determined by summing the products of the fuzzy weights of each environmental type, the fuzzy weights of each fuzzy performance score within that environment.

(6) Calculate the fuzzy space mission risk for each mission alternative

To evaluate each mission alternative's fuzzy space mission risk, apply the fuzzy algebraic model described in the next section. This risk assessment considers the variation in the fuzzy weights and the fuzzy performance scores assigned to each factor within an environment. Broader boundaries of the space mission risk fuzzy number suggest a higher risk of not achieving the anticipated benefits of the mission alternative.

(7) Evaluate potential strategy

To evaluate each mission alternative, calculate its space mission value per unit of risk by dividing the fuzzy space mission value by the fuzzy space mission risk. Afterward, we defuzzify them to obtain a crisp Mission Selection Score. A higher space mission value enhances desirability, while greater space mission risk reduces it. Therefore, the mission alternative with the highest Mission Selection Score is preferred if the decision maker is risk-neutral. A utility function can be employed to determine the most suitable mission alternative for decision-makers who are not risk-neutral. The following section presents our model's weights, probabilities, and values.

4.2. Development of the fuzzy algebraic model

The algebraic fuzzy model includes many symbols, shown in Table 2; the tilde on the respective symbols indicates the use of fuzzy numbers.

The final decision is based on the defuzzified values of $\widetilde{E}_m$ for the three environments and mission alternatives. To determine the most attractive mission alternative, we aim to maximize the defuzzified value of the $\widetilde{E}_m$—the Mission Selection Score. A higher Mission Selection Score indicates a more desirable mission alternative; see Eq. (10) and the corresponding if-then statement for this inference. A mission alternative is considered acceptable only if its opportunity value exceeds its threat value, according to the following equations:

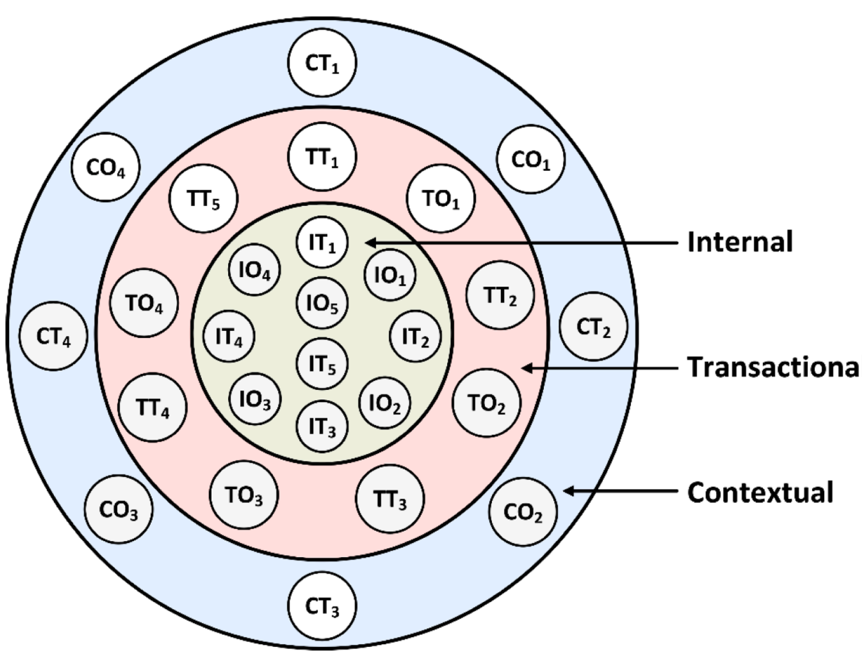

Fig. 5. Environmental layers and factors.

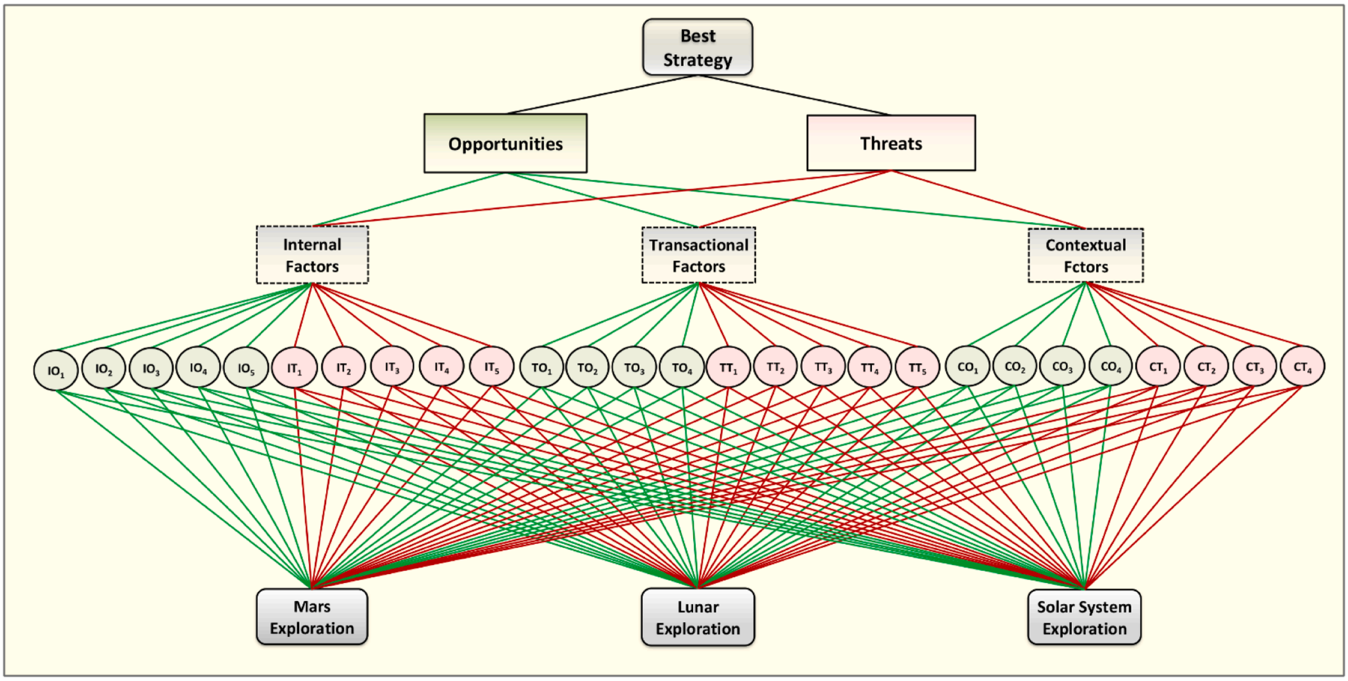

Fig. 6. Hierarchical model of fuzzy space mission assessment.

Table 3
Linguistic variables for importance weights and fuzzy numbers.

Linguistic variable	Fuzzy number
Very Low (VL)	(0,0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Moderately Low (ML)	(0.2, 0.3, 0.4, 0.5)
Moderate (M)	(0.4, 0.5, 0.5, 0.6)
Moderately High (MH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.8, 0.9)
Very High (VH)	(0.8, 0.9, 1, 1)

Table 4
Linguistic variables for performance scores and fuzzy numbers.

Linguistic variable	Fuzzy number
Very Poor (VP)	(0,0, 1, 2)
Poor (P)	(1,2, 2, 3)
Moderately Poor (MP)	(2,3, 4, 5)
Fair (F)	(4,5, 5, 6)
Moderately Good (MG)	(5,6, 7, 8)
Good (G)	(7,8, 8, 9)
Very Good (VG)	(8,9, 10, 10)

$$\widetilde{U}_m = \sum_{i=1}^{3} \widetilde{W}_i^u \otimes \left(\sum_{j=1}^{N_i^u} \widetilde{R}_{ij}^u \otimes \widetilde{P}_{ij}^{u,m} \right) \tag{11}$$

$$\widetilde{T}_m = \sum_{i=1}^{3} \widetilde{W}_i^t \otimes \left(\sum_{j=1}^{N_i^t} \widetilde{R}_{ij}^t \otimes \widetilde{P}_{ij}^{t,m} \right) \tag{12}$$

$$\widetilde{V}_m^u = \sum_{i=1}^{3} \widetilde{W}_i^u \otimes \left(\sum_{j=1}^{N_i^u} \left[\left(\widetilde{P}_{ij}^{u,m} \ominus \widetilde{U}_m \right)^2 \otimes \widetilde{R}_{ij}^u \right] \right) \tag{13}$$

$$\widetilde{V}_m^t = \sum_{i=1}^{3} \widetilde{W}_i^t \otimes \left(\sum_{j=1}^{N_i^t} \left[\left(\widetilde{P}_{ij}^{u,m} \ominus \widetilde{T}_m \right)^2 \otimes \widetilde{R}_{ij}^t \right] \right) \tag{14}$$

$$\widetilde{S}_m = \sqrt{\widetilde{V}_m^u \oplus \widetilde{V}_m^t} \tag{15}$$

$$\widetilde{V}_m = \widetilde{U}_m \ominus \widetilde{T}_m \tag{16}$$

$$\widetilde{E}_m = \widetilde{V}_m \oslash \widetilde{S}_m \tag{17}$$

$$\widetilde{P}_{ij}^{u,m} \geq 0 \ \forall \ i, j, m \tag{18}$$

$$\widetilde{P}_{ij}^{t,m} \geq 0 \ \forall \ i, j, m \tag{19}$$

The above equations are generally straightforward, building upon the foundational explanations provided in Section 3. Eq. (11) calculates the fuzzy opportunity value by aggregating the weighted opportunities (within the parentheses) across the internal, transactional, and contextual environments. Each environmental layer is weighted by $\widetilde{W}_i^u$ for the specific mission alternative *m*. The functioning of Eq. (12) is analogous to Eq. (11), but it calculates the fuzzy threat value instead of the fuzzy opportunity value. Eq. (13) follows the classical variance definition translated into fuzzy set theory and measures the variability of the opportunity scores $\widetilde{P}_{ij}^{u,m}$ around the aggregate opportunity value $\widetilde{U}_m$; similarly, Eq. (14) applies this approach to the threat scores $\widetilde{P}_{ij}^{t,m}$ around the aggregate threat value $\widetilde{T}_m$. Eq. (15) determines the standard deviation of each mission alternative, while Eq. (16) calculates the net fuzzy value as the difference between the aggregate opportunity value and the aggregate threat value. Finally, Eq. (17) relates the net fuzzy value to the standard deviation, representing a fuzzy-based return-to-risk ratio. However, particular attention is required for Eqs. (13, 14, 16), and (17), as they involve operations with fuzzy numbers. In Eqs. (13, 14, 16), and (17), we need to pay attention to the order of the fuzzy boundaries during subtraction and division—see again Table 1 in Section 3. Moreover, in Eqs. (13) and (14), if the lower boundaries become negative, we must ensure that squaring does not cause the lower boundaries to exceed the upper ones. The next section develops the above equations progressively in the context of space mission planning at NASA.

Table 5
Initial project matrix with weights and scores for opportunities.

ID	Opportunities	Environmental weight	Factor weight	Performance scores		
				Mars exploration	Lunar exploration	Solar system exploration
Internal Factors						
IO_1	Human Presence in the Universe	M	ML	P	MP	MP
IO_2	New Jobs		L	MP	MP	F
IO_3	Technology		ML	MP	F	F
IO_4	DOE Partnership		VL	MP	MP	MP
IO_5	Promotes Safety		L	F	F	F
Transactional Factors						
TO_1	Homeland Security	L	MH	P	P	P
TO_2	International Partnerships		VL	MP	F	F
TO_3	Commercial Participation		ML	MG	MG	MG
TO_4	Motivates youth in Science		L	F	F	F
Contextual Factors						
CO_1	Inspiration	ML	L	F	F	MG
CO_2	Increase Budgets		MH	F	F	F
CO_3	Improve Earth's Environment		VL	MG	P	F
CO_4	Growth in Economy		ML	F	F	F

Table 6
Initial project matrix with weights and scores for threats.

ID	Threats	Environmental weight	Factor weight	Performance scores		
				Mars exploration	Lunar exploration	Solar system exploration
Internal Factors						
IT_1	Skilled Expert Shortage	VL	ML	F	MG	F
IT_2	High R&D Costs		L	MG	MG	MG
IT_3	Robotics Availability and Applicability		L	G	G	VG
IT_4	Long-Term Space Travel Effects		ML	G	G	G
IT_5	Dependency on Other Programs		VL	F	MG	F
Transactional Factors						
TT_1	Accident Possibilities	ML	ML	G	MG	MG
TT_2	Conflict with Whitehouse		L	G	G	G
TT_3	Lack of Congressional Support		L	F	F	F
TT_4	Injuries to Crew		M	G	F	F
TT_5	Adverse Environmental Impacts		L	P	P	P
Contextual Factors						
CT_1	Budget Cuts	M	M	MP	F	MP
CT_2	Weather Delays and Cancellations		L	G	G	G
CT_3	Lack of Measurable ROI		ML	MG	G	F
CT_4	Unfavorable Publicity and Media		VL	MP	P	F

Table 7
Translating linguistic fuzzy variables to crisp values for opportunities.

Opportunities	Environmental importance weights	Evaluation factor importance weight	Performance scores		
			Mars exploration	Lunar exploration	Solar system exploration
Internal Factors					
IO_1	(0.4,0.5,0.5,0.6)	(0.2,0.3,0.4,0.5)	(1,2,2,3)	(2,3,4,5)	(2,3,4,5)
IO_2		(0.1,0.2,0.2,0.3)	(2,3,4,5)	(2,3,4,5)	(4,5,5,6)
IO_3		(0.2,0.3,0.4,0.5)	(2,3,4,5)	(4,5,5,6)	(4,5,5,6)
IO_4		(0,0,0.1,0.2)	(2,3,4,5)	(2,3,4,5)	(2,3,4,5)
IO_5		(0.1,0.2,0.2,0.3)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)
Transactional Factors					
TO_1	(0.1, 0.2, 0.2, 0.3)	(0.5,0.6,0.7,0.8)	(1,2,2,3)	(1,2,2,3)	(1,2,2,3)
TO_2		(0,0,0.1,0.2)	(2,3,4,5)	(4,5,5,6)	(4,5,5,6)
TO_3		(0.2,0.3,0.4,0.5)	(5,6,7,8)	(5,6,7,8)	(5,6,7,8)
TO_4		(0.1,0.2,0.2,0.3)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)
Contextual Factors					
CO_1	(0.2, 0.3, 0.4, 0.5)	(0.1,0.2,0.2,0.3)	(4,5,5,6)	(4,5,5,6)	(5,6,7,8)
CO_2		(0.5,0.6,0.7,0.8)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)
CO_3		(0,0,0.1,0.2)	(5,6,7,8)	(1,2,2,3)	(4,5,5,6)
CO_4		(0.2,0.3,0.4,0.5)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)

5. Space mission selection at NASA

5.1. Application of fuzzy SAM

The 21st century is set to be a transformative period for both NASA and the world, especially as we confront emerging global political and resource challenges. NASA and the European Space Agency (ESA) are tackling new exploration obstacles, hoping their efforts might help address some of these issues. Building on research and projects from previous decades [35,20,18], NASA, in collaboration with international

Table 8
Translating linguistic fuzzy variables to crisp values for threats.

Threats	Environmental importance weights	Evaluation factor importance weight	Performance scores		
			Mars exploration	Lunar exploration	Solar system exploration
Internal Factors					
IT_1	(0,0,0.1,0.2)	(0.2,0.3,0.4,0.5)	(4,5,5,6)	(5,6,7,8)	(4,5,5,6)
IT_2		(0.1,0.2,0.2,0.3)	(5,6,7,8)	(5,6,7,8)	(5,6,7,8)
IT_3		(0.1,0.2,0.2,0.3)	(7,8,8,9)	(7,8,8,9)	(8,9,10,10)
IT_4		(0.2,0.3,0.4,0.5)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)
IT_5		(0,0,0.1,0.2)	(4,5,5,6)	(5,6,7,8)	(4,5,5,6)
Transactional Factors					
TT_1	(0.2, 0.3, 0.4, 0.5)	(0.2,0.3,0.4,0.5)	(7,8,8,9)	(5,6,7,8)	(5,6,7,8)
TT_2		(0.1,0.2,0.2,0.3)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)
TT_3		(0.1,0.2,0.2,0.3)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)
TT_4		(0.4,0.5,0.5,0.6)	(7,8,8,9)	(4,5,5,6)	(4,5,5,6)
TT_5		(0.1,0.2,0.2,0.3)	(1,2,2,3)	(1,2,2,3)	(1,2,2,3)
Contextual Factors					
CT_1	(0.4, 0.5, 0.5, 0.6)	(0.4,0.5,0.5,0.6)	(2,3,4,5)	(4,5,5,6)	(2,3,4,5)
CT_2		(0.1,0.2,0.2,0.3)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)
CT_3		(0.2,0.3,0.4,0.5)	(5,6,7,8)	(7,8,8,9)	(4,5,5,6)
CT_4		(0,0,0.1,0.2)	(2,3,4,5)	(1,2,2,3)	(4,5,5,6)

Table 9
Total weighted opportunity and threats value.

Opportunities	Performance scores		
	Mars exploration	Lunar exploration	Solar system exploration
Internal Factors			
IO_1	(0.2,0.6,0.8,1.5)	(0.4,0.9,1.6,2.5)	(0.4,0.9,1.6,2.5)
IO_2	(0.2,0.6,0.8, 1.5)	(0.2,0.6,0.8, 1.5)	(0.4,1,1,1.8)
IO_3	(0.4,0.9,1.6,2.5)	(0.8,1.5,2,3)	(0.8,1.5,2,3)
IO_4	(0,0,0.4,1)	(0,0,0.4,1)	(0,0,0.4,1)
IO_5	(0.4,1,1,1.8)	(0.4,1,1,1.8)	(0.4,1,1,1.8)
Transactional Factors			
TO_1	(0.5,1.2,1.4,2.4)	(0.5,1.2,1.4,2.4)	(0.5,1.2,1.4,2.4)
TO_2	(0,0,0.4,1)	(0,0,0.5,1.2)	(0,0,0.5,1.2)
TO_3	(1,1.8,2.8,4)	(1,1.8,2.8,4)	(1,1.8,2.8,4)
TO_4	(0.4,1,1,1.8)	(0.4,1,1,1.8)	(0.4,1,1,1.8)
Contextual Factors			
CO_1	(0.4,1,1,1.8)	(0.4,1,1,1.8)	(0.5,1.2,1.4,2.4)
CO_2	(2,3,3.5,4.8)	(2,3,3.5,4.8)	(2,3,3.5,4.8)
CO_3	(0,0,0.7,1.6)	(0,0,0.2,0.6)	(0,0,0.5,1.2)
CO_4	(0.8,1.5,2,3)	(0.8,1.5,2,3)	(0.8,1.5,2,3)
$\widetilde{U}_m = \sum_{i=1}^{3} \widetilde{W}_i^u \otimes \left(\sum_{j=1}^{N_i^u} \widetilde{R}_{ij}^u \otimes \widetilde{P}_{ij}^{u,m} \right)$	(1.31,4,6.3,13.34)	(1.55,4.45,6.72,13.8)	(1.65,4.71,7.1,14.58)
Internal Factors			
IT_1	(0.8,1.5,2,3)	(1,1.8,2.8,4)	(0.8,1.5,2,3)
IT_2	(0.5,1.2,1.4,2.4)	(0.5,1.2,1.4,2.4)	(0.5,1.2,1.4,2.4)
IT_3	(0.7,1.6,1.6,2.7)	(0.7,1.6,1.6,2.7)	(0.8,1.8,2,3)
IT_4	(1.4,2.4,3.2,4.5)	(1.4,2.4,3.2,4.5)	(1.4,2.4,3.2,4.5)
IT_5	(0,0,0.5,1.2)	(0,0,0.7,1.6)	(0,0,0.5,1.2)
Transactional Factors			
TT_1	(1.4,2.4,3.2,4.5)	(1,1.8,2.8,4)	(1,1.8,2.8,4)
TT_2	(0.7,1.6,1.6,2.7)	(0.7,1.6,1.6,2.7)	(0.7,1.6,1.6,2.7)
TT_3	(0.4,1,1,1.8)	(0.4,1,1,1.8)	(0.4,1,1,1.8)
TT_4	(2.8,4,4,5.4)	(1.6,2.5,2.5,3.6)	(1.6,2.5,2.5,3.6)
TT_5	(0.1,0.4,0.4,0.9)	(0.1,0.4,0.4,0.9)	(0.1,0.4,0.4,0.9)
Contextual Factors			
CT_1	(0.8,1.5,2,3)	(1.6,2.5,2.5,3.6)	(0.8,1.5,2,3)
CT_2	(0.7,1.6,1.6,2.7)	(0.7,1.6,1.6,2.7)	(0.7,1.6,1.6,2.7)
CT_3	(1,1.8,2.8,4)	(1.4,2.4,3.2,4.5)	(0.8,1.5,2,3)
CT_4	(0,0,0.4,1)	(0,0,0.2,0.6)	(0,0,0.5,1.2)
$\widetilde{T}_m = \sum_{i=1}^{3} \widetilde{W}_i^t \otimes \left(\sum_{j=1}^{N_i^t} \widetilde{R}_{ij}^t \otimes \widetilde{P}_{ij}^{t,m} \right)$	(2.08,5.27,8.35,16.16.83)	(2.24,5.44,8.04,16.38)	(1.68,4.49,7.28,15.26)

partners, is pushing forward with a diverse array of exciting research and exploration initiatives. At the same time, NASA's leaders are developing innovative space exploration, development, and utilization strategies, shaping a forward-looking vision for the future.

This application concerns three different NASA missions: the first involves exploring Mars, the second focuses on lunar exploration, and the third encompasses exploring the solar system. From the stakeholders' perspective, these options naturally involve different manifestations of the opportunities and threats they contain. As the first step of our seven-stage approach demands, Fig. 5 shows the three environmental layers and the opportunities and threats embedded within them.

Fig. 6 summarizes the hierarchical structure between the three options (Mars exploration, lunar exploration, solar system exploration) and the three environmental factors, along with the associated opportunities and threats.

Table 10
Commutations summary.

	Mars exploration	Lunar exploration	Solar system exploration
$\widetilde{V}_m^u$	(0.58, 5.14, 31.21, 277.83)	(0.23, 5.92, 29.61, 288.20)	(0.21, 6.11, 32.08, 312.88)
$\widetilde{V}_m^t$	(0.54, 7.25, 50.25, 341.77)	(0.16, 7.37, 39.97, 315.80)	(0.22, 7.54, 37.67, 287.98)
$\widetilde{S}_m$	(1.06, 3.52, 9.03, 24.89)	(0.62, 3.65, 8.34, 24.58)	(0.65, 3.69, 8.35, 24.51)
$\widetilde{E}_m$	(-0.62, -0.48, 0.29, 10.63)	(-0.60, -0.43, 0.35, 18.58)	(-0.55, -0.31, 0.71, 19.84)
Defuzzified $\widetilde{E}_m$	2.46	4.48	4.92
Ranking	3	2	1

The importance of weights and performance scores, represented as fuzzy numbers, was derived through expert judgment by leveraging the expertise of a panel of specialists experienced in space mission planning. The process utilized structured linguistic evaluations, where experts assigned importance levels to environmental factors and opportunity and threat variables using a seven-point linguistic scale: Very Low (VL), Low (L), Moderately Low (ML), Moderate (M), Moderately High (MH), High (H), and Very High (VH). These linguistic terms were chosen based on their widespread use in MCDM and fuzzy decision models. They provide an intuitive and interpretable way for experts to express subjective assessments, aligning with established methods in fuzzy decision-making and computing with words [36].

These linguistic evaluations were subsequently translated into trapezoidal fuzzy numbers, as outlined in Tables 3 through 8, ensuring a consistent mapping between qualitative expert opinions and

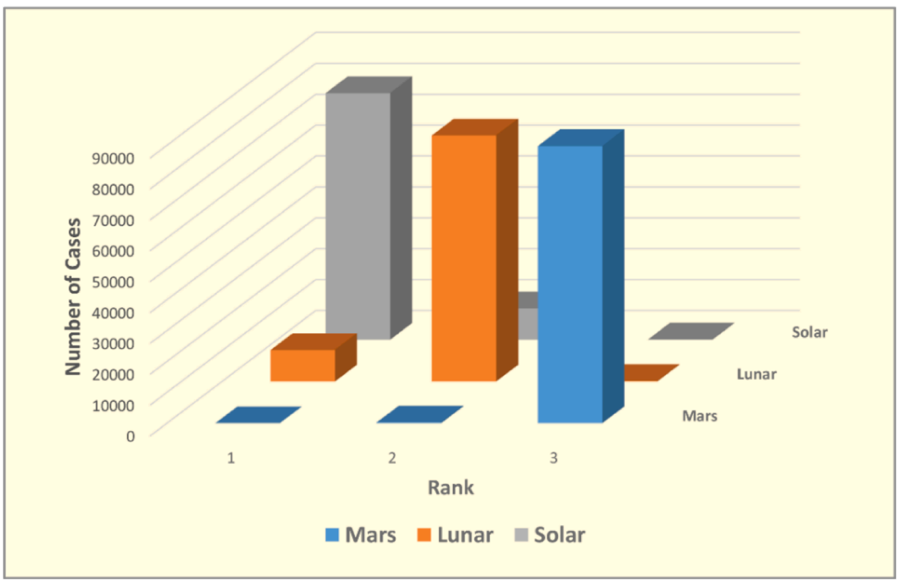

Fig. 7. Ranking counts for the three options.

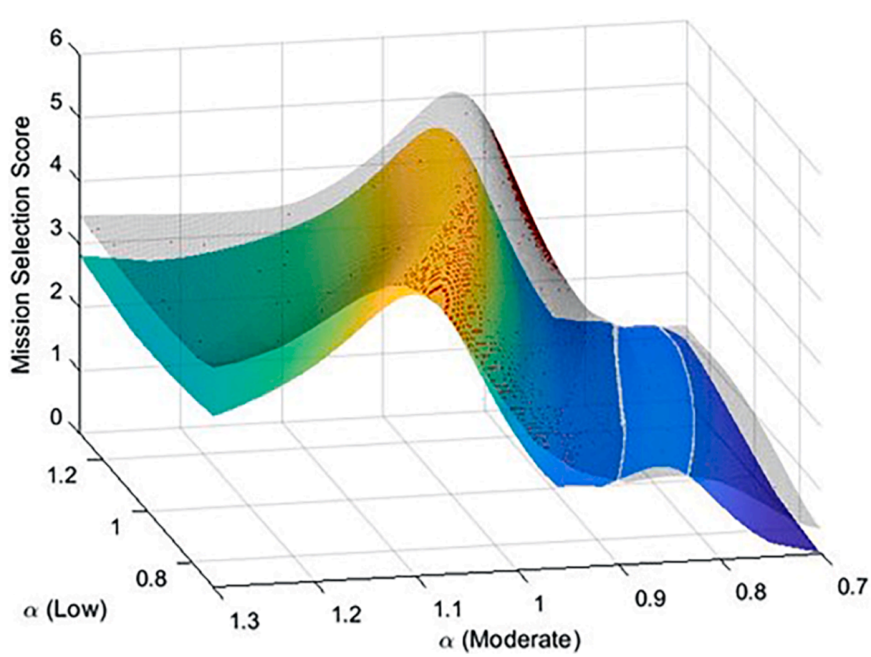

Fig. 8. 3D surfaces for the mission selection scores of Lunar and Solar.

quantitative fuzzy representations. A Delphi-based iterative process was implemented to reconcile differing expert opinions and achieve consensus. Initially, each expert provided independent assessments to minimize the influence of group dynamics. These assessments were aggregated, and areas of discrepancy were identified and addressed through iterative discussions, allowing experts to refine their evaluations based on collective insights. This approach aligns with modern fuzzy multiple-attribute decision-making frameworks, where linguistic terms may have different interpretations among decision-makers, requiring systematic aggregation methods [36].

This iterative process ensured that the final fuzzy numbers represented a balanced and inclusive perspective, effectively capturing the inherent uncertainty in subjective judgments while upholding methodological rigor. Specifically, Table 3 was used to generate environmental layer and factor weights, while Table 4 was used to determine the performance scores of the strategies. These tables illustrate the linguistic variables for importance weights and performance scores, along with their corresponding fuzzy numbers, and thus serve as guidelines for grading mission alternatives using linguistic variables.

As Table 5 demonstrates, for example, the performance score for Mars exploration in front of the technology factor includes the MP rate, which is moderately poor. The initial project matrices illustrate the complete grading of all mission alternatives for opportunities in Table 5 and threats in Table 6.

For each factor, the three mission alternatives—Mars exploration, lunar exploration, and solar system exploration—have been assigned fuzzy performance scores and weights, as shown in Tables 7 and 8. These scores and weights have been converted and translated from the linguistic variables in Tables 5 and 6. In other words, Tables 7 and 8 constitute the initial decision matrices used in the subsequent steps.

Mars generally performs equally or worse than Solar across opportunities and threats, establishing a near-dominance relationship between the two options. However, this dominance does not hold for specific factors, namely, one contextual opportunity (CO_3), one internal threat (IT_3), and one contextual threat (CT_4).

Table 9 shows the total weighted opportunity value ($\widetilde{U}_m$) and total weighted threat value ($\widetilde{T}_m$) for candidate mission alternatives identified according to Eqs. (11) and (12). The observed near-dominance relationship between Mars and Solar is also evident in the aggregated rankings derived from these values.

Next, we calculate the fuzzy variances for the opportunities and threats according to Eqs. (13) and (14). Flipping the vector of opportunity values to subtract it from the performance scores, as specified in Eq. (5), is essential. Since negative numbers may occur, we must ensure that the fuzzy boundaries are reordered after squaring. The results of these operations are shown in the following two equations:

$$\widetilde{V}_m^u = [(0.58,\ 5.14,\ 31.21,\ 277.83),\ (0.23,\ 5.92,\ 29.61,\ 288.20),\ (0.21,\ 6.11,\ 32.08,\ 312.88)]$$

$$\widetilde{V}_m^t = [(0.54,\ 7.25,\ 50.25,\ 341.77),\ (0.16,\ 7.37,\ 39.97,\ 315.80),\ (0.22,\ 7.54,\ 37.67,\ 287.98)]$$

The standard deviation of all opportunity and threat factors in all three environments for each mission alternative ($\widetilde{S}_m$) must be calculated according to Eq. (15):

$$\widetilde{S}_m = [(1.06,\ 3.52,\ 9.03,\ 24.89),\ (0.62,\ 3.65,\ 8.34,\ 24.58),\ (0.65,\ 3.69,\ 8.35,\ 24.51)]$$

Additionally, the total weighted space mission value assigned to each mission alternative is calculated by applying Eq. (16):

$$\widetilde{V}_m = [(-15.52,\ -4.35,\ 1.03,\ 11.26),(-14.83,\ -3.59,\ 1.28,\ 11.56),(-13.61,\ -2.57,\ 2.61,\ 12.90)]$$

Finally, the space mission value per unit of space mission risk is derived using Eq. (17), as shown in the following equation:

$$\widetilde{E}_m = [(-0.62,\ -0.48,\ 0.29,\ 10.63),(-0.60,\ -0.43,\ 0.35,\ 18.58),(-0.55,\ -0.31,\ 0.71,\ 19.84)]$$

Here again, it is essential to flip the components in $\widetilde{S}_m$ when performing the fuzzy division according to Eq. (8) to $\widetilde{V}_m$. These fuzzy trapezoidal numbers already indicate an order, as the pairwise comparison clearly shows that the components of one mission alternative are always greater than those of another. Hence, the order is Solar $\succ$ Lunar $\succ$ Mars, where, for example, Solar $\succ$ Lunar reflects the preference of Solar over Lunar. For completeness, we convert fuzzy trapezoidal numbers into real numbers using the defuzzification process, as shown in Eq. (10). This process yields the following Mission Selection Scores:

$$(Mars,\ Lunar,\ Solar) = (2.46,\ 4.48,\ 4.92)$$

Table 10 summarizes the results of our Fuzzy SAM procedure.

Overall, solar exploration is preferable to the other two mission alternatives based on the Mission Selection Score. This evaluation is, of course, significantly dependent on the assigned fuzzy numbers.

The fuzzy SAM framework is inherently flexible and adaptable, making it well-suited for a wide range of strategic decision-making scenarios, including evaluating entirely new missions. However, as with any MCDM technique, including new alternatives or additional information can influence the rankings due to the reliance on subjective expert opinions. If a new mission, such as an asteroid mining mission, were introduced, the existing framework and seven-step process could be applied without structural modifications. Nevertheless, the specific opportunities and threats would need to be carefully reviewed and potentially revised to reflect the unique characteristics of the new mission. Such a mission would likely involve distinct considerations, including the cost of mining operations, potential revenue from extracted materials, and additional environmental risks, such as debris generation or planetary defense concerns; for more details, see Probst et al. [37]. These factors, which are not particularly relevant to evaluating the current three alternatives, would need to be integrated into the analysis to ensure a fair, accurate, and comprehensive evaluation.

The following section conducts a sensitivity analysis regarding the fuzzy weights to strengthen the framework's robustness and validate the assessment. This analysis demonstrates the fuzzy SAM framework's adaptability and reliability for space mission selection scenarios.

5.2. Robustness of the fuzzy SAM results

This section examines the impact of changing the fuzzy weights, representing variations in the associated vagueness. To do this, we dilate the fuzzy weights given in Table 3. Therefore, let $\widetilde{a} = (a_1, a_2, a_3, a_4)$ be a trapezoidal fuzzy number, and $\alpha \in \mathrm{R}_+$ be a dilation parameter; the

Table 11
Defuzzifeid matrix of the opportunities.

Mission	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Mars	2	3.5	3.5	3.5	5	2	3.5	6.5	5	5	5	6.5	5
Lunar	3.5	3.5	5	3.5	5	2	5	6.5	5	5	5	2	5
Solar	3.5	5	5	3.5	5	2	5	6.5	5	6.5	5	5	5

Table 12
Defuzzifeid matrix of the threats.

Mission	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Mars	5	6.5	8	8	5	8	8	5	8	2	3.5	8	6.5	3.5
Lunar	6.5	6.5	8	8	6.5	6.5	8	5	5	2	5	8	8	2
Solar	5	6.5	9.25	8	5	6.5	8	5	5	2	3.5	8	5	5

Table 13
Importance weights of the opportunities.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
0.099	0.057	0.099	0.021	0.057	0.17	0.02	0.092	0.052	0.052	0.17	0.02	0.092

dilation then is applied as $\alpha \odot \widetilde{a} = \left(\frac{1}{\alpha}\cdot a_1, \frac{1}{\alpha}\cdot a_2, \alpha\cdot a_3, \alpha\cdot a_4\right)$. A parameter smaller than 1 represents a reduction in uncertainty, while a factor greater than 1 indicates an increase in uncertainty.

Examining Tables 5 and 6 more closely, it becomes apparent that the weight assessments only fall into one of the low or moderate categories. Therefore, we will now compress and expand the fuzzy numbers in these categories by varying α from 0.7 to 1.3 in increments of 0.002. More precisely, we increment over two α parameters, where the first one simultaneously changes the weights of the low categories and the second one changes the weights of the moderate categories. In total, we obtain 300 by 300 scenarios. Fig. 7 shows the number of rankings for the three mission alternatives. This indicates that solar energy is the preferred option in most cases (79,822 out of 90,000).

However, it also shows that Lunar is the best option in 10,177 out of 90,000 cases. We present Fig. 8 for a more detailed analysis of the risk dependencies of such cases.

It shows the Mission Selection Scores of the two alternatives, Lunar (surface with a color gradient) and Solar (surface shaded in light red), as a function of both dilation parameters. At first glance, the surface of the mission alternative Solar might always be above that of the mission alternative Lunar. However, the graph seems to be more erratic in the lower ranges of the dilation parameter for the moderate-weight categories.

Interestingly, when focusing on the Mission Selection Scores in the compression range of approximately 0.8 to 0.9, the Mission Selection Score for Lunar exceeds that of Solar. With greater certainty about the moderate category's environment- and factor-related weights, lunar exploration could also be viable. The outcomes depend heavily on the subjective performance scores and weights. For example, as shown in Table 9, Solar (weakly) dominates Lunar regarding opportunities; however, this dominance does not hold for threats, particularly in the internal and contextual factors. The compression of vagueness through weight adjustments leads to a better return-to-risk ratio within a small parameter range. Our analysis of 90,000 scenarios demonstrated that Solar outperforms Lunar in nearly 90 % of cases. The exceptions occur only when the certainty regarding the vagueness of the fuzzy numbers is compressed within a specific range, which contradicts the inherently ambiguous nature of such projects. This result underscores the robustness of the fuzzy SAM approach, as it consistently produces reliable rankings across most scenarios.

The Fuzzy SAM assessment is a good choice for merging space mission risks and space mission values. However, the next section will examine whether other methods support or contradict the evaluation of this method.

5.3. Comparison with other MCDM methods

This section presents the application of multi-criteria decision methods and a comparison with Fuzzy SAM. To begin with, the MCDM, the decision-making matrix, and the relevant criteria weights are required. We use the data in Tables 7 and 8 for opportunities and threats, respectively. First, the fuzzy trapezoidal data is converted to the corresponding real crisp values, enabling us to compose an initial decision matrix for MCDM tools.

It should be noted that we compute the ranking of the candidate strategies using Threats and Opportunity matrices, and then by using Euclidean distance, we measure a final (unique) score. For example, Table 11 shows the defuzzyfied performance scores of three mission alternatives based on the opportunities. Analogously, one can find the defuzzyfied performance scores in Table 12 regarding the threat variables. In addition, we need to generate both defuzzyfied global weighting schemes for the opportunities and threats given in Tables 13 and 14. First, we defuzzyfy the environment-related weights and then merge them with each defuzzyfied factor weight. Finally, we normalize both schemes so that each sum is one.

The next step is to apply several MCDM tools, check the results, and compare them to the Fuzzy SAM model. For this, we have chosen the Combined Compromise For Ideal Solution (CoCoFISo), Simple Additive Weighting (SAW), Weighted Aggregated Sum Product ASsessment (WASPAS), and Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) methods. Details on these methods

Table 14
Importance weights of the threats.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
0.099	0.057	0.057	0.099	0.021	0.08	0.046	0.046	0.115	0.046	0.148	0.059	0.104	0.022

Table 15
Initial matrix for MARCOS method.

Mission	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Anti-ideal	2.000	3.500	3.500	3.500	5.000	2.000	3.500	6.500	5.000	5.000	5.000	2.000	5.000
Mars	2.000	3.500	3.500	3.500	5.000	2.000	3.500	6.500	5.000	5.000	5.000	6.500	5.000
Lunar	3.500	3.500	5.000	3.500	5.000	2.000	5.000	6.500	5.000	5.000	5.000	2.000	5.000
Solar	3.500	5.000	5.000	3.500	5.000	2.000	5.000	6.500	5.000	6.500	5.000	5.000	5.000
Ideal	3.500	5.000	5.000	3.500	5.000	2.000	5.000	6.500	5.000	6.500	5.000	6.500	5.000

Table 16
Normalized matrix.

Mission	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Anti-ideal	0.571	0.700	0.700	1.000	1.000	1.000	0.700	1.000	1.000	0.769	1.000	0.308	1.000
Mars	0.571	0.700	0.700	1.000	1.000	1.000	0.700	1.000	1.000	0.769	1.000	1.000	1.000
Lunar	1.000	0.700	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.769	1.000	0.308	1.000
Solar	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.769	1.000
Ideal	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 17
Weighted normalized matrix.

Mission	C11	C12	C13	C14	C15	C16	C17	C21	C22	C23	C24	C25	C37	s_m^u
Anti-ideal	0.057	0.04	0.07	0.021	0.057	0.17	0.014	0.092	0.052	0.04	0.17	0.006	0.092	0.8791
Mars	0.057	0.04	0.07	0.021	0.057	0.17	0.014	0.092	0.052	0.04	0.17	0.02	0.092	0.8927
Lunar	0.099	0.04	0.099	0.021	0.057	0.17	0.02	0.092	0.052	0.04	0.17	0.006	0.092	0.9573
Solar	0.099	0.057	0.099	0.021	0.057	0.17	0.02	0.092	0.052	0.052	0.17	0.015	0.092	0.9955
Ideal	0.099	0.057	0.099	0.021	0.057	0.17	0.02	0.092	0.052	0.052	0.17	0.02	0.092	1

can be found in Podvezko [38], Stević et al. [39], and Rasoanaivo et al. [40].

We briefly outline the MARCOS method process for evaluating opportunities. The first step is to compose the decision matrix (which we have already obtained) and find the ideal and anti-ideal solutions by determining the column-wise maxima and minima, as shown in Table 15. The next step is to determine the normalized matrix by dividing the column entries by the column maximum, as shown in Table 16. To compute the weighted normalized matrix, we need to combine the data from Tables 13 and 16, and the results are shown in Table 17; the row sums are represented by s_m^u. Table 18 shows the intermediate ranking for the opportunities, where k_m^{u-} is the row sum s_m^u divided by the row sum of the anti-ideal, and k_m^{u+} is the row sum s_m^u divided by the row sum of the ideal. fk_m^{u-} and fk_m^{u+} are the normalized versions of k_m^{u-} and k_m^{u+}. Ultimately, we determine the final MARCOS opportunity scores $K_m^u = \frac{k_m^{u-}+k_m^{u+}}{1+\left(\left(1-fk_m^{u-}\right)/fk_m^{u-}\right)+\left(\left(1-fk_m^{u+}\right)/fk_m^{u+}\right)}$. As previously indicated, each method will produce two ranking scores (for threats and opportunities). By using an Euclidean distance measure, we obtain a unique and solid ranking for each alternative. In addition to MARCOS, we applied several other MCDM tools to compare rankings. Table 19 provides an overview of those rankings. Fig. 9 shows the comparative ranking of Mars, Lunar, and Solar strategies based on the Fuzzy SAM and MCDM methods.

All methods yield consistent evaluations for the space mission selection problem, underscoring the robustness of the Fuzzy SAM framework in this context. While new information may influence rankings, minor scores or weight adjustments can be quickly recalculated. However, if significant new factors emerge or priorities shift fundamentally, the seven-step process may need to be revisited to ensure alignment with stakeholder perspectives and maintain the framework's relevance.

The variability often observed in MCDM outcomes reflects the complexity of real-world decision-making. Rather than a limitation, this diversity enhances decision-making by providing tailored insights that align with specific priorities. Since no single MCDM method is universally optimal, combining different approaches helps decision-makers triangulate insights, evaluate trade-offs, and develop context-specific solutions.

5.4. *Practical implications for decision-makers at space agencies*

The fuzzy SAM framework developed in this study offers a structured and adaptable decision-support tool that can significantly enhance strategic space mission selection. As NASA and other (private) space agencies navigate an increasingly complex space exploration landscape, incorporating uncertainty-resilient decision methodologies becomes critical for ensuring optimal resource allocation, risk assessment, and mission prioritization.

One of the key advantages of this model is its ability to facilitate comprehensive evaluations under uncertainty. Space agencies often face decision environments characterized by incomplete, imprecise, or evolving data, particularly in early-stage mission planning. The fuzzy SAM model addresses this challenge by integrating linguistic assessments and fuzzy numbers, allowing decision-makers to analyze qualitative factors alongside quantitative metrics systematically. This capability ensures that strategic mission alternatives can be evaluated even in scenarios where precise numerical data is unavailable, a common limitation in strategic space exploration planning.

Additionally, the model's ability to categorize mission criteria into internal, transactional, and contextual factors provides a holistic assessment framework that aligns with NASA's strategic goals (e.g., discovering the solar system) and broader governmental and international collaboration efforts. By decomposing opportunities and threats into these structured layers, decision-makers can better prioritize investments, mitigate risks, and align mission objectives with long-term policy and economic considerations. The application of fuzzy SAM to NASA's Mars, lunar, and solar system exploration missions demonstrates how this approach can quantify mission trade-offs and resilience in varying uncertainty conditions. The solar system exploration mission consistently emerges as a robust choice, even under different fuzzy weight variations. This reinforces the model's potential to provide consistent and reliable recommendations for future mission selection scenarios, including interplanetary exploration, commercial partnerships, and planetary defense initiatives.

For NASA and other space agencies, integrating this model into existing decision workflows could substantially benefit multi-mission planning and funding allocation. The model can be adapted to compare and rank competing strategic mission proposals, ensuring that

Table 18
Intermediate ranking for opportunities.

Mission	k_m^{u-}	k_m^{u+}	fk_m^{u-}	fk_m^{u+}	K_m^u	Rank	Normalized K_m^u
Mars	1.015	0.893	0.468	0.532	0.633	**3**	0.314
Lunar	1.089	0.957	0.468	0.532	0.678	**2**	0.336
Solar	1.132	0.995	0.468	0.532	0.705	**1**	0.350

Table 19
Comparative ranking.

Mission	CoCoFISo	SAW	MARCOS	WASPAS	SAM
Mars	3	3	3	3	3
Lunar	2	2	2	2	2
Solar	1	1	1	1	1

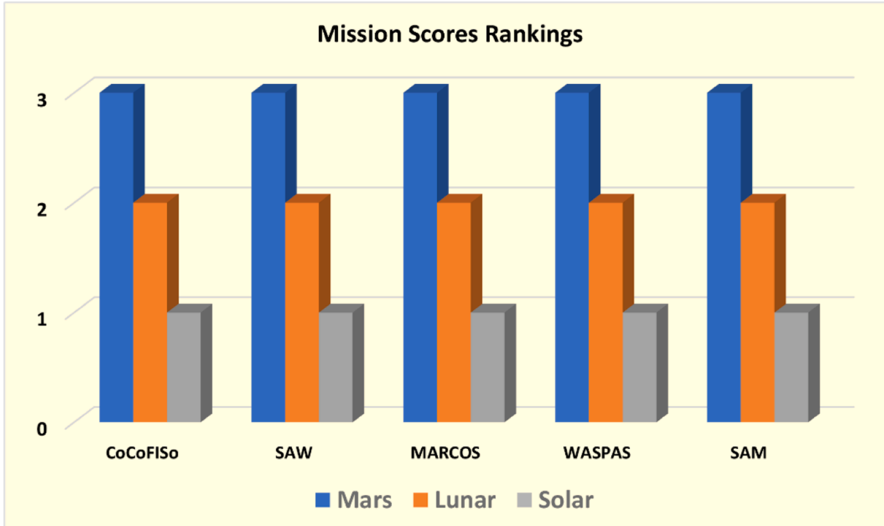

Fig. 9. Comparative chart of mission score ranking for Mars, Lunar, and Solar.

selections are not solely based on deterministic criteria but also consider strategic uncertainties, expert knowledge, and external environmental influences. This is particularly relevant in an era of increasing privatization, international partnerships, and geopolitical complexities, where mission selection requires balancing scientific, technological, economic, and diplomatic considerations.

In strategic space mission selection, where decisions involve multiple stakeholders and evolving conditions, the flexibility of MCDM models is crucial. While methods like the Analytic Network Process (ANP) explicitly model interdependencies, they add complexity that may not be practical when defining relationships between high-level strategic factors. The fuzzy SAM framework maintains a hierarchical structure, ensuring systematic evaluation while avoiding overlapping effects that could distort priority assessments. Although interdependencies among criteria are generally minimized to maintain clarity, future research could explore hybrid approaches that integrate ANP to capture interconnections better while preserving methodological transparency. Leveraging the strengths of different MCDM techniques can enhance decision-making, ensuring that strategic space exploration choices remain adaptable and well-informed.

6. Conclusion and future works

This study presents a novel fuzzy analytical model that extends the Strategic Assessment Model (SAM) by integrating trapezoidal fuzzy numbers to enhance strategic decision-making in space mission selection. Unlike conventional MCDM approaches, this model explicitly incorporates uncertainty into mission selection by systematically decomposing environmental opportunities and threats into internal, transactional, and contextual factors. The proposed seven-step fuzzy SAM framework offers a structured methodology for evaluating space mission alternatives, demonstrating its effectiveness in assessing Mars, lunar, and solar system exploration missions. Our findings show that solar system exploration consistently emerges as a robust strategic choice by analyzing the effect of trapezoidal fuzzy weights with parameterized dilation. One of the key advantages of this model is its ability to support decision-making under partial or insufficient quantitative data conditions, making it particularly valuable for space exploration scenarios where precise numerical data is often unavailable or incomplete.

This work makes several novel contributions to the literature on strategic decision-making and fuzzy MCDM. First, it is the first application of fuzzy SAM in space mission selection, introducing a systematic algebraic framework that extends fuzzy decision models beyond traditional applications in business and engineering. Second, it demonstrates how fuzzy parameterized dilation can influence decision outcomes, providing new insights into the stability and sensitivity of fuzzy weights in mission selection.

While the study successfully applies fuzzy SAM to space mission selection, future research could explore further refinements to enhance collaborative decision-making within a group decision-support system (GDSS). One open challenge is the aggregation of expert opinions in a fuzzy environment, where individual assessments vary due to differences in expertise, preferences, and interpretations of linguistic terms. These variations can lead to conflicting weight assignments and performance scores, making it difficult to derive a consensus-driven fuzzy decision outcome. Addressing this challenge requires the development of adaptive aggregation mechanisms that preserve the richness of expert insights without oversimplification. Potential solutions include fuzzy preference programming or consensus measures, which can help identify and resolve inconsistencies while ensuring a balanced representation of expert judgments.

Another promising avenue for future research is the integration of the ANP within the fuzzy SAM framework to enhance mission ranking results. While the current model evaluates missions using a hierarchical structure, ANP could capture interdependencies among internal, transactional, and contextual factors, providing a more interconnected decision model. Future work could also explore hybrid decision-support methodologies, such as combining machine learning with fuzzy SAM, to develop more adaptive, data-driven strategic planning tools for space exploration agencies.

By addressing these open questions, future studies can expand the applicability of fuzzy SAM, improving its ability to support collaborative, uncertainty-resilient, and data-informed strategic decision-making. This study serves as a foundation for further advancements in fuzzy MCDM for space mission selection, offering a scalable and adaptable approach to strategic planning in high-uncertainty environments.

CRediT authorship contribution statement

Madjid Tavana: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Andreas Dellnitz:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Morteza Yazdani:** Writing – original draft, Visualization, Software, Methodology, Formal analysis.

Declaration of competing interest

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

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Disclaimer

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Data availability

The data that has been used is confidential.

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