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A group AHP-TOPSIS framework for human spaceflight mission planning at NASA

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ABSTRACT

Human spaceflight mission planning is a complex task with many interacting systems and mission phases. Analog missions are Earth-based science missions whose purpose is to help understand the complexities inherent in future human spaceflight missions. The goal of performing an analog mission is to prepare crewmembers and support teams for future space missions in a low risk-low cost environment by repeatedly testing vehicles, habitats, and surface terrain simulators. This study presents a group multi-attribute decision making (MADM) framework developed at the Johnson Space Center (JSC) for the *Integrated* human exploration mission simulation facil*ity* (INTEGRITY) project to assess the priority of human spaceflight mission simulators. The proposed framework integrates subjective judgments derived from the analytic hierarchy process (AHP) with the entropy information and the technique for order preference by similarity to the ideal solution (TOPSIS) into a series of preference models for the human exploration of Mars. Three different variations of TOPSIS including conventional, adjusted and modified TOPSIS methods are considered in the proposed framework.

1. Introduction

The primary goal in multi-criteria decision making (MCDM) is to provide a set of attribute aggregation methodologies that enable the development of models considering the decision makers' (DMs') preferential system and judgment policy (Doumpos & Zopounidis, 2002). Achieving this goal requires the implementation of complex procedures. While intuition and simple rules are still favorite decision making methods, they may be dangerously inaccurate for complex decision problems.

Roy (1990) argues that solving MCDM problems is not searching for an optimal solution, but rather helping DMs master the complex judgments and data involved in their problems and advance towards an acceptable solution. Multi-attributes analysis is not an off-the-shelf recipe that can be applied to every problem and situation. The development of MCDM models has often been dictated by real-life problems. Therefore, it is not surprising that methods have appeared in a rather diffuse way, without any clear general methodology or basic theory (Vincke, 1992). The selection of a MCDM framework or method should be done carefully according to the nature of the problem, types of choices, measurement scales, dependency among the attributes, type of uncertainty, expectations of the DMs, and quantity and quality of the available data and judgments (Vincke, 1992). Finding the "best" MCDM framework is an elusive goal that may never be reached (Triantaphyllou, 2000).

The MCDM methods are frequently used to solve real-world problems with multiple, conflicting, and incommensurate attributes. Several authors have used MCDM to effectively solve complex space exploration problems at the National Aeronautic and Space Administration (NASA). Tavana (2003) developed a MCDM model with crisp data to evaluate and prioritize advanced-technology projects at the Kennedy Space Center (KSC). Tavana and Sodenkamp (2009) extended this model with fuzzy data and proposed a fuzzy MCDM model for technology assessment at KSC. Tavana (2004) proposed a MCDM model to evaluate a set of alternative mission architectures for the human exploration of Mars. Tavana, Smither, and Anderson (2007) and Tavana (2008) developed two group multi-criteria decision support systems at JSC, a workforce planning system, and an environmental benchmarking system, respectively.

MCDM problems are generally categorized as continuous or discrete, depending on the domain of alternatives. Hwang and Yoon (1981) have classified the MCDM methods into two general categories: multi-objective decision making (MODM) and multi-attribute decision making (MADM). MODM has been widely studied by means of mathematical programming methods with well-formulated theoretical frameworks. MODM methods have decision variable values that are determined in a continuous or integer domain

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with either an infinitive or a large number of alternative choices, the best of which should satisfy the DMs constraints and preference priorities (Hwang & Masud, 1979; Ehrgott & Wiecek, 2005). MADM methods, on the other hand, have been used to solve problems with discrete decision spaces and a predetermined or a limited number of alternative choices. Churchman, Ackoff, and Arnoff (1954) initially proposed a simple additive weighting method for selecting a business investment policy. The MADM solution process requires inter and intra-attribute comparisons and involves implicit or explicit tradeoffs (Hwang & Yoon, 1981). A detailed analysis of the theoretical foundations of different MCDM methods and their comparative strengths and weaknesses is presented in Larichev and Olson (2001), Belton and Stewart (2002) and Figueira et al. (2005).

This study presents a group MADM framework based on the analytic hierarchy process (AHP), entropy and the technique for order preference by similarity to the ideal solution (TOPSIS) that were developed for the *Integ*rated Human Exploration Mission Simulation Facil*ity* (INTEGRITY) project at the Johnson Space Center (JSC) to assess the priority of a set of human spaceflight mission simulators. The proposed MADM framework integrates subjective judgments derived from the AHP with entropy data and TOPSIS into a series of preference models to prioritize five mission simulators for the human exploration of Mars. The structured framework presented in this study has some obvious attractive features:

a. The generic nature of the framework proposed in this study allow for the subjective evaluation of a finite number of decision alternatives on a finite number of performance attributes by a group of DMs.
b. The mathematical and computational properties of the models are applicable to a wide range of real-world decision making problems in MADM.
c. The information requirements of the proposed framework are stratified into a hierarchy to simplify information input and allow the DMs to focus on a small area of the large problem. This process is also useful for seeking input from multiple DMs.
d. Inconsistencies are inevitable when dealing with subjective information from different DMs. The built-in inconsistency checking mechanism of the proposed framework helps to identify inconsistencies in judgments at very early stages of the computation process.

The remainder of the paper is organized as follows. Section 2 presents a brief overview of AHP. In Section 3, we provide a detailed description of three TOPSIS models considered for the proposed framework. Section 4 demonstrates the problem of rank reversal in MADM and TOPSIS through numerical examples. In Section 5, we introduce the INTEGRITY project at NASA. Section 6 presents the details of the group MADM framework proposed in this study along with the results of the INEGRITY problem. Section 7 summarizes our conclusions and future research directions.

2. A brief overview of AHP

The AHP developed by Saaty (1977, 1994, 2000) is a MADM approach that simplifies complex and ill-structured problems by arranging the decision attributes and alternatives in a hierarchical structure with the help of a series of pairwise comparisons. Dyer and Forman (1992) describe the advantages of AHP in a group setting as follows: (1) the discussion focuses on both tangibles and intangibles, individual and shared values; (2) the discussion can be focused on objectives rather than alternatives; (3) the discussion can be structured so that every attribute can be considered in turn; and (4) the discussion continues until all relevant information has been considered and a consensus choice of the decision alternative is achieved.

Saaty (2000) argues that a DM naturally finds it easier to compare two things than to compare all things together in a list. AHP also examines the consistency of the DMs and allows for the revision of their responses. AHP has been applied to many diverse decisions because of the intuitive nature of the process and its power in resolving the complexity in a judgmental problem. A comprehensive list of the major applications of AHP, along with a description of the method and its axioms, can be found in Saaty (1994, 2000), Weiss and Rao (1987) and Zahedi (1986). AHP has proven to be a popular technique for determining weights in multi-attribute problems (Shim, 1989; Zahedi, 1986). The importance of AHP and the use of pairwise comparisons in decision making are best illustrated in the more than 1,000 references cited in Saaty (2000).

AHP calculations are not complex, and if the judgments made about the relative importance of the attributes have been made in good faith, then, AHP calculations lead inexorably to the logical consequence of those judgments. AHP has been a controversial technique in the operations research community. Harker and Vargas (1990) show that AHP does have an axiomatic foundation, the cardinal measurement of preferences is fully represented by the eigenvector method, and the principles of hierarchical composition and rank reversal are valid. On the other hand, Dyer (1990a, 1990b) has questioned the theoretical basis underlying AHP and argues that it can lead to preference reversals based on the alternative set being analyzed. In response, Saaty (1990) contends that rank reversal is a positive feature, when new reference points are introduced.

3. A detailed description of TOPSIS

The TOPSIS method was initially presented by Hwang and Yoon (1981). It has been applied to a large number of application cases in advanced manufacturing (Agrawal, Kohli, & Gupta, 1991; Parkan & Wu, 1999), purchasing and outsourcing (Kahraman, Engin, Kabak, & Kaya, 2009; Shyura & Shih, 2006), and financial performance measurement (Feng & Wang, 2001). Its basic principle is that the chosen alternatives should have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) (Lai, Liu, & Hwang, 1994; Yoon & Hwang, 1995; Zeleny, 1974).

TOPSIS has been shown to be one of the best MADM methods in addressing the rank reversal issue, which is the change in the ranking of alternatives when a non-optimal alternative is introduced (Zanakis, Solomon, Wishart, & Dublish, 1998). This consistency feature is largely appreciated in practical applications. Moreover, the rank reversal in TOPSIS is insensitive to the number of alternatives and has its worst performance only in the case of a very limited number of attributes (Triantaphyllou & Lin, 1996; Zanakis et al., 1998). A relative advantage of TOPSIS is its ability to identify the best alternative quickly (Paxkan & Wu, 1997).

The INTEGRITY team in charge of evaluating the human spaceflight mission simulators at NASA had agreed to use TOPSIS in the final phase of the MADM framework. Their reasons for selecting TOPSIS were: (1) a sound logic that represents the rationale of human choice; (2) a unique visualization of the alternatives on a polyhedron; (3) a scalar value that accounts for the best and worst alternative choices simultaneously; and (4) a simple computation process that can be easily programmed into a spreadsheet (Kim, Park, & Yoon, 1997; Shyura & Shih, 2006). However, shortly after the decision to incorporate TOPSIS in the proposed framework, the team came across several variations of TOPSIS in the MADM literature. We decided to consider three different variations of

TOPSIS in this project including: conventional TOPSIS (Hwang & Yoon, 1981), adjusted TOPSIS (A-TOPSIS) (Deng, Yeh, & Willis, 2000), and modified TOPSIS (M-TOPSIS) (Ren, Zhang, Wang, & Sun, 2007). In the next section, we provide the mathematical details of TOPSIS, A-TOPSIS, and M-TOPSIS.

3.1. The TOPSIS method

Let us assume that A_i ($i = 1,2,\ldots,n$) and C_j ($j = 1,2,\ldots,m$) are a set of n INTEGRITY simulators and a set of m attributes, respectively. The main procedure for the conventional TOPSIS can be described in a series of steps:

Step 3.1.1. Construct a matrix based on the priority scores assigned to each alternative simulator on each attribute denoted by $X = (x_{ij})_{n\times m}$.

Step 3.1.2. Determine the importance weight (w_j) of the attributes such that:

$$\sum_{j=1}^{m} w_j = 1, \quad j = 1,2,\ldots,m. \tag{1}$$

Step 3.1.3. Obtain the normalized decision matrix (r_{ij}):

$$r_{ij} = x_{ij} \Bigg/ \left(\sum_{k=1}^{n} x_{kj}^2\right)^{0.5}; \quad j = 1,2,\ldots,m; \quad i = 1,2,\ldots,n. \tag{2}$$

Step 3.1.4. Obtain the weighted normalized decision matrix, (V_{ij}):

$$V_{ij} = w_j r_{ij}; \quad j = 1,2,\ldots,m; \quad i = 1,2,\ldots,n. \tag{3}$$

Step 3.1.5. Determine the PIS and NIS:

$$\begin{aligned} A^+ &= (v_1^+, v_2^+, \ldots, v_n^+) = \left\{\left(\max_i\{v_{ij}\}|j\in B\right), \left(\min_i\{v_{ij}\}|j\in C\right)\right\},\\ A^- &= (v_1^-, v_2^-, \ldots, v_n^-) = \left\{(\min_i\{v_{ij}\}|j\in B), (\max_i\{v_{ij}\}|j\in C)\right\}. \end{aligned} \tag{4}$$

where B and C are associated with the benefit and cost attribute sets, respectively.

Step 3.1.6. Calculate the separation measures denoted by $M = (S_i^+, S_i^-)$. The separation measure of each alternative simulator from the PIS and NIS is calculated by the Euclidean distance:

$$\begin{aligned} S_i^+ &= \left\{\sum_{j=1}^{m}(v_{ij} - v_j^+)^2\right\}^{0.5}; \quad i = 1,\ldots,n,\\ S_i^- &= \left\{\sum_{j=1}^{m}(v_{ij} - v_j^-)^2\right\}^{0.5}; \quad i = 1,\ldots,n. \end{aligned} \tag{5}$$

Step 3.1.7. The relative closeness of a particular alternative simulator to the ideal simulator, T_i, can be expressed in this step as follows:

$$T_i = \frac{S_i^-}{(S_i^+ + S_i^-)}; \quad i = 1,\ldots,n. \tag{6}$$

Step 3.1.8. A set of alternative simulators is generated in the descending order based on the value of P_i indicating the most preferred and least preferred feasible solutions.

3.2. The A-TOPSIS method

The normalized decision matrix (r_{ij}) in the TOPSIS method is weighted by multiplying each column of the matrix by its associated attribute weight. The overall performance of an alternative is then determined by its Euclidean distance to PIS and NIS. All the alternatives are compared with PIS and NIS, rather than directly among themselves. Deng et al. (2000) presented the weighted Euclidean distances, rather than creating a weighted decision matrix. The A-TOPSIS method consists of the following steps:

Steps 3.2.1–3.2.3 for A-TOPSIS are identical to steps 3.1.1–3.1.3 for the conventional TOPSIS method described in Section 3.1.

Step 3.2.4. In A-TOPSIS, the PIS (A^+) and NIS (A^-), which are not dependent on the weighted decision matrix, are defined as:

$$\begin{aligned} A^+ &= (v_1^+, v_2^+, \ldots, v_n^+) = \left\{\left(\max_i\{r_{ij}\}|j\in B\right), \left(\min_i\{r_{ij}\}|j\in C\right)\right\},\\ A^- &= (v_1^-, v_2^-, \ldots, v_n^-) = \left\{\left(\min_i\{r_{ij}\}|j\in B\right), \left(\max_i\{r_{ij}\}|j\in C\right)\right\}. \end{aligned} \tag{7}$$

Step 3.2.5. The weighted Euclidean distances are calculated as:

$$\begin{aligned} S_i^+ &= \left\{\sum_{j=1}^{m} w_j(r_{ij} - v_j^+)^2\right\}^{0.5}; \quad i = 1,\ldots,n,\\ S_i^- &= \left\{\sum_{j=1}^{m} w_j(r_{ij} - v_j^-)^2\right\}^{0.5}; \quad i = 1,\ldots,n. \end{aligned} \tag{8}$$

Step 3.2.6. The relative closeness of a particular alternative to the ideal solution, T_i^A, can be expressed in this step as follows:

$$T_i^A = \frac{S_i^-}{(S_i^+ + S_i^-)}; \quad i = 1,\ldots,n. \tag{9}$$

Step 3.2.7. A set of alternative simulators is generated in the descending order in this step, according to the value of T_i^A indicating the most preferred and least preferred feasible solutions.

3.3. The M-TOPSIS method

Ren et al. (2007) has introduced a modified synthetic evaluation method (M-TOPSIS) based on the concept of the conventional TOPSIS to avoid rank reversals. M-TOPSIS considers the evaluation failure that often occurs in the conventional TOPSIS. The procedure for M-TOPSIS can be described in a series of steps:

Steps 3.3.1–3.3.5 for M-TOPSIS are identical to steps 3.1.1–3.1.5 for the conventional TOPSIS method described in Section 3.1.

Step 3.3.6. Determine the ideal reference point (S):

$$S = (S^I, S^N) = (\min(S_i^+), \max(S_i^-)); \quad i = 1,\ldots,n. \tag{10}$$

Step 3.3.7. Determine the Euclidean distance between S_i^+ and S_i^- for each alternative simulator and point S:

$$T_i^M = \left\{\left[S_i^+ - \min(S_i^+)\right]^2 + \left[S_i^- - \max(S_i^-)\right]^2\right\}^{0.5}; \quad i = 1,2,\ldots,n. \tag{11}$$

Step 3.3.8. Rank the preference order of the alternative simulators according to T_i^M. The alternative simulator A_i is closer to S^I and farther from S^N as T_i^M approaches to 0.

4. The rank-reversal phenomenon in TOPSIS

In MADM, several authors have looked into the rank reversal phenomenon which is the alteration of the ranking of alternatives by the addition (or deletion) of irrelevant alternatives. (e.g., Bana e Costa & Vansnick, 2008; Wang & Luo, 2009; Wang & Ehang, 2006). Buede and Maxwell (1995), Wang and Luo (2009) and Zanakis et al. (1998) have conducted a series of rank reversal experiments to demonstrate the rank reversal phenomenon in TOPSIS. The three TOPSIS models described in the previous section were somewhat similar. However, Ren et al. (2007) has suggested that M-TOPSIS prevents rank-reversal and it should be used in lieu of the conventional TOPSIS. In order to investigate this claim, we considered three counter examples as well as a graphical representation of the rank reversal phenomenon in M-TOPSIS.

4.1. Three counter examples

In this section we show that the M-TOPSIS method proposed by Ren et al. (2007) does not prevent rank reversal through three examples in the MADM literature:

Example 1. We examined a numerical example investigated by Ren et al. (2007) in which a synthetic evaluation desire to rank three alternatives A_1, A_2 and A_3 with respect to three benefit attribute C_1, C_2 and C_3. Table 1 presents the separation measure of each alternative from the PIS and NIS, the Euclidean distance between S_i^+ and S_i^- for each alternative and point S, and the overall ranking of the alternatives (A_3, A_1 and A_2).

Next, we add a new alternative, $A_4 = (1,7,7)$, to the current set of alternatives. A_4 was ranked fourth before using M-TOPSIS. Ren et al. (2007) have claimed that their M-TOPSIS method preserves the ranking order of the alternatives in TOPSIS when an alternative is added or deleted. We used M-TOPSIS to rank the four alternatives. The ranking order of the three initial alternatives was changed from A_3, A_1 and A_2 to A_2, A_1 and A_3 and the M-TOPSIS did not prevent the rank reversal in this example (see Table 2).

Example 2. Consider another example investigated by Ren et al. (2007), in which ten alternatives $A_1,\ldots,A_{10}$ were assessed with respect to seven benefit attribute $C_1,\ldots,C_7$. We calculated the Euclidean distance of $M = (S_i^+, S_i^-)$ from $S = (S^I, S^N)$ for each alternative and determined the overall ranking order of the ten alternatives (R_i) presented in Table 3.

Table 1
The distance values and the final rankings for Example 1.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0458	0.0458	0.0260	2
A_2	0.0718	0.0569	0.0299	3
A_3	0.0569	0.0718	0.0111	1
S	0.0458	0.0718	–	–

Table 2
The distance values and the final rankings for Example 1 when A_4 is added.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0423	0.1510	0.0224	2
A_2	0.0642	0.1734	0.0218	1
A_3	0.0553	0.1383	0.0374	3
A_4	0.1849	0	0.2244	4
S	0.0423	0.1743	–	–

Table 3
The distance values and the final rankings for Example 2.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.1275	1.2014	0.0000	1
A_2	1.1522	0.4402	1.2765	9
A_3	0.7865	0.6861	0.8365	3
A_4	0.9695	0.4498	1.1287	7
A_5	1.1405	0.3468	1.3253	10
A_6	0.8835	0.5032	1.0291	6
A_7	0.7964	0.6704	0.8541	4
A_8	0.8951	0.8038	0.8644	5
A_9	1.0005	0.3957	1.1880	8
A_{10}	0.5661	0.8224	0.5796	2
S	0.1275	1.2014	–	–

Next, we removed A_8 from the evaluation process and re-evaluated this decision problem with M-TOPSIS. As is shown in Table 4, when A_8 was removed, the ranking between A_3 and A_7 was reversed.

We then add a new alternative, $A_{11} = (106,100,95,53,96,100,85)$, to the current set of alternatives in this example. As is shown in Table 5, when A_{11} is added as a new alternative, the ranking between A_3 and A_8 is reversed. Again, the M-TOPSIS did not prevent the rank reversal in this example.

Example 3. Wang and Luo (2009) introduced an example with four alternatives $A_1,\ldots,A_4$ and four benefit attributes $C_1,\ldots,C_4$. They illustrated the rank reversal between A_2 and A_3 by deleting alternative A_4 and adding alternative A_5 to the initial set of four alternatives. We present the separation measure of each alternative from the PIS and NIS, the Euclidean distance between S_i^+ and S_i^- for each alternative and point S, and the overall ranking of the alternatives (A_2, A_3, A_1 and A_4) in Table 6.

Table 4
The distance values and the final rankings for Example 2 when A_8 is removed.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0857	1.2712	0.0000	1
A_2	1.1879	0.4683	1.3636	8
A_3	0.8050	0.7315	0.8992	4
A_4	0.9775	0.4958	1.1817	6
A_5	1.1823	0.3594	1.4261	9
A_6	0.8903	0.5545	1.0775	5
A_7	0.7979	0.7339	0.8922	3
A_9	1.0309	0.4279	1.2667	7
A_{10}	0.5757	0.8903	0.6206	2
S	0.0857	1.2712	–	–

Table 5
The distance values and the final rankings for Example 2 when A_{11} is added.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.1151	0.9559	0.2150	2
A_2	0.9109	0.4073	1.1029	10
A_3	0.6040	0.6000	0.7516	6
A_4	0.7478	0.4039	0.9942	8
A_5	0.8958	0.3117	1.1609	11
A_6	0.6680	0.4482	0.9099	7
A_7	0.5742	0.5930	0.7380	5
A_8	0.6435	0.7150	0.6978	4
A_9	0.7690	0.3564	1.0445	9
A_{10}	0.4669	0.6784	0.6052	3
A_{11}	0.2000	1.1709	0.0849	1
S	0.1151	1.1709	–	–

Table 6
The distance values and the final rankings for Example 3.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0496	0.0357	0.0111	3
A_2	0.0420	0.0396	0.0027	1
A_3	0.0392	0.0339	0.0058	2
A_4	0.0524	0.0337	0.0144	4
S	0.0392	0.0396	–	–

Table 7
The distance values and the final rankings for Example 3 when A_4 is removed.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0464	0.0352	0.0127	3
A_2	0.0410	0.0369	0.0072	2
A_3	0.0338	0.0339	0.0031	1
S	0.0338	0.0369	–	–

Table 8
The distance values and the final rankings for Example 3 when A_5 is added.

Alternative	S_i^+	S_i^-	R_i	Rank
A_1	0.0447	0.0332	0.0113	3
A_2	0.0374	0.0388	0.0025	2
A_3	0.0349	0.0388	0.0000	1
A_4	0.0469	0.0356	0.0124	4
A_5	0.0455	0.0229	0.0191	5
S	0.0349	0.0388	–	–

Next, we removed alternative A_4 from consideration and re-applied M-TOPSIS without A_4. As is shown in Table 7, the ranking between A_2 and A_3 was reversed when A_4 was removed from this example.

We then added a new alternative A_5 (30, 43, 40, 85) to the set of alternatives and re-applied M-TOPSIS. As is shown in Table 8, the ranking between A_2 and A_3 was reversed when A_5 was added to this example.

The three examples presented in this paper illustrate that the M-TOPSIS method proposed by Ren et al. (2007) is also subject to the rank reversal. In the next section, we present a graphical representation of this rank reversal in M-TOPSIS to gain additional insight into this phenomenon.

4.2. A graphical representation of the rank reversal phenomenon

Let us consider Example 1. The scatter diagram presented in Fig. 1 is used to plot the x-coordinate (S_i^+) and the y-coordinate (S_i^-) of the alternatives A_1, A_2, A_3 and the ideal point (S). Next, we add a new alternative, A_4, to the current set of alternatives. Similarly, we plot the new S_i^+ and the new S_i^- of the four alternatives $A_{1\text{new}}$, $A_{2\text{new}}$, $A_{3\text{new}}$, $A_{4\text{new}}$ and the new S_{new}.

As is shown in Fig. 1, the Euclidean distance between A_1 and S before adding the new alternative A_4 is 0.026. However, the Euclidean distance between $A_{1\text{new}}$ and S_{new} after adding the new alternative A_4 is decreased slightly by 0.0036 to 0.0224. In contrast, the Euclidean distance between A_3 and S before adding the new alternative A_4 is 0.0111. However, the Euclidean distance between $A_{3\text{new}}$ and S_{new} after adding the new alternative A_4 is increased significantly by 0.0263 to 0.0374. In other words, when alternative A_4 is added to the decision matrix, the coordinates of the ideal point are changed from (0.0458, 0.0718) to (0.0423, 0.1743). Consequently, the Euclidean distance of the alternatives is changed and a new ranking order of the alternatives emerges.

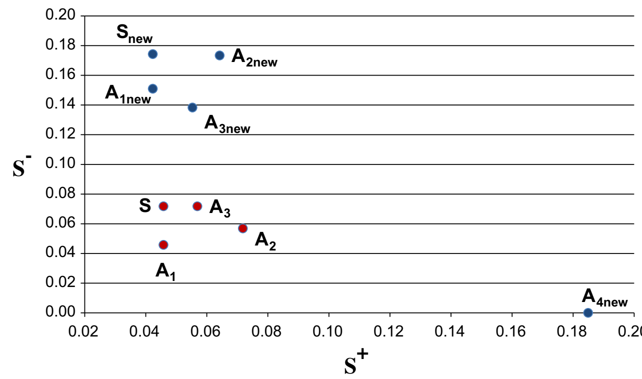

Fig. 1. A graphical representation of Example 1.

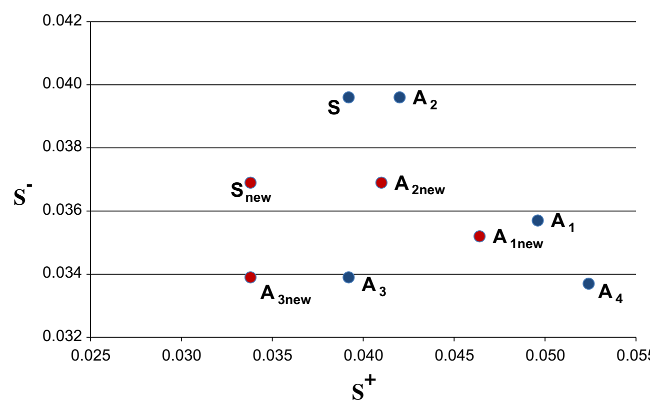

Fig. 2. A graphical representation of Example 3 with alternative A_4 removed.

The scatter diagram presented in Fig. 2 presents a graphical representation of the rank reversal phenomenon in the Example 3 when alternative A_4 is removed. As is shown in this figure, the ranking between A_2 and A_3 is reversed when A_4 is removed from this example since the removal of A_4 from consideration has resulted in a significant reduction (0.0263) in the Euclidean distance between $A_{3\text{new}}$ and S_{new}.

The scatter diagram presented in Fig. 3 presents a graphical representation of the rank reversal phenomenon in Example 3 when alternative A_5 is added. As is shown in this figure, the ranking between A_2 and A_3 is reversed when A_5 is added to this example because the addition of A_5 has resulted in a significant reduction

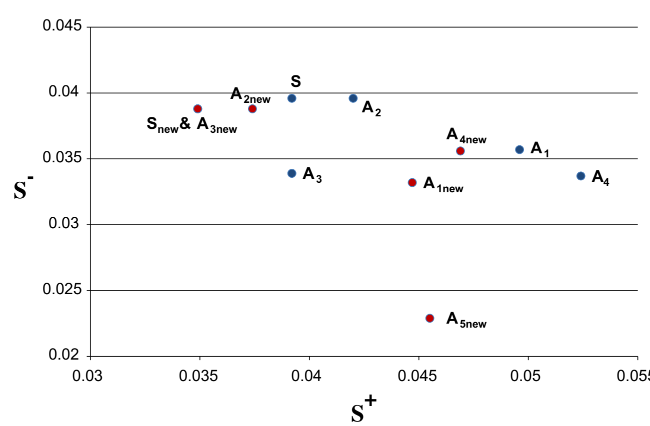

Fig. 3. A graphical representation of Example 3 with alternative A_5 added.

(0.0374) in the Euclidean distance between $A_{3\text{new}}$ and S_{new}. A similar graphical analysis could be performed for Example 2.

The rank reversal phenomenon is not unique to M-TOPSIS and changing the decision environment in some MADM methods may lead to rank reversal (Wang & Luo, 2009). In summary, the M-TOPSIS method did not prevent rank reversal in TOPSIS. Therefore, the INTEGRITY team decided to proceed with all three TOPSIS methods in the proposed framework and to see if there are any differences in the results.

5. The INTEGRITY case study

The INTEGRITY project initiated at the JSC is expected to play an important role in increasing the success of analog missions. Analog missions are real-life, Earth-based science missions whose primary purpose is to help understand the operations, techniques, and technologies required to perform similar tasks during future human spaceflight missions. The goal of performing an analog mission is to prepare crewmembers and support teams as well as increasing the productivity and scientific return during future space-based science missions in a low risk-low cost environment. As nearly anyone with field experience can attest, even the most well-planned experiments typically does not go as expected – hardware does not work as desired, unforeseen logistical problems arise, planned procedures need to be modified to fit changing situations, etc. Theoretically, analog missions are designed to work these kinks out of the process before a similar mission is attempted in space. Although analog missions are able to perform these functions in a fashion that is considerably less costly than performing the missions in space, they still require budgets that are significant.

The INTEGRITY team (IT) is a 17-member team of experts and scientists from different divisions within the JSC. IT supports analog missions by providing human exploration mission vehicle, habitat, and planetary surface terrain simulation facilities and infrastructure. These simulation facilities are used to conduct integrated testing with human crews in support of advanced research and technology development efforts associated with future human exploration missions beyond low Earth orbit. Five simulators, capable of simulating the crew cabin architecture, integrated systems operations, and crew operations associated with a 1000-day class mission transit vehicle, will be housed within these simulation facilities. The IT is chartered with the task of assessing each of the following five simulators and developing an implementation plan that is in sync with JSC's priorities.

- *Transit Vehicle Simulator (TVS):* A transit vehicle for manned exploration missions would be used to transfer the mission crews between low Earth orbit, a gateway station such as the International Space Station, and the orbits for a mission destination such as an asteroid, the Moon or Mars. The TVS will be habitable and will attempt to accurately reflect appropriate mission scenarios and constraints by supporting a crew for 6 to 12 months.
- *Lander Vehicle Simulator (LVS):* After the transit vehicle reaches orbit around a mission destination, the crew must descend to the surface by means of a landing vehicle. The lander vehicle must also provide ascent capability for rendezvous with and return to the transit vehicle in orbit. The Lander Vehicle Simulator (LVS), a ground-based version of such a lander vehicle, will be habitable for short durations of several hours to several days.
- *Surface Habitat Simulator (SHS):* A surface habitat on an extra-terrestrial surface must support and provide capabilities for a human crew to live and conduct an extra-terrestrial surface mission. It is likely that the duration of a surface mission will be in the range of one month to a year or more. The opportunities for Earth-based re-supply of a surface habitat will be limited, so the habitat must be largely self-supporting.
- *Roving Vehicle Simulator (RVS):* Rovers offer several capabilities including surface translation for the crew, access to places considered too dangerous for manned exploration, maintenance of surface habitat, and scouting before surface operations by the crew. Exploration mission rovers which consist of one or more surface-roving vehicles may be manned or unmanned and may have various levels of autonomy.
- *Surface Terrain Simulator (STS):* Distinct from the other INTEGRITY simulators, the STS does not involve designing and building a piece of technology or vehicle. Rather, it is a re-creation of an extra-terrestrial surface within the INTEGRITY facility. The surface simulation is expected to integrate and evaluate the technical abilities and operations of the lander (LVS), surface habitat (SHS), and rovers (RVS). It will consist of materials and features that are deliberately constructed to present mission simulations with realistic features of an extra-terrestrial surface.

Fig. 4 shows how the analog mission vehicle, habitat, and surface terrain simulators will be utilized for a manned exploration mission to Mars. The diagram depicts outbound phases of the mission. Starting with mission phase 1, a crew would travel from Earth-orbit to a way station or Gateway in a Crew Transfer Vehicle.

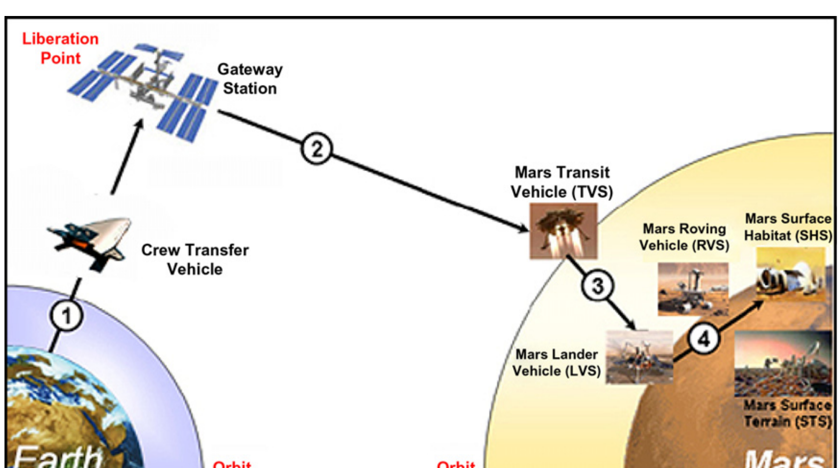

Fig. 4. Mars mission elements and phases.

INTEGRITY would simulate this phase using the TVS. Continuing in a TVS, phase 2 would take the crew from the gateway station into orbit around Mars. From orbit, the crew would descend to the Martian surface in a lander vehicle (LVS) in phase 3. In phase 4, the crew would egress the lander vehicle and traverse the Martian surface (STS) to man the surface habitat (SHS) using a roving vehicle (RVS).

6. The proposed framework

The MADM models presented in this study were used by the IT to assess the importance of each INTEGRITY simulator. Schoemaker and Russo (1993) describe four general approaches to decision making ranging from intuitive to highly analytical. These methods include intuitive judgments, rules and shortcuts, importance weighting, and value analysis. They argue that analytical methods such as importance weighting and value analysis are more complex but also more accurate than the intuitive approaches (Schoemaker & Russo, 1993). Our approach is a simple and yet sophisticated MADM that attempts to uncover some of the complexities inherent in the evaluation. The proposed approach which uses a series of intuitive and analytical methods in a four-phase process as depicted in Fig. 5 was used by the IT for this prioritization:

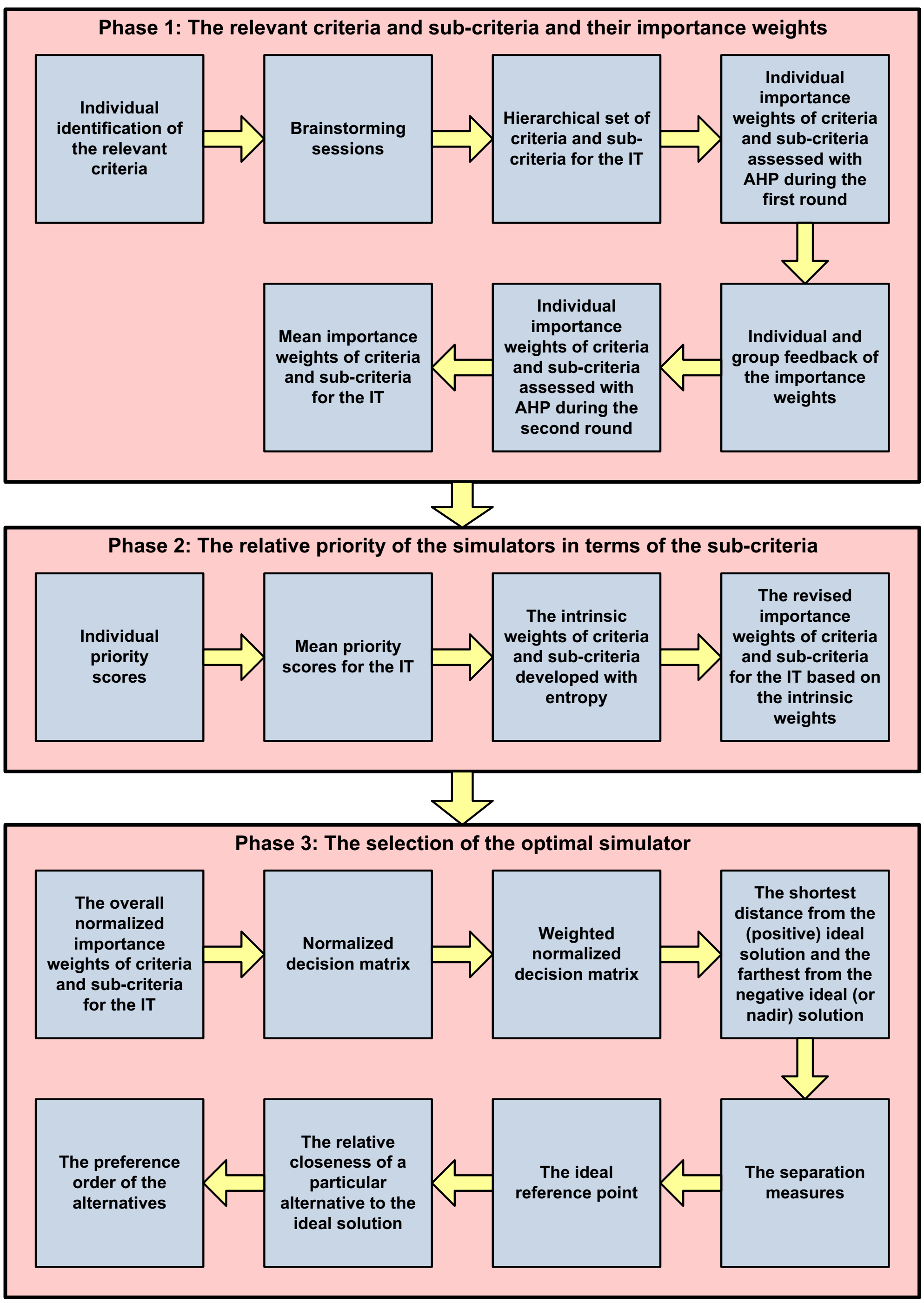

Fig. 5. The proposed MADM framework.

6.1. Phase 1. The relevant attributes and sub-attributes and their importance weights

Each IT member was asked to develop a list of all possible attributes relevant to the simulator evaluation. All the individual responses were collated by the facilitator into a comprehensive list which was shared with the IT at subsequent meetings. After several meetings and lengthy discussions, the list was revised by the IT into the hierarchical set of attributes and sub-attributes presented in Appendix A.

The discussions about attributes and sub-attributes raised some concerns about the natural sequencing that may or may not exist among the simulators. The facilitator developed a questionnaire for the IT to investigate this question further. The IT was asked in this questionnaire to offer their sequencing perception by providing a ranking between 1 and 5 to each simulator. They were instructed to give a ranking of 1 to the simulator that they believed had to be built first, 2 for to the second simulator, etc. They were also instructed to use an average ranking for cases where they believed two or more simulators had to be built simultaneously. For example, a score of 2.5 was used for simulators B and C, if it was believed that both of them had to be built simultaneously after A. Table 9 presents the mean sequencing scores of the five simulators for each IT member along with the median scores of the simulators. We performed the Kruskal–Wallis Test to see if there is a significant difference among the medians. The high p-value of 0.804 (relative to $\alpha = 0.1$) shows that there is no statistical difference between the medians of the five simulators. In addition, because all the z-values are considerably less than 1.96 ($\alpha = 0.05$), there is no difference for each individual simulator from the overall median.

AHP was used to develop a set of importance weights for the attributes and sub-attributes. The IT identified j attributes ($j = 1,2,\ldots,m$) and l sub-attributes ($l = 1,2,\ldots,u$) to be used in the evaluation process. The importance weight of each attribute (w_j) and sub-attribute (w_{jl}) was captured and measured with AHP using a complete version of the sample questionnaire presented in Appendix B. The IT members were asked to provide their subjective assessment of each pairwise comparison. Assuming that an IT member believes, $c_1, c_2, \ldots, c_j$ are the j attributes that contribute to the importance of a simulator, the team member's goal is to assess the relative importance of these factors.

Table 9
Simulator sequencing scores.

IT Member	TVS	LVS	SHS	RVS	STS
A	4.0	5.0	1.0	3.0	2.0
B	1.5	3.0	1.5	4.0	5.0
C	1.0	2.5	2.5	5.0	4.0
D	5.0	2.0	1.0	4.0	3.0
E	5.0	3.0	2.0	1.0	4.0
F	3.5	3.5	5.0	2.0	1.0
G	3.0	1.0	2.0	5.0	4.0
H	5.0	2.0	3.0	4.0	1.0
I	2.0	4.0	1.0	5.0	3.0
J	5.0	4.0	2.5	1.0	2.5
K	3.5	5.0	3.5	1.0	2.0
L	1.0	5.0	2.0	3.0	4.0
M	4.0	1.5	5.0	1.5	3.0
N	1.0	4.0	2.5	5.0	2.5
O	4.0	1.0	5.0	3.0	2.0
P	2.0	4.0	3.0	5.0	1.0
Q	2.0	4.5	4.5	1.0	3.0
Median	3.5	3.5	2.5	3.0	3.0
z-value	0.27	0.76	−0.77	0.48	−0.75

Saaty's AHP (Forman & Gass, 2001; Saaty & Vargas, 1998) is a method of deriving a set of weights to be associated with each of the j attributes or jl sub-attributes. Initially, the team member is asked to compare each possible pair c_l, c_k of attributes and provide judgments about which attributes are more important and by how much. AHP quantifies these judgments and represents them in an $j \times j$ matrix:

$$A = (a_{lk}) \quad (l, k = 1, 2, \ldots, m).$$

If c_l is judged to be of equal importance as c_k, then $a_{lk} = 1$

If c_l is judged to be more important than c_k, then $a_{lk} > 1$

If c_l is judged to be less important than c_k, then $a_{lk} < 1$

$$a_{lk} = 1/a_{lk} \quad a_{lk} \neq 0$$

Because the entry a_{lk} is the inverse of the entry a_{lk}, the matrix A is a reciprocal matrix. A_{lk} reflects the relative importance of c_l compared with attribute c_k. For example, $a_{12} = 1.25$ indicates that c_1 is 1.25 times as important as c_2.

Then, the vector w representing the relative weights of each of the j attributes can be found by computing the normalized eigenvector corresponding to the maximum eigenvalue of the matrix A. An eigenvalue of A is defined as λ which satisfies the following matrix equation:

$$A\,w = \lambda\,w$$

where λ is a constant, called the eigenvalue, associated with the given eigenvector w. Saaty (1994) has shown that the best estimate of w is the one associated with the maximum eigenvalue (λ_{max}) of the matrix A. Because the sum of the weights should be equal to 1.00, the normalized eigenvector is used. Saaty's (1977) algorithm for obtaining this w is incorporated in the software Expert Choice (Expert Choice, 2000).

One of the advantages of AHP is that it encourages team members to be consistent in their pairwise comparisons. Saaty (1977) suggests a measure of consistency for the pairwise comparisons. When the judgments are perfectly consistent, the maximum eigenvalue, λ_{max}, should equal j, the number of attributes that are compared. In general, the responses are not perfectly consistent, and λ_{max} is greater than n. The larger the λ_{max}, the greater is the degree of inconsistency. Saaty (1977) defines the consistency index (CI) as $(\lambda_{max} - j)/(j - 1)$, and provides the following random index (RI) table for matrices of order *3* to *10*:

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.32	1.41	1.45	1.49	1.51

This RI is based on a simulation of a large number of randomly generated weights. Saaty (1977) recommends the calculation of a consistency ratio (CR), which is the ratio of CI to the RI for the same order matrix. A CR of 0.10 or less is considered acceptable. When the CR is unacceptable, the team member is made aware that his or her pairwise comparisons are logically inconsistent, and he or she is encouraged to revise them.

The responses were processed with Expert Choice (Expert Choice, 2000) and those with inconsistency ratios greater than 0.10 were asked to reconsider their judgments as suggested by Saaty. The mean importance weights were calculated for the IT after the necessary adjustments were made to inconsistent responses. Each IT member was presented with his/her individual score along with the group mean weights. IT members were given the opportunity to revisit their judgments and make revisions to their pairwise comparison scores based on this feedback. Some IT members took advantage of this opportunity and revised their judgments in the second round. The mean importance weights for the first and second round are presented in Table 10. While

Table 10
Rounds 1 and 2 importance weights of the attributes and sub-attributes.

ATTRIBUTE	Round-1	Round-2
1. Cost	0.167	0.170
2. Strategic plan relevance	0.439	0.429
3. Complexity	0.113	0.124
4. Science, operations, and technology	0.281	0.278
1. Cost sub-attributes		
1.1. Cost to design (C)	0.234	0.231
1.2. Cost to build (C)	0.166	0.163
1.3. Cost to operate (C)	0.286	0.286
1.4. Cost to reconfigure (C)	0.125	0.125
1.5. Cost to maintain (C)	0.189	0.195
Inconsistency ratio	0.070	0.049
2. Strategic plan relevance sub-attributes		
2.1. Exploration development relevance (B)	0.274	0.273
2.2. Mission architecture commonality (B)	0.167	0.168
2.3. Usefulness outside INTEGRITY (B)	0.086	0.086
2.4. Publicity value (B)	0.084	0.084
2.5. Mission requirements understanding (B)	0.175	0.179
2.6. Risk mitigation (B)	0.215	0.211
Inconsistency ratio	0.069	0.058
3. Complexity sub-attributes		
3.1. Design & manufacturing difficulty (C)	0.202	0.197
3.2. Operational & safety difficulty (C)	0.436	0.431
3.3. Disorder in the stepping stone (C)	0.167	0.170
3.4. Infrastructure impacts (C)	0.195	0.202
Inconsistency ratio	0.071	0.061
4. Science, operations, and technology sub-attributes		
4.1. Basic science opportunities (B)	0.163	0.157
4.2. Exploration science diversity (B)	0.170	0.174
4.3. Operations scenarios (B)	0.204	0.206
4.4. Cross cutting technology (B)	0.126	0.126
4.5. Interfaces/integration (B)	0.203	0.201
4.6. Technology gap/innovation (B)	0.135	0.136
Inconsistency ratio	0.064	0.049

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

the second round results differ slightly from the first round results, the inconsistency was improved significantly. A similar approach was used to determine the relative importance of each sub-attribute.

6.2. Phase 2. The relative priority of the simulators in terms of the sub-attributes

The priority scores of the five simulators for all sub-attributes were needed to develop the preference scores in our model. A complete version of the sample simulator assessment questionnaire presented in Appendix C was given to the IT to capture their perception of the relative importance of each simulator for each sub-attribute using a 10-point Lickert scale. The individual priority scores were averaged into the group priority scores given in Table 11.

Next, we used the group priority scores presented in Table 11 to revise the initial weights of the sub-attributes (w'_{jl} – second-round weights in Table 10) using the entropy concept. The essential idea in the entropy method is that the relative importance of an attribute is directly related to the information conveyed by the attribute relative to the set of alternatives under consideration. This means that the greater the dispersion in the evaluations of the alternatives for a given attribute, the more important the attribute. In other words, the most important attribute are those which have the greatest discriminating power between alternatives. In this method the importance weight of attributes could be determined without the direct involvement of the DM, in terms of the values derived from the evaluation of the alternatives. However, this is a complete contradiction to the notion that weights should represent the relative importance the DM attaches to the attributes. Therefore, we multiply the values of weights obtained by the entropy method (intrinsic weights) by the subjective weights representing the judgments of DMs obtained by the AHP. The final result, once normalized, is used in our model to represent the importance weight of the attributes and the sub-attributes.

Each sub-attribute is an information source; therefore, the more information a sub-attribute reveals, the more relevant it is. Consequently, the more information the lth sub-attribute of the jth attribute reveals, the more relevant the sub-attribute is to the decision analysis. Zeleny (1982) argues that this intrinsic information must be used in parallel with the initial weights the DMs assigned to various sub-attributes. In other words, the overall importance

Table 11
The IT mean priority scores.

ATTRIBUTE	LVS	RVS	SHS	STS	TVS
1. Cost sub-attributes					
1.1. Cost to design (C)	3.88	4.76	3.88	8.00	4.00
1.2. Cost to build (C)	3.94	4.53	3.12	7.94	3.76
1.3. Cost to operate (C)	4.71	5.29	3.41	8.65	4.35
1.4. Cost to reconfigure (C)	4.53	5.24	3.94	7.88	4.06
1.5. Cost to maintain (C)	4.53	4.12	3.76	7.65	4.35
2. Strategic plan relevance sub-attributes					
2.1. Exploration development relevance (B)	6.29	6.53	9.06	5.53	8.53
2.2. Mission architecture commonality (B)	7.12	6.53	8.94	4.29	8.59
2.3. Usefulness outside INTEGRITY (B)	5.53	4.82	8.00	3.88	7.65
2.4. Publicity value (B)	6.76	8.35	8.18	6.76	7.24
2.5. Mission requirements Understanding (B)	6.88	7.12	8.88	4.76	8.35
2.6. Risk mitigation (B)	7.24	6.88	9.00	5.29	8.82
3. Complexity sub-attributes					
3.1. Design & manufacturing difficulty (C)	4.76	5.18	3.82	7.24	4.35
3.2. Operational & safety difficulty (C)	4.47	5.53	4.18	7.18	4.94
3.3. Disorder in the stepping stone (C)	6.76	5.12	7.82	5.29	7.71
3.4. Infrastructure impacts (C)	5.00	5.59	4.53	5.76	4.47
4. Science, operations, and technology sub-attributes					
4.1. Basic science opportunities (B)	5.18	5.24	9.00	4.88	7.18
4.2. Exploration science diversity (B)	4.53	5.88	8.12	5.82	5.94
4.3. Operations scenarios (B)	6.76	6.41	8.59	6.00	7.41
4.4. Cross cutting technology (B)	6.53	5.94	8.94	3.82	7.82
4.5. Interfaces/integration (B)	7.76	6.47	9.06	3.94	8.35
4.6. Technology gap/innovation (B)	6.71	7.06	9.29	3.76	7.94

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

weight of a attribute, w_{jl}, is directly related to the intrinsic weight, w''_{jl}, reflecting the average intrinsic information developed by the priority scores of the simulators, and the subjective weight, w'_{jl}, reflecting the IT members' subjective assessment of its importance.

The more different the scores of a sub-attribute are for a set of simulators, the larger is the contrast intensity of the sub-attribute, and the greater is the amount of information transmitted by that sub-attribute. Assuming that the vector $p_{jl} = (p_{jl}^1, \ldots, p_{jl}^q)$ characterizes the jth attribute, the lth sub-attribute, and the qth simulator; the entropy measure of the lth sub-attribute for the jth attribute is:

$$e(p_{jl}) = -K \sum_{k=1}^{q} \frac{p_{jl}^k}{P_{jl}} \ln \frac{p_{jl}^k}{P_{jl}}, \tag{12}$$

where

$$P_{jl} = \sum_{k=1}^{q} p_{jl}^k \quad (j = 1, 2, \ldots, m \text{ and } l = 1, 2, \ldots, u) \tag{13}$$

and $K > 0$, ln is the natural logarithm, $0 \leqslant p_{jl}^k \leqslant 1$, and $e(p_{jl}) \geqslant 0$. When all p_{jl}^k are equal for a given j and l, then $p_{jl}^k / P_{jl} = 1/q$, and $e(p_{jl})$ assumes its maximum value, which is $e_{\max} = \ln q$. By setting $K = 1/e_{\max}$, we achieve $0 \leqslant e(p_{jl}) \leqslant 1$. This normalization is necessary for meaningful comparisons. In addition, the total entropy is defined as:

$$E = \sum_{l=1}^{u} e(p_{jl}). \tag{14}$$

The smaller $e(p_{jl})$ is, the more information the lth sub-attribute transmits for the jth attribute, and the larger $e(p_{jl})$ is, the less information it transmits. When $e(p_{jl}) = e_{\max} = \ln q$, the lth sub-attribute for the jth attribute transmits no useful information. Next, the intrinsic weight is calculated as

$$w''_{jl} = \frac{1}{I - E}\left[1 - e(p_{jl})\right], \tag{15}$$

where I is the total number of sub-attributes for a particular attribute under consideration.

Because w''_{jl} is inversely related to $e(p_{jl})$, $1 - e(p_{jl})$ is used instead and normalized to make sure $0 \leqslant w''_{jl} \leqslant 1$ and $\sum_{l=1}^{u} w''_{jl} = 1$. The higher $e(p_{jl})$, the less information content is provided by the lth sub-attribute for the jth attribute. When the information content of the lth sub-attribute for the jth attribute is low, the corresponding intrinsic weight (w''_{jl}) should be low. Thus, the intrinsic weight is assumed to be inversely related to the entropy and therefore, we use $1 - e(p_{jl})$ in the definition of the intrinsic weight.

The more different the priority scores p_{jl}^k are, the larger w''_{jl} is and the more important the lth sub-attribute for the jth attribute is. When all the priority scores p_{jl}^k are equal for the lth sub-attribute for the jth attribute, then $w''_{jl} = 0$ for that sub-attribute. However, this is not true if the priority scores p_{jl}^k are equal for all the sub-attributes l. In that case, the weights are assumed to be equal or $w''_{jl} = 1/u$ where u is the number of sub-attributes for a given attribute. Entropy multiplies the intrinsic weight w''_{jl} by the subjective weight w'_{jl} and normalizes the product to calculate the overall importance weight of the$l$th sub-attribute for the jth attribute w_{jl},

$$W_{jl} = \frac{w''_{jl} . w'_{jl}}{\sum_{l=1}^{u} w''_{jl} . w'_{jl}}. \tag{16}$$

When there is more than one priority score (u-ary sub-attributes), these priority scores are used to calculate the entropy within each simulator. These within-simulator intrinsic weights can influence the overall weight of the sub-attributes. In other words, the overall importance weight for an u-ary sub-attribute w_{jl} is related to its between-simulator intrinsic weight w''_{jl} the subjective weight w'_{jl} and the within-simulator intrinsic weight. We then normalized the overall weights. Table 12 presents the initial weights, the intrinsic weights, the overall weights, and the normalized overall weights of each sub-attribute.

There are two other methods for calculating the intrinsic weights of attributes. Diakoulaki, Mavrotas, and Papayannakis (2000) proposes a method based on the correlation between the columns of the decision matrix. Another method consists in measuring the importance of each attribute as a member of a coalition by means of the Shapley value (Grabisch & Roubens, 1999). We use the entropy method suggested by Zeleny (1982, Chapter 7) in this

Table 12
The initial, intrinsic, revised, and normalized importance weights of sub-attributes.

ATTRIBUTE	Initial weight	Intrinsic weight	Overall weight	Normalized overall weight
1. Cost sub-attributes				
1.1. Cost to design (C)	0.231	0.199	0.226	0.057
1.2. Cost to build (C)	0.163	0.257	0.205	0.051
1.3. Cost to operate (C)	0.286	0.227	0.318	0.080
1.4. Cost to reconfigure (C)	0.125	0.157	0.097	0.024
1.5. Cost to maintain (C)	0.195	0.160	0.153	0.038
2. Strategic plan relevance sub-attributes				
2.1. Exploration development relevance (B)	0.273	0.142	0.236	0.059
2.2. Mission architecture commonality (B)	0.168	0.233	0.239	0.060
2.3. Usefulness outside INTEGRITY (B)	0.086	0.288	0.151	0.038
2.4. Publicity value (B)	0.084	0.033	0.017	0.004
2.5. Mission requirements understanding (B)	0.179	0.165	0.181	0.045
2.6. Risk mitigation (B)	0.211	0.138	0.177	0.044
3. Complexity sub-attributes				
3.1. Design & manufacturing difficulty (C)	0.197	0.383	0.290	0.073
3.2. Operational & safety difficulty (C)	0.431	0.296	0.490	0.123
3.3. Disorder in the stepping stone (C)	0.170	0.239	0.156	0.039
3.4. Infrastructure impacts (C)	0.202	0.083	0.064	0.016
4. Science, operations, and technology sub-attributes				
4.1. Basic science opportunities (B)	0.157	0.182	0.180	0.045
4.2. Exploration science diversity (B)	0.174	0.107	0.117	0.029
4.3. Operations scenarios (B)	0.206	0.049	0.063	0.016
4.4. Cross cutting technology (B)	0.126	0.221	0.175	0.044
4.5. Interfaces/integration (B)	0.201	0.213	0.270	0.068
4.6. Technology gap/innovation (B)	0.136	0.228	0.195	0.049

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

Table 13
The normalized decision matrix.

ATTRIBUTE	LVS	RVS	SHS	STS	TVS
1. Cost sub-attributes					
1.1. Cost to design (C)	0.3367	0.4131	0.3367	0.6943	0.3471
1.2. Cost to build (C)	0.3553	0.4085	0.2814	0.7160	0.3391
1.3. Cost to operate (C)	0.3777	0.4242	0.2734	0.6936	0.3488
1.4. Cost to reconfigure (C)	0.3800	0.4396	0.3305	0.6611	0.3406
1.5. Cost to maintain (C)	0.3987	0.3626	0.3309	0.6733	0.3829
2. Strategic plan relevance sub-attributes					
2.1. Exploration development relevance (B)	0.3845	0.3992	0.5538	0.3380	0.5214
2.2. Mission architecture commonality (B)	0.4370	0.4008	0.5487	0.2633	0.5272
2.3. Usefulness outside INTEGRITY (B)	0.3997	0.3484	0.5783	0.2805	0.5530
2.4. Publicity value (B)	0.4037	0.4986	0.4885	0.4037	0.4323
2.5. Mission requirements understanding (B)	0.4193	0.4339	0.5412	0.2901	0.5089
2.6. Risk mitigation (B)	0.4277	0.4064	0.5317	0.3125	0.5211
3. Complexity sub-attributes					
3.1. Design & manufacturing difficulty (C)	0.4090	0.4451	0.3283	0.6221	0.3738
3.2. Operational & safety difficulty (C)	0.3725	0.4608	0.3483	0.5984	0.4117
3.3. Disorder in the stepping stone (C)	0.4552	0.3448	0.5266	0.3563	0.5192
3.4. Infrastructure impacts (C)	0.4387	0.4904	0.3974	0.5053	0.3922
4. Science, operations, and technology sub-attributes					
4.1. Basic science opportunities (B)	0.3569	0.3610	0.6201	0.3362	0.4947
4.2. Exploration science diversity (B)	0.3285	0.4264	0.5888	0.4220	0.4307
4.3. Operations scenarios (B)	0.4263	0.4042	0.5417	0.3784	0.4673
4.4. Cross cutting technology (B)	0.4273	0.3886	0.5849	0.2499	0.5117
4.5. Interfaces/integration (B)	0.4728	0.3942	0.5520	0.2400	0.5087
4.6. Technology gap/innovation (B)	0.4175	0.4392	0.5780	0.2339	0.4940

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

study because it is readily available in MCDM, provides consistent results, and easily accepted by DMs (Pomero & Brba-Romero, 2000, Chapter 4).

6.3. Phase 3. The selection of the optimal simulator

In this phase we determined the optimal solution for the INTEGRITY problem according to the TOPSIS, A-TOPSIS, and M-TOPSIS methods described in Section 3:

6.3.1. The TOPSIS results

We obtained the normalized decision matrix and the weighted normalized decision matrix presented in Tables 13 and 14. We then determined the positive and negative ideal solutions (PIS and NIS, respectively) presented in Table 15.

The PIS and NIS values were used to calculate the following separation measures for each alternative simulator:

$$S_i^+ = (LVS = 0.0271, RVS = 0.0341, SHS = 0.0071, STS = 0.0747, TVS = 0.0163),$$
$$S_i^- = (LVS = 0.0560, RVS = 0.0451, SHS = 0.0750, STS = 0.0072, TVS = 0.0623).$$

Table 14
The weighted normalized decision matrix in the TOPSIS method.

ATTRIBUTE	LVS	RVS	SHS	STS	TVS
1. Cost sub-attributes					
1.1. Cost to design (C)	0.0190	0.0233	0.0190	0.0392	0.0196
1.2. Cost to build (C)	0.0182	0.0209	0.0144	0.0367	0.0174
1.3. Cost to operate (C)	0.0300	0.0337	0.0217	0.0551	0.0277
1.4. Cost to reconfigure (C)	0.0092	0.0107	0.0080	0.0160	0.0083
1.5. Cost to maintain (C)	0.0153	0.0139	0.0127	0.0258	0.0146
2. Strategic plan relevance sub-attributes					
2.1. Exploration development relevance (B)	0.0227	0.0236	0.0327	0.0199	0.0308
2.2. Mission architecture commonality (B)	0.0261	0.0239	0.0328	0.0157	0.0315
2.3. Usefulness outside INTEGRITY (B)	0.0151	0.0132	0.0218	0.0106	0.0209
2.4. Publicity value (B)	0.0017	0.0021	0.0021	0.0017	0.0018
2.5. Mission requirements understanding (B)	0.0190	0.0196	0.0245	0.0131	0.0230
2.6. Risk mitigation (B)	0.0189	0.0180	0.0235	0.0138	0.0231
3. Complexity sub-attributes					
3.1. Design & manufacturing difficulty (C)	0.0297	0.0323	0.0238	0.0451	0.0271
3.2. Operational & safety difficulty (C)	0.0456	0.0565	0.0427	0.0733	0.0504
3.3. Disorder in the stepping stone (C)	0.0178	0.0134	0.0205	0.0139	0.0202
3.4. Infrastructure impacts (C)	0.0070	0.0078	0.0064	0.0081	0.0063
4. Science, operations, and technology sub-attributes					
4.1. Basic science opportunities (B)	0.0161	0.0162	0.0279	0.0151	0.0223
4.2. Exploration science diversity (B)	0.0096	0.0125	0.0172	0.0123	0.0126
4.3. Operations scenarios (B)	0.0067	0.0064	0.0085	0.0060	0.0074
4.4. Cross cutting technology (B)	0.0187	0.0170	0.0256	0.0109	0.0224
4.5. Interfaces/integration (B)	0.0319	0.0266	0.0373	0.0162	0.0343
4.6. Technology gap/innovation (B)	0.0204	0.0214	0.0282	0.0114	0.0241

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

Table 15
The positive and negative ideal solutions in the TOPSIS method.

ATTRIBUTE	PIS	NIS
1. Cost sub-attributes		
1.1. Cost to design (C)	0.0190	0.0392
1.2. Cost to build (C)	0.0144	0.0367
1.3. Cost to operate (C)	0.0217	0.0551
1.4. Cost to reconfigure (C)	0.0080	0.0160
1.5. Cost to maintain (C)	0.0127	0.0258
2. Strategic plan relevance sub-attributes		
2.1. Exploration development relevance (B)	0.0327	0.0199
2.2. Mission architecture commonality (B)	0.0328	0.0157
2.3. Usefulness outside INTEGRITY (B)	0.0218	0.0106
2.4. Publicity value (B)	0.0021	0.0017
2.5. Mission requirements understanding (B)	0.0245	0.0131
2.6. Risk mitigation (B)	0.0235	0.0138
3. Complexity sub-attributes		
3.1. Design & manufacturing difficulty (C)	0.0238	0.0451
3.2. Operational & safety difficulty (C)	0.0427	0.0733
3.3. Disorder in the stepping stone (C)	0.0134	0.0205
3.4. Infrastructure impacts (C)	0.0063	0.0081
4. Science, operations, and technology sub-attributes		
4.1. Basic science opportunities (B)	0.0279	0.0151
4.2. Exploration science diversity (B)	0.0172	0.0096
4.3. Operations scenarios (B)	0.0085	0.0060
4.4. Cross cutting technology (B)	0.0256	0.0109
4.5. Interfaces/integration (B)	0.0373	0.0162
4.6. Technology gap/innovation (B)	0.0282	0.0114

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

Table 16
The positive and negative ideal solutions in the A-TOPSIS method.

ATTRIBUTE	PIS	NIS
1. Cost sub-attributes		
1.1. Cost to design (C)	0.3367	0.6943
1.2. Cost to build (C)	0.2814	0.7160
1.3. Cost to operate (C)	0.2734	0.6936
1.4. Cost to reconfigure (C)	0.3305	0.6611
1.5. Cost to maintain (C)	0.3309	0.6733
2. Strategic plan relevance sub-attributes		
2.1. Exploration development relevance (B)	0.5538	0.3380
2.2. Mission architecture commonality (B)	0.5487	0.2633
2.3. Usefulness outside INTEGRITY (B)	0.5783	0.2805
2.4. Publicity value (B)	0.4986	0.4037
2.5. Mission requirements understanding (B)	0.5412	0.2901
2.6. Risk mitigation (B)	0.5317	0.3125
3. Complexity sub-attributes		
3.1. Design & manufacturing difficulty (C)	0.3283	0.6221
3.2. Operational & safety difficulty (C)	0.3483	0.5984
3.3. Disorder in the stepping stone (C)	0.3448	0.5266
3.4. Infrastructure impacts (C)	0.3922	0.5053
4. Science, operations, and technology sub-attributes		
4.1. Basic science opportunities (B)	0.6201	0.3362
4.2. Exploration science diversity (B)	0.5888	0.3285
4.3. Operations scenarios (B)	0.5417	0.3784
4.4. Cross cutting technology (B)	0.5849	0.2499
4.5. Interfaces/integration (B)	0.5520	0.2400
4.6. Technology gap/innovation (B)	0.5780	0.2339

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

Next, we determined the following relative closeness measures for the alternative simulators:

$$T_i = (\mathrm{LVS} = 0.6739, \mathrm{RVS} = 0.5690, \mathrm{SHS} = 0.9136, \mathrm{STS} = 0.0877, \mathrm{TVS} = 0.7928),$$

Finally, we used the P_i values and generated a ranking of the alternative simulators in the descending order indicating the most preferred and least preferred simulators as shown below:

$$\mathrm{SHS} \succ \mathrm{TVS} \succ \mathrm{LVS} \succ \mathrm{RVS} \succ \mathrm{STS}.$$

According to this ranking, the surface habitat simulator has the highest priority and must be implemented first. Following the implementation of the surface habitat simulator, JSC should implement the transit vehicle simulator, the lander vehicle simulator, the roving vehicle simulator, and the surface terrain simulator.

6.3.2. The A-TOPSIS method

As discussed in Section 3, the steps 1–3 for A-TOPSIS are identical to the steps 1–3 for TOPSIS. We used the normalized decision matrix presented in Table 13 and determined the PIS (A^+) and NIS (A^-) presented in Table 16 using the A-TOPSIS method:

Next, we used this information and calculated the following weighted Euclidean distances:

$$S_i^+ = (\mathrm{LVS} = 0.0153, \mathrm{RVS} = 0.0203, \mathrm{SHS} = 0.0013, \mathrm{STS} = 0.0903, \mathrm{TVS} = 0.0050),$$
$$S_i^- = (\mathrm{LVS} = 0.0470, \mathrm{RVS} = 0.0336, \mathrm{SHS} = 0.0914, \mathrm{STS} = 0.0014, \mathrm{TVS} = 0.0640).$$

Then, we used the weighted Euclidean distances and determined the relative closeness of the alternative simulators given below:

$$T_i^A = (\mathrm{LVS} = 0.7538, \mathrm{RVS} = 0.6230, \mathrm{SHS} = 0.9861, \mathrm{STS} = 0.0151, \mathrm{TVS} = 0.9278).$$

Finally, we used the T_i^A values and generated the following ranking of the alternative simulators in the descending order indicating the most preferred and least preferred simulators:

$$\mathrm{SHS} \succ \mathrm{TVS} \succ \mathrm{LVS} \succ \mathrm{RVS} \succ \mathrm{STS}.$$

As shown here, the results from A-TOPSIS were similar to the results from TOPSIS.

6.3.3. The M-TOPSIS method

As discussed in Section 3, the steps 1–5 for M-TOPSIS are identical to the steps 1–5 in TOPSIS. We used the positive and negative ideal solutions (PIS and NIS, respectively) presented in Table 15 and determined the following ideal reference point (S) according to the method:

$$S = (S^I, S^N) = (\min(S_i^+), \max(S_i^-)) = (0.0071, 0.0750).$$

Next, we determined the following Euclidean distances between S_i^+ and S_i^- for each alternative simulator and point S:

$$T_i^M = (\mathrm{LVS} = 0.00076, \mathrm{RVS} = 0.00163, \mathrm{SHS} = 0, \mathrm{STS} = 0.00917, \mathrm{TVS} = 0.00025).$$

Finally, we obtained the following preference order of the alternative simulators according to T_i^M.

$$\mathrm{SHS} \succ \mathrm{TVS} \succ \mathrm{LVS} \succ \mathrm{RVS} \succ \mathrm{STS}.$$

As shown here, the results from M-TOPSIS was similar to the results from TOPSIS and A-TOPSIS. In summary, all three TOPSIS methods arrived at the same solution to implement the surface habitat simulator first, the transit vehicle simulator second, the lander vehicle simulator third, the roving vehicle simulator fourth, and the surface terrain simulator last. The INTEGRITY team communicated their recommendation to the management at JSC who agreed to consider this recommendation.

7. Conclusions and future research directions

Recent technological advances and availability of data have made MCDM more challenging than ever. Schoemaker and Russo (1993) argue that as the complexity and the amount of data increases in a decision problem, so does the importance of the solution quality. Although some mangers may favor simple approaches, they can be dangerously inaccurate for complex decision problems. Our model helps DMs (i) decompose a complex problem into manageable steps, (ii) ensure the consistency and completeness of the information, and (iii) synthesize the results through a series of logically sound techniques and structured frameworks. This decomposition and synthesis is not intended to replace DMs; rather, it provides a systematic approach to enhance their decision making capabilities and supplement their judgments. Our model has several attractive features that address some of the limitations inherent in the current MCDM tools and techniques:

(i) *Analytical:* The analytical procedures in our model help a DM decompose complex MADM problems into manageable steps, making this model accessible to a wide range of DMs and situations.
(ii) *Comprehensive:* The model processes a wide range of importance weights and preferences concerning multiple attributes, multiple alternatives, and multiple DMs.
(iii) *Structured:* The model stratifies the information requirements into a hierarchy that simplifies information input and helps DMs focus on a small area of the large problem.
(iv) *Flexible:* Our model does not limit the number of attributes, alternatives, or DMs.

We should note that using the step-by-step and structured framework presented here does not imply a deterministic approach to decision making. While our MADM model enables DMs crystallize their thoughts and organize their judgments, it should be used very carefully. As with any MADM model, the DMs must be aware of the limitations of subjective estimates. When empirical analysis is feasible and makes economic sense, it should be used to improve these estimates (Lodish, 1982). Although technical details of the model may be beyond the reach of average DMs, the basic concepts are not difficult to understand or implement. As such, the DMs can use available analytical tools and techniques with some assistance from the experts (Schoemaker & Russo, 1993).

For future research, we suggest researchers study and develop fuzzy MADM approaches when the decision data are unquantifiable or incomplete. We are particularly interested in extending our model to real-world problems with imprecise, ambiguous or unknown data.

Disclaimer

The views and opinions expressed in this paper are those of the authors and do not reflect the views of the National Aeronautic and Space Administration and Johnson Space Center.

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Appendix A. Simulator ranking attributes and sub-attributes

1. *Cost:* Cost-savings on future exploration should be an important benefit of the INTEGRITY Project. Each INTEGRITY simulator should therefore provide high value to the project relative to its cost. This attribute is a measure of the resources required to accomplish a portion of the project.
   1.1. *Cost to design (C):* The relative cost of designing the simulator, inclusive of all design efforts.
   1.2. *Cost to build (C):* The relative cost of building the simulator including both material and labor costs
   1.3. *Cost to operate (C):* The relative cost of performing test operations in the simulator.
   1.4. *Cost to reconfigure (C):* The relative cost of reconfiguring the simulator between tests.
   1.5. *Cost to maintain (C):* The relative cost of maintaining the simulator over the "long haul."
2. *Strategic plan relevance:* The NASA Strategic Plan identifies a list of exploration, science, and discovery questions that will drive the mission of the Agency. "Using our unique knowledge and expertise, we build the tools that enable revolutionary robotic and human missions. Through scientific research and strategic investments in transformational technologies, we open new pathways toward missions that were impossible only a few years ago." This attribute examines how well a simulator under consideration meets the needs identified in the Agency Strategic Plan and enables exploration. It is a measure of the degree to which a simulator reflects, supports, or incorporates specific, identifiable features of the NASA Strategic Plan, the Code U/Bioastronautics Strategic Plan, the Integrated Space Plan, and/or the Bioastronautics Critical Questions List.
   2.1. *Exploration development relevance (B):* The degree to which the element under consideration helps to resolve critical issues, answers critical science, operations, or technology questions, or clarifies exploration mission requirements.
   2.2. *Mission architecture commonality (B):* All missions have certain operational methods and technology requirements that are common to all destinations (e.g., sparing, approach to maintenance, repair, and redundancy, degree of automation, etc.). Therefore, investigation of one of these issues will have benefits to all future missions, regardless of the destination. INTEGRITY should maximize the efforts to investigate the use of common operations and/or technology.
   2.3. *Usefulness outside INTEGRITY (B):* A measure of the potential a simulator has to be useful for applications outside of the INTEGRITY project – including International Space Station, Space Shuttle Program, exploration, commercial, and other non-NASA.
   2.4. *Publicity value (B):* Does this simulator have inspirational value from a visual and public/educational outreach perspective? What is its publicity value or "cool factor"?
   2.5. *Mission requirements understanding (B):* Many of the requirements for a future exploration mission are not yet understood or even identified. This sub-attribute measures the value of a simulator in uncovering hidden requirements and for defining requirements that are currently unspecified.
   2.6. *Risk mitigation (B):* Consider all Programmatic risks, not only technical and operational risks, but also cost and schedule. Does this element have value to decrease the risk for a future exploration mission?
3. *Complexity:* This attribute is a measure of the overall intricacy of any simulator, relative to all of the other simulators or common NASA test facilities.

3.1. *Design and manufacturing difficulty (C):* A measure of the technical challenge of creating each simulator, as measured by things like number of drawings required, complex fabrication techniques, hard-to-work-with or rare materials, etc.
3.2. *Operational and safety difficulty (C):* The degree of complexity required for operating each simulator safely. The complexity may be revealed through number of failure modes, frequency/duration of required human interaction/operation; architecture-introduced safety risks (e.g. confined spaces, elevated walkways, low passageways, etc.)
3.3. *Disorder in the stepping stone (C):* INTEGRITY will use a stepping stone approach to gradually build up to a complete long-duration ground mission capability. The degree of disorder among the simulators under consideration is captured by this attribute.
3.4. *Infrastructure impacts (C):* A measure of the degree to which the facility infrastructure must be modified to accommodate a simulator. Infrastructure includes buildings, utilities, data networks, etc.

4. *Science, operations, and technology:* INTEGRITY is part of a larger Agency effort aimed and developing our capabilities to fulfill our strategic vision for exploration. This attribute is a measure of the ability of a simulator to accommodate the range of exploration mission technologies, science and operations and the degree to which a simulator allows their evaluation.
4.1. *Basic science opportunities (B):* This sub-attribute measures inherent or serendipitous opportunities for conducting basic science investigations within the facility & simulation whether it coincides with the test mission's science objectives or not.
4.2. *Exploration science diversity (B):* A measure of the degree to which a simulator reflects the spectrum of science activities and equipment needed to conduct exploration science (the science that will be conducted during exploration missions). These elements of exploration science may be simulations rather than actual experiments, scripted operational activities that are part of the overall simulation.
4.3. *Operations scenario diversity (B):* A reflection of the number and diversity of operations areas that can be evaluated in a particular simulator.
4.4. *Cross cutting technology (B):* The number of cross cutting or in-common technologies that are included or can be evaluated in a particular simulator. Cross cutting technologies are those with broad applications for the entire Agency. This sub-attribute also reflects science and operations elements (e.g. medical contingency operations must be present at every phase of the mission and have applications for all manned space flight activities).
4.5. *Interfaces/integration (B):* The number of different interfaces and the level of systems integration that can be investigated with each simulator.
4.6. *Technology gaps/innovation (B):* The degree to which a simulator will require or can incorporate emerging and/or innovative technologies, science, or operations that address critical technology gaps.

Note: Cost factors are identified by (C) and benefit factors are identified by (B).

Instructions

Please respond by placing an 'X' on the appropriate location to indicate your perception of the relative importance of the integrity attributes for each of the following pairwise comparisons.

Placing an 'X' at equal indicates that attributes A and Bare equally important

Integrity attribute A	Placing an 'X' to the left of equal indicates that attribute A is more important than attribute B				⇨	Placing an 'X' to the right of equal indicates that attribute B is more important than attribute A				Integrity attribute B
	O	o O	o O	o O	o O	o O	o O	o O	o O	
	Extreme	Very strong	Strong	Moderate	Equal	Moderate	Strong	Very strong	Extreme	
Cost	O	o O	o O	o O	o O	o O	o O	o O	o O	Strategic plan relevance
Cost	O	o O	o O	o O	o O	o O	o O	o O	o O	Complexity
Cost	O	o O	o O	o O	o O	o O	o O	o O	o O	Science, operations, and technology
Strategic plan relevance	O	o O	o O	o O	o O	o O	o O	o O	o O	Complexity
Strategic plan relevance	O	o O	o O	o O	o O	o O	o O	o O	o O	Science, operations, and technology
Complexity	O	o O	o O	o O	o O	o O	o O	o O	o O	Science, o perations, and technology

Appendix B

B.1. A sample simulator attribute weight assessment questionnaire

Appendix C

C.1. A sample simulator assessment questionnaire

INTEGRITY is designed to provide the building facilities and infrastructure required to house and operate all analog mission vehicle, habitat, and surface terrain simulators and to manage and coordinate all test mission operations associated with these simulators. INTEGRITY planners have identified five simulators, all capable of simulating the crew cabin architecture, integrated systems operations, and crew operations associated with a 1000-day class mission transit vehicle:

Transit Vehicle Simulator (TVS)
Lander Vehicle Simulator (LVS)
Surface Habitat Simulator (SHS)
Roving Vehicle Simulator (RVS)
Surface Terrain Simulator (STS)

The purpose of this questionnaire is to capture your perception of the sub-attributes scores for the simulators using a 10-point Lickert Scale (1 = Very Bad…10 = Very Good). For example, when evaluating "Cost to Design", note that lower cost is preferred to higher cost. If you think a simulator is very costly (bad), provide a low (bad) score and if you think the simulator is not too costly (good), provide a high (good) score. However, when evaluating "Publicity Value", it should be noted that higher publicity value is preferred to lower value. Therefore, if you think a simulator has a great publicity value (good), provide a high (good) score and if you think it provides little value (bad), provide a low (bad) score.

	TVS	LVS	SHS	RVS	STS
	(1 = Very Bad……10 = Very Good)				
1.1. Cost to Design (Minimize)					
1.2. Cost to Build (Minimize)					
1.3. Cost to Operate (Minimize)					
1.4. Cost to Reconfigure (Minimize)					
1.5. Cost to Maintain (Minimize)					
2.1. Exploration Development Relevance (Maximize)					
2.2. Mission Architecture Commonality (Maximize)					
2.3. Usefulness Outside INTEGRITY (Maximize)					
2.4. Publicity Value (Maximize)					
2.5. Mission Requirements Understanding (Maximize)					
2.6. Risk Mitigation (Maximize)					
3.1. Design and Manufacturing Difficulty (Minimize)					
3.2. Operational and Safety Difficulty (Minimize)					
3.3. Sequencing with other					

Appendix C (*continued*)

	TVS	LVS	SHS	RVS	STS
	(1 = Very Bad……10 = Very Good)				
Stepping Stones (Maximize)					
3.4. Infrastructure Impacts (Minimize)					
4.1. Basic Science Opportunities (Maximize)					
4.2. Exploration Science Diversity (Maximize)					
4.3. Operations Scenario Diversity (Maximize)					
4.4. Cross Cutting Technology (Maximize)					
4.5. Interfaces/Integration (Maximize)					
4.6. Technology Gaps/Innovation (Maximize)					

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