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A general Best-Worst method considering interdependency with application to innovation and technology assessment at NASA

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ABSTRACT

The Best-Worst Method (BWM) is a relatively new and popular method for obtaining criteria weights in multi-criteria decision-making. The BWM uses very few comparisons and produces consistent comparisons, leading to more reliable criteria weights. Despite its popularity and reliability, the decision criteria in the BWM are considered independent of one another. However, in most real-world problems, the decision criteria are interdependent. We propose a general form of the BWM (GBWM) to consider the interdependencies and the intensity of the dependencies among the decision criteria in producing relative influence-intensity weights. The new GBWM is simple to understand and implement and delivers reliable results with a high level of consistency in problems with interdependent decision criteria. The results are more reliable than BWM in problems with interdependencies because we consider both their existence and the intensity of the dependencies. In addition, the results are equally or more consistent than BWM because we start with a BWM solution and adjust the BWM solution with a completely consistent vector. We also present a case study for evaluating and prioritizing advanced technology and innovation projects at NASA to demonstrate the applicability of the proposed method.

1. Introduction

The Best-Worst Method (BWM) is a multi-criteria decision-making (MCDM) method recently developed by Rezaei (2015) to obtain the decision criteria weights using two evaluation vectors of the best criterion against the other criteria and the other criteria against the worst criterion. The criteria weights are obtained by solving a non-linear (Rezaei, 2015), an interval, or a linear model (Rezaei, 2016). The BWM is a pairwise comparison-based method similar to the Analytic Hierarchy Process (AHP) and its general form, Analytic Network Process (ANP), proposed by Saaty (1977, 2001). In an MCDM problem with n decision criteria, the AHP requires $n(n\text{-}1)/2$ pairwise comparisons, and the BWM requires only $2n\text{-}3$ comparisons. Compared to AHP, the BWM uses fewer comparisons and produces more consistent comparisons. This leads to more reliable criteria weights in MCDM. The intuitive characterization of the BWM has also fostered the application of the best-worst scales to improve discrimination among the attributes of the alternatives (Heo et al., 2022).

There has been a growing interest in MCDM. However, most MCDM methods (e.g., BWM) do not consider the interdependencies among the decision criteria. Interdependency in MCDM is a fairly obvious concept. Consider a decision problem with three criteria (c_1, c_2, and c_3). Unless obvious, assigning importance weights to these three criteria becomes complex if we are told c_1 influences c_2 and c_3, and c_2 and c_3 influence each other. For this reason, the standard assumption in MCDM is to assume the decision criteria are independent. This restrictive assumption makes an MCDM solution less useful than it could be.

AHP is one of the most widely used MCDM methods. However, the decision criteria in AHP are considered to be independent. The ANP was proposed by Saaty (2001) as a general form of AHP to eliminate this drawback in real-world problems. Similarly, the BWM has been widely used to solve various MCDM problems due to its simplicity and reliability. Statistical results have shown that the BWM outperforms AHP in consistency, minimum violation, total deviation, and conformity

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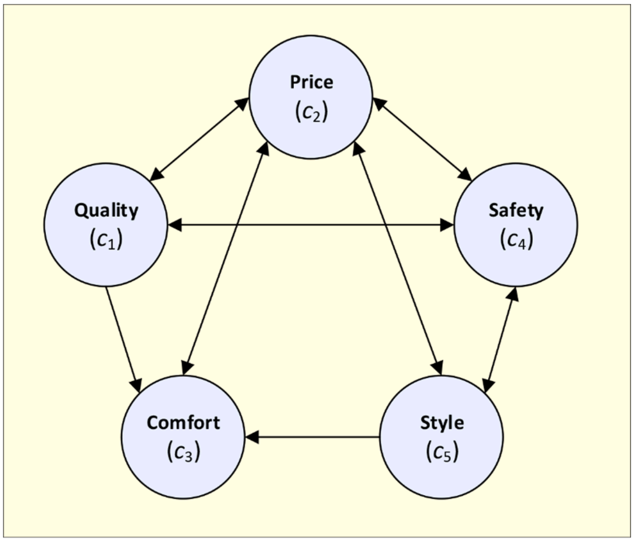

Fig. 1. Influence diagram (car-buying problem).

Table 1
Influence chart (car-buying problem).

Criteria	Quality (c_1)	Price (c_2)	Comfort (c_3)	Safety (c_4)	Style (c_5)
Quality (c_1)	–	Yes	Yes	Yes	No
Price (c_2)	Yes	–	Yes	Yes	Yes
Comfort (c_3)	No	Yes	–	No	No
Safety (c_4)	Yes	Yes	No	–	Yes
Style (c_5)	No	Yes	Yes	Yes	–

(Rezaei, 2015; Mi et al., 2019). Readers should refer to Mi et al. (2019) for a recent state-of-the-art survey of the research and applications of the BWM.

Despite its popularity and reliability, the decision criteria in the BWM are considered independent of one another, while the decision criteria in most real-world problems are interdependent. In this study, we propose a general form of the BWM (GBWM) that enhances the original BWM by considering the interdependencies and the intensity of the dependencies among the decision criteria. Experts perceive the intrinsic importance of criteria and their dependencies on other criteria. The proposed GBWM model acknowledges the initial intrinsic evaluations while incorporating dependency through the second set of weights to account for the influence of every criterion on the others. The main novelty of our optimization procedure builds on formalizing the intensity of the dependencies through an enhanced BWM setting. We also revisit and update a real-world application for evaluating and prioritizing advanced-technology projects at NASA (Tavana, 2003) to demonstrate the applicability of the proposed GBWM.

The method proposed in this study has six unique and attractive features. The GBWM:

a. is a general form of the BWM,
b. considers interdependencies among decision criteria,
c. delivers results that are more reliable than BWM in problems with interdependencies (because we consider the intensity of the dependencies),
d. produces solutions that are equally or more consistent than BWM because we start with a BWM solution and adjust the BWM solution with a completely-consistent vector,
e. is simple to understand and implement (unlike the competing hybrid dependency network models), and
f. produces relative influence-intensity criteria weights that reflect the interdependencies and the intensity of the dependencies among decision criteria.

The remainder of the paper is organized as follows. Section 2 presents an overview of the BWM. In Section 3, we present the proposed framework. In Section 4, we apply the GBWM to a car-buying example introduced by Rezaei (2016). Section 5 applies the proposed method to a real-world application at the Kennedy Space Center (KSC). In Section 6, we present our conclusions and future research directions.

2. Proposed GBWM

In order to illustrate the existence of interdependencies among criteria and their effect on the decision-making process, consider the car-buying problem in Rezaei (2016), where a buyer considers Quality (c_1), Price (c_2), Comfort (c_3), Safety (c_4), and Style (c_5). Rezaei (2016) assumes these five decision criteria are independent. In other words, the BWM does not consider that the buyer could get more Safety, Comfort, or Quality by paying more for the car (or less Safety, Comfort, or Quality by paying less for the car).

Consider the interdependencies among the five car-buying criteria presented in Fig. 1. The influence diagram in Fig. 1 presents the interdependencies in the car-buying network with sources and sinks. A source node is the origin of an influence path, and a sink node is the destination of an influence path. For example, Price is a source node when influencing Quality, Comfort, Style, and Safety, or Quality is a source node when influencing Price, Safety, and Comfort. In contrast, Price is a sink node when influenced by Quality, Comfort, Style, and Safety, or Quality is a sink node when influenced by Price and Safety. The GBWM considers all interdependencies presented in Table 1 to obtain the relative influence-intensity weights of the decision criteria in an MCDM problem (e.g., car-buying problem).

The resulting influence-intensity matrix contains sufficient information to represent the relative interdependencies arising across criteria (influence) and the strength of the dependencies existing within criteria (intensities). We use this information to define our evaluation framework and compute the corresponding interdependent criteria weights.

Experts are assumed to understand the intrinsic importance of criteria and their dependences comprehensively. This feature constitutes the basic premise on which the proposed method is built, where the weights obtained using BWM are enhanced through a second dependency stage. Both processes will be distinctly separated in our model. The first stage of the weighting process is determined by the relative importance of each criterion absent the influence of other criteria. The second stage of the process is based on the relative influence of the criteria and defined so that the BWM can be applied to every column criterion. That is, the consistency of our method follows that of BWM.

The capacity of experts to evaluate influences across criteria is not a novel assumption but the basis on which MCDM models accounting for multiple interacting variables are built. These interactions are generally dealt with through hybrid models incorporating the Decision Making Trial and Evaluation Laboratory (DEMATEL) (Si et al., 2018). These models require sufficient information from experts to formalize the whole set of interdependencies and influences existing across variables. In the same way, BWM simplifies the evaluation requirements of AHP. We simplify the requirements arising from this hybrid structure and introduce a simple technique to manage complex interdependencies across criteria together with their relative strength. This type of reasoning has already been introduced in the literature to try to simplify the complex requirements imposed by the evaluation framework of DEMATEL (Du and Li, 2021).

2.1. Implementation

Each numerical interdependency evaluation received from an expert

Table 2
Information contained in the influence-intensity matrix.

Criteria		C_1	C_2	C_3	C_4	C_5
		↔ influence across criteria				
C_1	↕ intensity within a criterion	–			↑	
C_2			–	←	C_{24}	→
C_3			↑	–	↓	
C_4		←	C_{42}	→	–	
C_5			↓			–

Table 3
Relative importance scale.

Verbal Phrase	Relative importance score
Extremely important	9
Very strongly to extremely important	8
Very strongly important	7
Strongly to very strongly important	6
Strongly important	5
Moderately to strongly important	4
Moderately important	3
Equally to moderately important	2
Equally important	1

contains two different information streams, which is a fact that is acknowledged but not generally exploited in the MCDM literature. One of them describes the influence of a given criterion on the others. The other stream of information is contained in the columns of the corresponding matrix and is usually overlooked. DEMATEL constitutes an important exception because it measures the intensity of the influence across variables by multiplying the rows by the columns an infinite number of times until the sequential increment derived from both effects is negligible.

However, the experts have already provided the information extracted through this procedure and made the required comparisons when assigning their interdependency evaluations. Consider the definition of the influence-intensity matrix and the two evaluations provided by the experts, c_{24} andc_{42}, represented in Table 2.

Note how, by assigning a numerical value toc_{42}, experts are providing two different pieces of information. Intuitively, the value of c_{42} describes the direct influence that the fourth criterion has on the second by comparing influences along a given row. At the same time, experts are delimiting the range of the evaluations, i.e., their relative intensity, within each column criterion. Each expert applies the same procedure and intuition when creating an interval range for each criterion per column. This paper exploits both information streams, which simplify the computational complexity required by DEMATEL and other similar MCDM techniques.

The need for interdependency considerations in the BWM has been addressed indirectly through hybrid methods. For example, the BWM is often used to determine the criteria weights and DEMATEL to extract the influential interrelationships among them (Liu et al., 2020; Yang et al., 2020; Yazdi et al., 2020; Kumar et al., 2019). The use of DEMATEL in the construction of hybrid MCDM structures remains a standard approach in the business literature when considering fuzzy (Yasmin et al., 2020), grey (Paul et al., 2021), and intuitionistic (Orki et al., 2022) environments introduced to deal with information uncertainty and knowledge hiding (Jafari-Sadeghi et al., 2022). Haeri and Rezaei (2019) have also proposed a hybrid grey relational analysis with the BWM for assigning weights and capturing the interdependencies among the decision criteria using fuzzy grey cognitive maps.

We propose a stand-alone GBWM to determine the weights of the criteria and the influence-intensity of their interrelationships. Rezaei (2015) introduced the non-linear BWM and later proposed interval and linear versions of the original model (Rezaei, 2016). The linear version of the BWM (Rezaei, 2016) is used to develop GBWM due to its simplicity and malleability. Our work is also inspired by the network concept proposed by Dağdeviren and Yüksel (2010). The proposed GBWM is composed of two stages. In Stage 1, we use the linear version of the BWM (Rezaei, 2016) to calculate the weights of the criteria absent interdependency considerations. In Stage 2, we determine the relative weights of the decision criteria by adjusting the weights obtained in Stage 1 according to the interdependencies and strength of the dependencies among criteria (that is, the influence-intensity of their interrelationships).

2.1.1. Stage 1 (Implementing BWM and calculating the independent criteria weights)

The BWM considers a set of independent criteria selected to rank a series of alternatives. This technique assigns a weight to each criterion, reflecting its relative importance by performing a basic set of comparisons among criteria. In particular, experts identify the best and worst criteria and perform a series of pairwise comparisons between the remaining criteria and those identified as the best and worst ones. An optimization problem is then applied to identify the exact weight assigned to each criterion based on the set of initial comparisons. The entire procedure is described in detail through the current stage.

Step 1.1. Identify the decision criteria$(c_1, c_2, \ldots, c_n)$.

Step 1.2. Select the best (the most desirable or the most important) and the worst (the least desirable or the least important) criteria.

Step 1.3. Construct the best-to-others vector (V_{BTO}) by comparing the best criterion with the other criteria using the verbal phrases and the relative importance scale presented in Table 3:

$$V_{BTO} = (x_{B1}, \ldots, x_{Bj}, \ldots, x_{Bn})$$

where x_{Bj} represents the preference of the best criterion (i.e., criterion *B*) over other criteria (i.e., criterion *j*) with$x_{BB} = 1$.

Step 1.4. Construct the others-to-worst vector (V_{OTW}) by comparing the other criteria with the worst criterion using the verbal phrases and the relative importance scores presented in Table 3:

$$V_{OTW} = (x_{1W}, \ldots, x_{jW}, \ldots, x_{nW})^T$$

where x_{jW} represents the preference of the other criterion (i.e., criterion *j*) over the worst criterion (i.e., criterion *W*) with$x_{WW} = 1$.

Given the absence of interdependencies across criteria, a unique interval scale, such as,$[1, 9]$, is applied to perform the entire set of comparisons. However, when the relative influences across criteria are incorporated into the analysis, the width of the domain is bounded by the experts through their evaluations. In this regard, the limits imposed by the experts will define the relative intensity assigned to the criteria under consideration.

Step 1.5. Calculate the criteria weights using the linear model proposed by Rezaei (2016):

$$\begin{aligned} & Min\ \delta \\ & s.t. \\ & |\omega_B - x_{Bj} \times \omega_j| \leqslant \delta \\ & |\omega_j - x_{jW} \times \omega_W| \leqslant \delta \\ & \sum_j \omega_j = 1 \\ & \omega_j \geqslant 0,\ \forall j \end{aligned} \tag{1}$$

where ω_j indicates the weight of criterion *j* and δ is used to examine the consistency of pairwise comparisons. The closer this number is to zero, the higher the consistency of the pairwise comparisons will be.

2.1.2. Stage 2 (calculating the interdependent criteria weights)

In this stage, we adjust the independent criteria weights obtained in Stage 1 and derive the relative influence-intensity weights of the decision criteria according to the interdependencies and the strength of the dependencies.

Table 4
Influence-intensity scale.

Verbal Phrase	Relative influence-intensity score
Extreme influence	9
Very significant to extreme influence	8
Very significant influence	7
Significant to very significant influence	6
Significant influence	5
Moderate to significant influence	4
Moderate influence	3
Equal to moderate influence	2
Equal Influence	1

Step 2.1: Construct an influence diagram and extract an intensity chart from the influence diagram.

Step 2.2: Construct the influence-intensity matrix according to the intensity chart using the influence intensity scale presented in Table 4. The influence-intensity matrix is used to represent the interdependencies and the strength of the dependencies (influence-intensities) in a problem.

Step 2.2.1: Define the influence-intensity relationships existing among decision criteria$(\varsigma_{i1},\varsigma_{i2},\dots,\varsigma_{in})$, with$i=1,\dots,n$. In particular, each expert consulted provides a value describing the influence of criterion i on criterion$j$, namely,ς_{ij}. If several experts are consulted, the subsequent matrix entries can be defined as the average of the experts' evaluations, a common aggregation procedure implemented in techniques such as DEMATEL.

Each expert k describes an influence-intensity matrix $C_k=\left[\varsigma_{ij}^k\right]_{n\times n}$ consisting of an empty principal diagonal and ς_{ij}^k values representing the opinion of expert k regarding the degree to which criterion i influences criterion$j$. The elements composing the resulting influence-intensity matrix can be defined by aggregating the opinions of all e experts as follows:

$$\varsigma_{ij}=\frac{1}{e}\sum_{k=1}^{e}\varsigma_{ij}^k \tag{2}$$

with$i,j=1,\dots,n$. The influence-intensity matrix is thus given by

$$C=\begin{pmatrix}\varsigma_{11} & \varsigma_{12} & \cdots & \varsigma_{1n}\\ \varsigma_{21} & \varsigma_{22} & \cdots & \varsigma_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \varsigma_{nn}\end{pmatrix} \tag{3}$$

Techniques such as DEMATEL proceed to normalize the matrix and define a geometric series using the normalized matrix as follows:$C+C^2+C^3+\cdots+C^n$, with$n\to\infty$. This procedure is designed to account for and exhaust all the (influence and intensity) effects that each criterion has on (and receives from) all the other criteria. The implementation of this procedure requires defining the inverse of the limit matrix and performing multiple computations, whose burden increases with the size of the matrix. DEMATEL delivers an influential relation map describing the structural dependence existing across criteria.

Note that the computational burden of a technique such as DEMATEL can be eased by acknowledging the fact that every evaluation provided by an expert describes not only the influence across criteria but also the relative intensity of these influences within each criterion. We illustrate and build on this intuition throughout the different steps composing the current stage.

Step 2.2.2: Identify the most and least influential criteria on each of the criteria described in the columns of the influence-intensity matrix. Denote the most influential criterion on column criterion j byc_j^h, while the least influential criterion on column criterion j will be denoted byc_j^l. Note that the relative intensity assigned by the experts to criterion j is reflected in the width of the interval$[c_j^l,c_j^h]$.

A main assumption of the BWM is that the domain of comparison across criteria is identical and characterized by a predefined interval. In other words, a unique pair of highest and lowest reference values is defined and applied to obtain the best-to-others and others-to-worst vectors. When identical $[c_j^l,c_j^h]$ are defined for all j criteria, each evaluation fully describes the influence and intensity with respect to the best and worst criteria. However, when dealing with evaluations defined within intervals of different width, the relative intensity depends on the actual width of the interval. Intuitively, even though the influence of a criterion on any other can be very strong, the relative intensity of this influence may be low if all the other criteria have a strong influence on the same criterion.

Consider the influence of any given criterion on criterion$j$, assume that the value is located within the interval$[c_j^l,c_j^h]$, and denote it byc_j^m. The relative importance of this value across criteria can be intuitively understood by comparing c_j^m for all different j criteria. However, the intensity of this value within criterion j depends on its relative position within the interval$[c_j^l,c_j^h]$. This information is contained in the evaluations provided by the experts and can be used to define the corresponding optimization problem.

Step 2.3: Building on the same intuition as V_{BTO} but applied to the relative influence received by each criterion j from the other criteria, construct the most-influential-intense-to-others column (V_{HTO}) by comparing the influence of the most influential criterion on criterion j relative to the influence of the other criteria on criterion j

$$V_{HTO}=\left(\frac{c_j^h}{c_j^1},\dots,\frac{c_j^h}{c_j^n}\right) \tag{4}$$

where $\frac{c_j^h}{c_j^i}$ represents the influence of the most influential criterion on criterion j (c_j^h) relative to the influence of other criteria on criterion j (c_j^i), with $\frac{c_j^h}{c_j^h}=1$.

Step 2.4: Building on the same intuition as V_{OTW} but applied to the relative influence received by each criterion j from the other criteria, construct the others-to-least-influential-intense column (V_{OTL}) by comparing the influence of the other criteria on criterion j relative to the influence of the least influential criterion on criterion$j$:

$$V_{OTL}=\left(\frac{c_j^1}{c_j^l},\dots,\frac{c_j^n}{c_j^l}\right) \tag{5}$$

where $\frac{c_j^i}{c_j^l}$ represents the influence of other criteria on criterion j (c_j^i) relative to the influence of the least influential criterion on criterion j (c_j^l), with$\frac{c_j^l}{c_j^l}=1$.

Step 2.5. Calculate the relative influence-intensity criteria weights by implementing the influence intensities within the linear BWM model proposed by Rezaei (2016):

$$\begin{aligned}&Min\ \delta_j\\ &\text{s.t.}\\ &\left|\omega_{c_j^h}-\frac{c_j^h}{c_j^i}\times\omega_{c_j^i}\right|\leqslant\delta_j\\ &\left|\omega_{c_j^i}-\frac{c_j^i}{c_j^l}\times\omega_{c_j^l}\right|\leqslant\delta_j\\ &\sum_i\omega_{c_j^i}=1\\ &\omega_{c_j^i}\geqslant 0,\ \forall i\end{aligned} \tag{6}$$

where $\omega_{c_j^i}$ describes the influence-intensity weight of criterion i on criterion$j$, and δ_j determines the consistency of pairwise comparisons

Table 5
Widening of evaluation intervals and total influence intensity scores.

Triple	Total influence intensity
$[4,5,6]$	2,45
$[3,5,6]$	2,86
$[4,5,7]$	2,65
$[3,5,7]$	3,06

within a given column criterion$j$. Note that the same procedure must be applied to each and every column criterion$j$. We use the GAMS software and CPLEX solver to find the optimum objective function value (consistency ratio), and the relative influence-intensity weights of criteria.

Once the corresponding $\omega_{c_j^i}$ values are obtained for each i and j criterion, the subsequent normalization procedure and final implementation steps follow.

Step 2.6: Construct and normalize the relative influence-intensity matrices. Initially, construct the relative influence-intensity matrix using the relative influence-intensity weights obtained in Step 2.5. The sum of the entries in each column of the relative influence-intensity matrix is always 2. To normalize the matrix, we divide each value in the column by the column sum.

Step 2.7: Construct the interdependent weights of criteria by multiplying the normalized relative influence-intensity matrix into the independent weights of criteria obtained in Stage 1.

2.2. On the influence and intensity effects

The method proposed in this paper is developed based on the premises of the classical BWM. The initial BWM weights are revised by considering interdependencies and the intensity of these dependencies. We introduce different intensities based on the width of the intervals defined by the experts per column criterion. In the best-to-others case, the higher the relative distance between evaluations, the stronger the intensity. The same intuition applies to the others-to-worst case, where the relative distance is computed for the least influential criterion.

That is, a large influence-intensity effect requires both a large influence value,c_j^i, and relatively high intensity arising from a wide evaluation interval$[c_j^l, c_j^h]$. If all criteria have a large influence on another criterion, with the corresponding c_j^i values being all similar and close toc_j^h, then a large influence effect is combined with relatively low intensity. The subsequent influence-intensity effects remain lower than those of less influential criteria contained within a wider interval$[c_j^l, c_j^h]$. In other words, the effect that a criterion exerts on another is not only measured directly through the influence score but also relative to the influence exerted by other criteria through its intensity score. This is the type of interdependency measure built in the current paper.

Consider the triple$[c_j^l, c_j^m, c_j^h]$. The influence effect is determined by the value of these evaluations, with $c_j^h > c_j^m > c_j^l$ describing the decrease in influence as the value of the evaluations decreases. The intensity effect is determined by the relative width of the interval and the position ofc_j^m, namely, $\frac{c_j^h}{c_j^m}$ and$\frac{c_j^m}{c_j^l}$, with increments in the width of the interval limits resulting in higher intensity values. Identical c_j^m values exhibit higher intensities when contained within wider evaluation intervals $[c_j^{l*}, c_j^{*h}]$ relative to$[c_j^l, c_j^h]$, for any given value ofc_j^m, $\frac{c_j^{h*}}{c_j^m} > \frac{c_j^h}{c_j^m}$ and $\frac{c_j^m}{c_j^{l*}} > \frac{c_j^m}{c_j^l}$, when $c_j^{h*} > c_j^h$ and$c_j^{l*} < c_j^l$, respectively.

Thus, an ordered structure designed according to BWM requirements is defined per column criterion. At least half the total intensity will be assigned to the initial weight of a criterion, which, together with the influence of this criterion on the others – and their relative initial weights – determine its final weight. That is, the initial evaluation of the BWM carries an important weight, which is then adjusted through the BWM extension implemented in the second stage.

It is important to note that intensities increase non-linearly with the width of the interval and are not equivalent to average expected values. To illustrate this point, define the total intensity of influence as follows:

$$T(c_j^l, c_j^m, c_j^h) = \frac{c_j^h}{c_j^m} + \frac{c_j^m}{c_j^l} \tag{7}$$

A simple numerical comparison serves to exemplify the corresponding intuition. Table 5 compares the total intensity of influence obtained from four different triples describing a widening of the evaluation intervals. This table illustrates the increase in intensity that takes place as the evaluation intervals widen. In particular, the results highlight the unequal increase in intensity that takes place as the intervals widen asymmetrically, an effect due to the value of the corresponding derivatives

$$\begin{aligned} \frac{\partial T(c_j^l, c_j^m, c_j^h)}{\partial c_j^h} &= \frac{1}{c_j^m} > 0 \\ \frac{\partial T(c_j^l, c_j^m, c_j^h)}{\partial c_j^l} &= -\frac{c_j^m}{(c_j^l)^2} < 0 \end{aligned} \tag{8}$$

The relative reference values defined by the interval limits and the evaluations within them determine the intensity of the influence exerted on the least influential criterion and received from the most influential one within the column criterion$j$. This benchmark evaluation framework provides more information regarding the influence-intensity among criteria than absolute intensity measures based on $(c_j^h - c_j^m)$ and$(c_j^m - c_j^l)$, where the relative positions of the influence values do not condition the subsequent intensities.

Note that the effects are similar when modifyingc_j^m, with the change in total intensity determined by the relative position of c_j^m within $[c_j^l, c_j^h]$ as follows

$$\frac{\partial T(c_j^l, c_j^m, c_j^h)}{\partial c_j^m} = -\frac{c_j^h}{(c_j^m)^2} + \frac{1}{c_j^l} \tag{9}$$

3. Numerical example

In this section, we demonstrate the behavior of the proposed GBWM using the simple car-buying problem in Rezaei (2016). In this problem, a buyer is considering Quality (c_1), Price (c_2), Comfort (c_3), Safety (c_4), and Style (c_5) as the decision criteria for purchasing a car.

3.1. Stage 1 (Implementing BWM and calculating the independent criteria weights for the car-buying problem)

Rezaei (2016) shows the details for calculating the independent criteria weights for the car-buying problem using steps 1.1 through 1.5 in Section 2.1. The independent criteria weight vector for the car-buying problem obtained by Rezaei (2016) is:

$$\begin{bmatrix} 0.2105 \\ 0.4211 \\ 0.1053 \\ 0.2105 \\ 0.0526 \end{bmatrix}$$

where$\omega_{c_1} = 0.2105$, $\omega_{c_2} = 0.4211$, $\omega_{c_3} = 0.1053$, $\omega_{c_4} = 0.2105$, and $\omega_{c_5} = 0.0526$.

3.2. Stage 2 (calculating the interdependent criteria weights for the car-buying problem)

Step 2.1: Construct the car-buying influence diagram and intensity chart. The influence diagram presents the interdependencies in the car-

Table 6
Intensity chart (car-buying problem).

Criteria	Quality (c_1)	Price (c_2)	Comfort (c_3)	Safety (c_4)	Style (c_5)
Quality (c_1)	–	Influence-intensity of Quality on Price	Influence-intensity of Quality on Comfort	Influence-intensity of Quality on Safety	None
Price (c_2)	Influence-intensity of Price on Quality	–	Influence-intensity of Price on Comfort	Influence-intensity of Price on Safety	Influence-intensity of Price on Style
Comfort (c_3)	None	Influence-intensity of Comfort on Price	–	None	None
Safety (c_4)	Influence-intensity of Safety on Quality	Influence-intensity of Safety on Price	None	–	Influence-intensity of Safety on Style
Style (c_5)	None	Influence-intensity of Style on Price	Influence-intensity of Style on Comfort	Influence-intensity of Style on Safety	–

Table 7
Influence-intensity matrix (car-buying problem).

Criteria	Quality	Price	Comfort	Safety	Style
Quality	–	7	4	6	N
Price	7**	–	5**	8**	6**
Comfort	N	4*	–	N	N
Safety	5*	8**	N	–	4*
Style	N	5	3*	4*	–

Note: **Most-influenced and * Least-influenced

Table 8
Influence-intensity of most influential-to-others (car-buying problem).

Criteria	Quality	Price	Comfort	Safety	Style
Quality	–	8/7	5/4	8/6	N
Price	7/7	–	5/5	8/8	6/6
Comfort	N	8/4	–	N	N
Safety	7/5	8/8	N	–	6/4
Style	N	8/5	5/3	8/4	–

Table 9
Influence-intensity of others-to-least influential (car-buying problem).

Criteria	Quality	Price	Comfort	Safety	Style
Quality	–	7/4	4/3	6/4	N
Price	7/5	–	5/3	8/4	6/4
Comfort	N	4/4	–	N	N
Safety	5/5	8/4	N	–	44
Style	N	5/4	3/3	4/4	–

buying network with sources and sinks, as shown in Fig. 1. The intensity chart shown in Table 6 is a detailed tabular representation of all the interdependencies existing between the decision criteria in the car buying problem.

Step 2.2: Construct the car-buying influence-intensity matrix. This matrix is used to show the intensity of the interactions between the decision criteria presented in Table 6 using the verbal phrases and the relative influence-intensity scale presented in Table 4.

As shown in the influence-intensity matrix presented in Table 7, each row represents the influence level of the row criterion on the column criteria (e.g., the influence of Quality in Row 1 on Price, Comfort, Safety, and Style in columns 2–5). In contrast, each column represents the intensity of the influences that the row criteria have on the column criterion (e.g., the intensity of the influence that Price, Comfort, Safety, and Style in rows 2–5 have on Quality in Column 1). In each column, the criterion with the highest influence-intensity is selected as the most influential criterion for the column criterion, and the criterion with the lowest influence-intensity is selected as the least influential criterion for the column criterion. In the car-buying example, we assume that the influence-intensity of Price on Quality is "very significant influence," which from Table 4 is "7" while the influence-intensity of Safety on Quality is "significant influence" which from Table 4 is "5". Thus, the numbers in Column 1 of Table 7 are 7 and 5. Using similar assumptions for the rest of the influence-intensity relationships, we construct the remaining of Table 7.

Note that the influences among criteria are not necessarily symmetric, as would be the case, for instance, when performing pairwise comparisons within AHP. In this regard, causality and the subsequent influence relations should be understood and determined accordingly by the experts. For instance, consider the influence values presented in Table 7. In this case, Safety affects Quality, since safer cars must incorporate novel features designed to enhance their Safety. The subsequent increase in Quality can be understood as a consequence of these additional features. However, Quality does not need to have a reciprocal effect on Safety. An increment in the Quality of its components enhances the Safety of the car but not necessarily by incorporating the same safety features as in the former case. Even if this was the case, the effect of quality improvements on Safety does not need to be equal to that of Safety on the general Quality of the car. As assumed when implementing MCDM techniques such as DEMATEL (Dalvi-Esfahani et al., 2019), experts should be able to tell these effects apart and assign the corresponding influence values accordingly.

Step 2.3: Construct the influence-intensity of the most influential-to-others vectors by considering the influence-intensity of the most influential criterion on criterion *j* relative to the influence-intensity of the other criteria on criterion *j*. For example, consider the Quality column in Table 7. Price is the most influential criteria for Quality, with an influence-intensity of 7. We divide 7 by the influence-intensity of others (Price and Safety). In other words, we divide 7 by 7 for Price and 7 by 5 for Safety.

A similar intuition applies to the remaining columns, highlighting the differences in the upper influence limit values defined by the experts across criteria. For instance, consider the Comfort column in Table 7. Price is also the most influential criterion on Comfort, but the value of its influence-intensity equals 5. Note the difference with respect to the Quality criterion, where the influence-intensity of Price was higher and equal to 7. Thus, while being the most influential criterion on both Quality and Comfort, the intensity of its influence varies between both criteria. In this latter case, we divide 5 by the influence-intensity of Price as well as that of the other criteria (Quality and Style). We continue this process and complete all most influential to others columns in Table 8. Clearly, Price displays the greatest influence on the other criteria, though the intensity of its influence differs across criteria.

Step 2.4: Construct the influence-intensity of the others-to-least influential vectors by considering the influence-intensity of the other criteria on criterion *j* relative to the influence-intensity of the least influential criterion on criterion *j*. For example, consider the Quality column in Table 7. Safety is the least influential criterion on Quality with an influence-intensity of 5. We divide the influence-intensity of others (Price and Safety) by 5. In other words, we divide 7 by 5 for Price and 5 by 5 for Safety. We continue this process and complete all others to the least influential columns in Table 9.

Step 2.5: Calculate the relative influence-intensity weights of criteria using the influence intensities in Table 8 and Table 9 and run the linear BWM model proposed by Rezaei (2016) in GAMS software applying the CPLEX solver. For instance, to calculate the relative influence-intensity weights for the price criterion, i.e.,$j = 2$, a linear

Table 10
Relative influence-intensity weights (car-buying problem).

Criteria	Quality ($\delta^* = 0$)	Price ($\delta^* = 0$)	Comfort ($\delta^* = 0$)	Safety ($\delta^* = 0$)	Style ($\delta^* = 0$)
Quality	–	0.292	0.333	0.333	N
Price	0.583	–	0.416	0.444	0.600
Comfort	N	0.167	–	N	N
Safety	0.416	0.332	N	–	0.400
Style	N	0.208	0.250	0.222	–

Table 11
Relative influence-intensity matrix (car-buying problem).

Criteria	Quality	Price	Comfort	Safety	Style
Quality	1	0.292	0.333	0.333	0
Price	0.583	1	0.416	0.444	0.600
Comfort	0	0.167	1	0	0
Safety	0.416	0.332	0	1	0.400
Style	0	0.208	0.250	0.222	1

Table 12
Normalized relative influence-intensity matrix (car-buying problem).

Criteria	Quality	Price	Comfort	Safety	Style
Quality	0.500	0.146	0.167	0.167	0
Price	0.292	0.500	0.208	0.222	0.300
Comfort	0	0.084	0.500	0	0
Safety	0.208	0.166	0	0.500	0.200
Style	0	0.104	0.125	0.111	0.500

model is developed as follows:

$$
\begin{aligned}
& \mathit{Min}\ \delta_2 \\
& \mathit{s.t.} \\
& \omega_{c_2^4} - \frac{8}{7} \times \omega_{c_2^1} \leq \delta_2; \omega_{c_2^4} - \frac{8}{7} \times \omega_{c_2^1} \geq -\delta_2 \\
& \omega_{c_2^4} - \frac{8}{4} \times \omega_{c_2^3} \leq \delta_2; \omega_{c_2^4} - \frac{8}{4} \times \omega_{c_2^3} \geq -\delta_2 \\
& \omega_{c_2^4} - \frac{8}{5} \times \omega_{c_2^5} \leq \delta_2; \omega_{c_2^4} - \frac{8}{5} \times \omega_{c_2^5} \geq -\delta_2 \\
& \omega_{c_2^1} - \frac{7}{4} \times \omega_{c_2^3} \leq \delta_2; \omega_{c_2^1} - \frac{7}{4} \times \omega_{c_2^3} \geq -\delta_2 \\
& \omega_{c_2^5} - \frac{5}{4} \times \omega_{c_2^3} \leq \delta_2; \omega_{c_2^5} - \frac{5}{4} \times \omega_{c_2^3} \geq -\delta_2 \\
& \omega_{c_2^1} + \omega_{c_2^3} + \omega_{c_2^4} + \omega_{c_2^5} = 1 \\
& \omega_{c_2^1}, \omega_{c_2^3}, \omega_{c_2^4}, \omega_{c_2^5} \geq 0
\end{aligned}
$$

Similarly, the model finds the relative influence-intensity of all criteria by minimizing the corresponding objective functions (consistency ratio). Table 10 presents the relative influence-intensity weights of the Quality, Price, Comfort, Safety, and Style criteria.

Step 2.6: Construct and normalize the relative influence-intensity matrix. The relative influence-intensity matrix is composed of the relative influence-intensity weights for each criterion in Table 10 complemented with a weight of 0 for criteria pairs with no interaction (represented by "N") and a weight of 1 for criteria pairs with complete interaction (represented by "-").

The sum of values in each column of Table 11 is always equal to 2. We normalize this table to ensure that the sum of the criteria weights in each column is equal to one, as shown in Table 12.

Step 2.7: Construct the interdependent criteria weight vector by multiplying the normalized relative influence-intensity matrix (Table 12) into the independent criteria weights obtained by Rezaei's (2016) BWM in Stage 1:

$$
\begin{bmatrix} 0.500 & 0.146 & 0.167 & 0.167 & 0 \\ 0.292 & 0.500 & 0.208 & 0.222 & 0.300 \\ 0 & 0.084 & 0.500 & 0 & 0 \\ 0.208 & 0.166 & 0 & 0.500 & 0.200 \\ 0 & 0.104 & 0.125 & 0.111 & 0.500 \end{bmatrix} \times \begin{bmatrix} 0.211 \\ 0.421 \\ 0.105 \\ 0.211 \\ 0.053 \end{bmatrix} = \begin{bmatrix} 0.2195 \\ 0.3564 \\ 0.0880 \\ 0.2295 \\ 0.1066 \end{bmatrix}
$$

Note how, besides their direct importance, defined by the initial independent weights, each criterion's influence on the others determines their relative importance. That is, the independent weights describe the importance of each criterion with respect to every other criterion. The interdependencies describe the relative importance of each criterion through their influence on the others. Simply put, our approach defines a weight per the criterion of the initial independent weights.

As shown above, the overall weight of Quality, Price, Comfort, Safety, and Style has changed – after considering the interdependencies and the strength of the dependencies (influence-intensities) among them – as follows:

$$
\begin{bmatrix} 0.2195 \\ 0.3564 \\ 0.0880 \\ 0.2295 \\ 0.1066 \end{bmatrix} - \begin{bmatrix} 0.2105 \\ 0.4211 \\ 0.1053 \\ 0.2105 \\ 0.0526 \end{bmatrix} = \begin{bmatrix} +0.0090 \\ -0.0647 \\ -0.0173 \\ +0.0190 \\ +0.0540 \end{bmatrix}
$$

The results show that Price has received the most significant weight change (-0.0647) followed by Style (+0.0540), Safety (+0.019), Comfort (-0.0173), and Quality (+0.0090). The reasons for the minor weight changes in this problem are the small influence-intensity scores and a large number of interdependencies. Problems with larger influence-intensity scores and a smaller number of interdependencies experience more significant weight changes. We provide additional intuition illustrating this result through the numerical examples described in Appendix 1.

It is worth noting that the GBWM proposed in this study is a general form of the original BWM. In cases where there are no interdependencies among the decision criteria, the criteria weights provided by the original BWM remain unchanged:

$$
\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 0.2105 \\ 0.4211 \\ 0.1053 \\ 0.2105 \\ 0.0526 \end{bmatrix} = \begin{bmatrix} 0.2105 \\ 0.4211 \\ 0.1053 \\ 0.2105 \\ 0.0526 \end{bmatrix}
$$

We demonstrate the extreme cases where the gap between BWM and GBWM is large in Appendix 1. The first two scenarios represent the Current Scenario and the case of No Influence. In Scenarios 2–6, we consider cases where all criteria equally influence criterion *j*. As shown in the appendix, the weights of Criterion *j* derived from BWM and GBWM differ significantly in these scenarios. In addition, other criteria also experienced weight changes. Scenario 7 examines the case where all criteria influence each other except for Comfort.

All in all, these scenarios show:

- In the case of no interdependencies, BWM and GBWM produce identical results.
- In the case of interdependency:
  - o The difference between methods depends on the number of influencing criteria and the distribution of their influences across criteria.
  - o The weight of the independent criteria remains unchanged in BWM and GBWM regardless of the number of influencing criteria.

4. Case study

In this section, we revisit an earlier application for evaluating and prioritizing advanced-technology projects at the KSC to demonstrate the

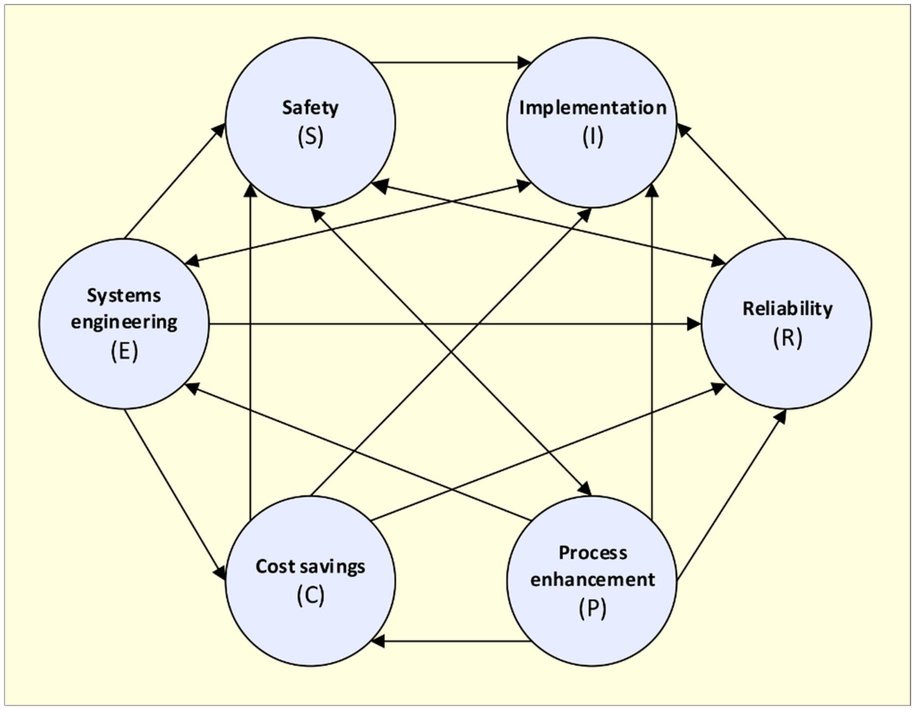

Fig. 2. Influence diagram (advanced technology selection problem).

Table 13
Influence-intensity chart (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	None	None	Influence-intensity of S on P	Influence-intensity of S on R	Influence-intensity of S on I
Systems engineering (E)	Influence-intensity of E on S	–	Influence-intensity of E on C	None	Influence-intensity of E on R	Influence-intensity of E on I
Cost-savings (C)	Influence-intensity of C on S	None	–	None	Influence-intensity of C on R	Influence-intensity of C on I
Process enhancement (P)	Influence-intensity of P on S	Influence-intensity of P on E	Influence-intensity of P on C	–	Influence-intensity of P on R	Influence-intensity of P on I
Reliability (R)	Influence-intensity of R on S	None	None	None	–	Influence-intensity of R on I
Implementation (I)	None	Influence-intensity of I on E	None	None	None	–

applicability of the proposed method. Readers should refer to (Tavana, 2003) for more details on the problem description. In this application, KSC management was considering ten advanced technology projects with a total cost of $15,038,000. However, budget cuts had limited spending to $6 million. Six departments consisting of Safety (S), Systems Engineering (E), Cost-savings (C), Process-Enhancement (P), Reliability (R), and Implementation (I) were selected to rank ten projects. Each department identified a set of criteria to be used in the evaluation process. The departments then developed a probability of occurrence for each criterion using numerical probabilities and the approach proposed by Tavana et al. (1997). Appendix 2 presents the criteria, sub-criteria, advanced technology projects, and their probability scores developed by the six departments at the KSC. We recently requested our colleagues at the KSC to revisit and update the problem by developing an influence diagram that considers the main interdependencies existing among the selected sub-criteria (see Fig. 2). The influence diagram was used to construct the influence intensity chart presented in Table 13.

Next, we calculate the sub-criteria's global influence-intensity weights using the proposed GBWM and integrate them with the project probability scores using a weighted sum method. This is done to obtain a success factor for each project and rank them.

Stage 1: In this stage, we calculate the independent weights of criteria and sub-criteria using the five-step process described in Stage 1.

Step 1.1: In this step, we used Safety, System Engineering, Cost-Saving, Process Enhancement, Reliability, and Implementation criteria and their relevant sub-criteria presented in Appendix 2.

Step 1.2: In this step, we identified the best (**) and the worst (*) criteria from the list of criteria and sub-criteria presented in Appendix 2.

Step 1.3: In this step, pairwise comparisons are made between the best criterion and other criteria to construct the best-to-others vector. This operation is also performed for the sub-criteria. Table A.1 in Appendix 3 presents the best-to-others vector for the criteria and sub-criteria.

Step 1.4: In this step, pairwise comparisons are made between other criteria and the worst criterion to construct the others-to-worst vector. This operation is also performed for the sub-criteria. Table A.2 in Appendix 3 presents the others-to-worst vector for the criteria and sub-criteria.

Step 1.5: In this step, the following linear model proposed by Rezaei (2016) and the vectors in Table A.1 and Table A.2 are used to calculate

Table 14
Influence-intensity matrix (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	N	N	-***	8**	9**
Systems engineering (E)	8**	–	6**	N	7	7
Cost-savings (C)	2*	N	–	N	5	4
Process enhancement (P)	3	2*	3*	–	3*	3*
Reliability (R)	4	N	N	N	–	8
Implementation (I)	N	3**	N	N	N	–

Note: **Most-influenced, * Least-influenced, and ***Single-influenced (Process Enhancement is only influenced by Safety)

Table 15
Global influence-intensity weights (advanced technology and innovation selection problem).

Criteria	interdependent criteria weights	Sub-criteria	independent criteria weights	Global influence-intensity weights
Safety (S)	0.324	S-DSI	0.493	0.1597
		S-LOF	0.250	0.0810
		S-PID	0.125	0.0405
		S-SVS	0.069	0.0224
		S-DVS	0.062	0.0201
Systems Engineering (E)	0.243	E-LSP	0.516	0.1254
		E-NTR	0.183	0.0445
		E-ONA	0.137	0.0333
		E-FAL	0.110	0.0267
		E-OBS	0.054	0.0131
Cost-savings (C)	0.093	C-LAB	0.380	0.0353
		C-MAT	0.206	0.0192
		C-TSI	0.138	0.0128
		C-MPC	0.103	0.0096
		C-MPS	0.083	0.0077
		C-ROM	0.052	0.0048
		C-CON	0.039	0.0036
Process Enhancement (P)	0.136	P-LPL	0.538	0.0732
		P-LPT	0.262	0.0356
		P-LPA	0.138	0.0188
		P-LPH	0.062	0.0084
Reliability (R)	0.134	R-SFP	0.303	0.0406
		R-CFP	0.177	0.0237
		R-MTR	0.118	0.0158
		R-IFI	0.089	0.0119
		R-SIM	0.071	0.0095
		R-AMT	0.059	0.0079
		R-TBF	0.059	0.0079
		R-ETT	0.051	0.0068
		R-COT	0.044	0.0059
		R-EQP	0.028	0.0038
Implementation (I)	0.070	I-MSA	0.423	0.0296
		I-IMI	0.171	0.0120
		I-FMC	0.129	0.0090
		I-MSC	0.103	0.0072
		I-EOH	0.073	0.0051
		I-SSR	0.064	0.0045
		I-TCH	0.037	0.0026

the weights of the criteria and sub-criteria:

$$
\begin{array}{ll}
\textit{Min } \delta & \\
\textit{s.t.} & \\
\omega_S - 4\omega_E \le \delta; \omega_S - 4\omega_E \ge -\delta; & \omega_E - 2\omega_I \le \delta; \omega_E - 2\omega_I \ge -\delta \\
\omega_S - 6\omega_C \le \delta; \omega_S - 6\omega_C \ge -\delta; & \omega_C - 2\omega_I \le \delta; \omega_C - 2\omega_I \ge -\delta \\
\omega_S - 7\omega_P \le \delta; \omega_S - 7\omega_P \ge -\delta; & \omega_P - \omega_I \le \delta; \omega_P - \omega_I \ge -\delta \\
\omega_S - 4\omega_R \le \delta; \omega_S - 4\omega_R \ge -\delta; & \omega_R - 2\omega_I \le \delta; \omega_R - 2\omega_I \ge -\delta \\
\omega_S - 8\omega_I \le \delta; \omega_S - 8\omega_I \ge -\delta; & \omega_S + \omega_E + \omega_C + \omega_P + \omega_R + \omega_I = 1 \\
\omega_S, \omega_E, \omega_C, \omega_P, \omega_R, \omega_I \ge 0 &
\end{array}
$$

We ran the above model in GAMS software to find the optimal value of the objective functions and the weights of the criteria presented in Table A.3 within Appendix 3. Similarly, the weights of the sub-criteria belonging to each criterion were calculated. The optimal value of the objective function and the independent local weights of criteria and sub-criteria are all presented in this table.

Stage 2 (calculating the interdependent global sub-criteria weights)

Step 2.1: This step describes the construction of the influence diagram and the intensity chart presented earlier in Fig. 2 and Table 13, respectively.

Step 2.2: In this step, we constructed the influence-intensity matrix presented in Table 14 based on the intensity chart described in Table 13 and the input from our colleagues at the KSC retrieved using the verbal phrases and the relative influence-intensity scale presented in Table 4. Each row of the influence-intensity matrix presented in Table 14 represents the influence level of the row criterion on the column criteria (e.g., the influence of Safety in Row 1 on Safety, Systems Engineering, Cost-savings, Process Enhancement, Reliability, and Implementation in columns 1–6). In contrast, each column represents the intensity of the influences that the row criteria have on the column criterion (e.g., the intensity of the influence that Systems Engineering, Cost-savings, Process Enhancement, Reliability, and Implementation in rows 2–6 have on Safety in Column 1). In each column, the criterion with the highest influence-intensity (**) is selected as the most influential criterion for the column criterion, and the criterion with the lowest influence-intensity (*) is selected as the least influential criterion for the column criterion.

Step 2.3: In this step, we constructed the influence-intensity of the most influential-to-others vectors by considering the influence-intensity of the most influential criterion on criterion *j* relative to the influence-intensity of the other criteria on criterion *j*. For example, consider the Safety column in Table 14. Systems engineering is the most influential criteria on Safety with an influence-intensity of 8. We divide 8 by the influence-intensity of others (Systems Engineering, Cost-savings, Process Enhancement, and Reliability). In other words, we divide 8 by 8 for Systems Engineering, 8 by 2 for Cost-savings, 8 by 3 for Process Enhancement, and 8 by 4 for Reliability. We continued this process and completed all most influential to other columns in Table A.4 within Appendix 3.

Step 2.4: In this step, we constructed the influence-intensity of the others-to-least influential vectors by considering the influence-intensity of the other criteria on criterion *j* relative to the influence-intensity of the least influential criterion on criterion *j*. For example, consider the Safety column in Table 14. Cost-savings are the least influential criteria on Safety with an influence-intensity of 2. We divide the influence-intensity of others (Systems Engineering, Cost-savings, Process Enhancement, and Reliability) by 2. In other words, we divide 8 by 2 for Systems Engineering, 2 by 2 for Cost-savings, 3 by 2 for Process Enhancement, and 4 by 2 for Reliability. We continued this process and completed all others-to-least influential columns in Table A.5 within Appendix 3.

Step 2.5: In this step, we calculated the relative influence-intensity weights of criteria using the influence intensities described in Table 14 and ran the linear BWM model proposed by Rezaei (2016) in GAMS. The model finds the relative influence-intensity of all criteria by minimizing the objective function (consistency ratio). Table A.6 in Appendix 3 presents the relative influence-intensity weights of the Safety, System Engineering, Cost-savings, Process Enhancement, and Reliability criteria.

Table 16
Project rankings (advanced technology and innovation selection problem).

Rank	Project	Project success score	Cost	Cumulative costs
1	Nebula	0.6088	$1,348,000	$1,348,000
2	Photovoltaic	0.5928	$1,908,000	$3,256,000
3	Babaloon	0.5789	$1,949,000	$5,205,000
4	Hubble	0.5449	$1,778,000	$6,983,000
5	Solar	0.5199	$1,176,000	$8,159,000
6	Centrifuge	0.5124	$1,790,000	$9,949,000
7	Planet-Finder	0.4713	$1,266,000	$11,215,000
8	Truss	0.4626	$1,347,000	$12,562,000
9	Airlock	0.4446	$1,515,000	$14,077,000
10	Tether	0.3889	$961,000	$15,038,000

Step 2.6: We then constructed and normalized the relative influence-intensity matrix. The relative influence-intensity matrix is composed of the relative influence-intensity weights for each criterion presented in Table A.7 within Appendix 3, complemented with a weight of 0 for criteria pairs with no interaction (represented by "N") and a weight of 1 for criteria pairs with complete interaction (represented by "-").

The sum of the values in each column of Table A.7 is always equal to 2. We normalized this table to ensure that the sum of the criteria weights in each column equals one, as shown in Table A.8 within Appendix 3.

Step 2.7: In this step, we constructed the interdependent criteria weight vector by multiplying the normalized relative influence-intensity matrix (Table A.8) into the independent criteria weights obtained using Rezaei's (2016) BWM in Stage 1 (see Table A.3):

$$\begin{bmatrix} 0.500 & 0 & 0 & 0.500 & 0.174 & 0.145 \\ 0.236 & 0.500 & 0.334 & 0 & 0.152 & 0.113 \\ 0.059 & 0 & 0.500 & 0 & 0.109 & 0.065 \\ 0.088 & 0.200 & 0.167 & 0.500 & 0.065 & 0.049 \\ 0.118 & 0 & 0 & 0 & 0.500 & 0.129 \\ 0 & 0.300 & 0 & 0 & 0 & 0.500 \end{bmatrix} \times \begin{bmatrix} 0.506 \\ 0.134 \\ 0.089 \\ 0.077 \\ 0.134 \\ 0.060 \end{bmatrix} = \begin{bmatrix} 0.3235 \\ 0.2433 \\ 0.0929 \\ 0.1363 \\ 0.1344 \\ 0.0702 \end{bmatrix}$$

Next, we multiplied these interdependent criteria weights by the independent criteria weights from Table A.3 to find the global influence-intensity weights presented in Table 15.

We then integrated the global influence-intensity weights from Table 15 with the project probability scores from Appendix 2 using a weighted sum method to obtain a success factor for each project, as shown in Appendix 4.

Finally, we ranked the ten projects according to the success factors given in Appendix 4. Table 16 presents the project rankings, success factors, costs, and cumulative costs. Given the $6 million budget, the top

Table 18
Project rankings within the Lower interdependent scenario.

Rank	Project	Project success score
1	Photovoltaic	0.5943
2	Nebula	0.5663
3	Babaloon	0.5360
4	Hubble	0.5016
5	Solar	0.4909
6	Planet-Finder	0.4810
7	Centrifuge	0.4503
8	Airlock	0.4340
9	Truss	0.4209
10	Tether	0.3726

Table 17
Influence-intensity matrix defined by the Lower interdependent scenario.

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	N	N	N	8**	9**
Systems engineering (E)	8**	–	6**	N	7	7
Cost-savings (C)	2*	N	–	N	5	4
Process enhancement (P)	3	2***	3*	–	3*	3*
Reliability (R)	N	N	N	N	–	8
Implementation (I)	N	N	N	N	N	–

Note: **Most-influenced, * Least-influenced, and ***Single-influenced

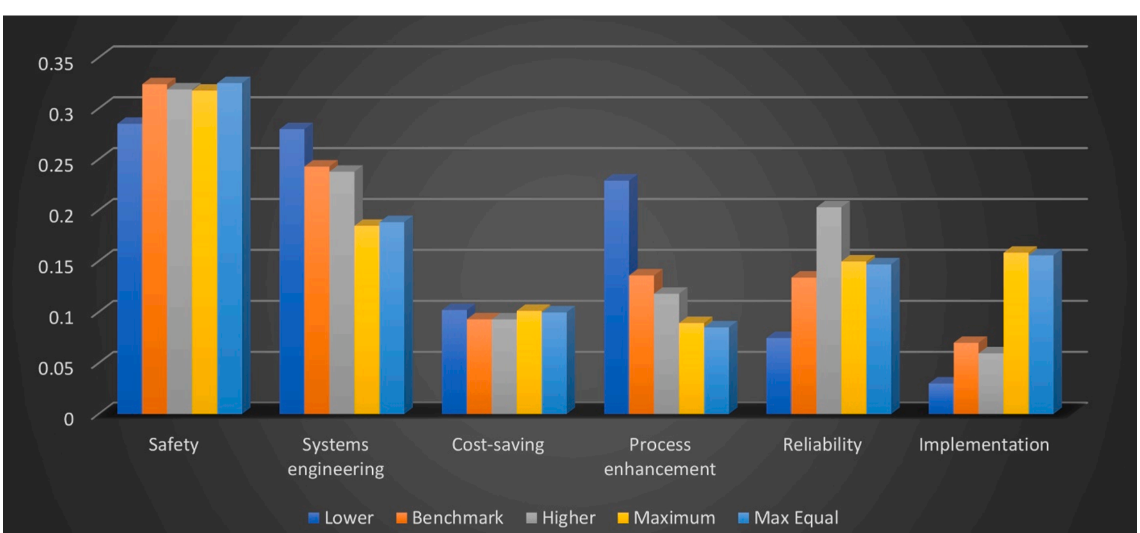

Fig. 3. Interdependent criteria weights obtained from the different evaluation scenarios.

Table 19
Influence-intensity matrix defined by the Higher interdependent scenario.

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	N	2*	6**	8**	9**
Systems engineering (E)	8**	–	6**	N	7	7
Cost-savings (C)	2*	N	–	N	5	4
Process enhancement (P)	3	2*	3*	–	3*	3*
Reliability (R)	4	7	N	N	–	8
Implementation (I)	N	3**	N	3*	N	–

Table 20
Influence-intensity matrix defined by the Maximum interdependent scenario.

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	8**	2*	6**	8**	9**
Systems engineering (E)	8	–	6**	2*	7	7
Cost-savings (C)	2*	6	–	3	5	4
Process enhancement (P)	3	2*	3	–	3*	3*
Reliability (R)	4	7	5	3	–	8
Implementation (I)	9**	3	4	3	8	–

Table 21
Influence-intensity matrix defined by the Max Equal interdependent scenario.

Criteria	Safety (S)	Systems engineering (E)	Cost-savings (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	9**	2*	9**	9**	9**
Systems engineering (E)	8	–	9**	2*	7	7
Cost-savings (C)	2*	6	–	3	5	4
Process enhancement (P)	3	2*	3	–	2*	2*
Reliability (R)	4	7	5	3	–	8
Implementation (I)	9**	3	4	3	8	–

Table 22
Project rankings within the higher, maximum, and max equal scenarios.

Scenario	Higher		Maximum		Max equal	
Rank	**Project**	**Project success score**	**Project**	**Project success score**	**Project**	**Project success score**
1	Nebula	0.64105	Nebula	0.6224	Nebula	0.6245
2	Photovoltaic	0.5992	Babaloon	0.6120	Babaloon	0.6144
3	Babaloon	0.5937	Photovoltaic	0.6072	Photovoltaic	0.6071
4	Hubble	0.5794	Hubble	0.5693	Hubble	0.5698
5	Solar	0.5358	Centrifuge	0.5632	Centrifuge	0.5651
6	Centrifuge	0.5311	Solar	0.5411	Solar	0.5426
7	Planet-Finder	0.4782	Truss	0.5114	Truss	0.5130
8	Truss	0.4657	Planet-Finder	0.4700	Planet-Finder	0.4700
9	Airlock	0.4631	Airlock	0.4629	Airlock	0.4616
10	Tether	0.3857	Tether	0.4332	Tether	0.4326

three projects, Nebula, Photovoltaic, and Babaloon should have been funded with a total budget of $5,205,000. It is worth noting that projects Nebula, Hubble, and Centrifuge were originally selected absent interdependency considerations, totaling a spending budget of $4,916,000.

5. Comparative and sensitivity analyses

The novelty of the proposed GBWM model, which combines the intuition of the BWM and DEMATEL within a hybrid structure, requires performing extensive sensitivity analysis and developing additional evaluation scenarios whose basic features and subsequent results can be compared. We modify the interdependencies defined within the influence-intensity matrix and their relative strength and compare the results obtained across scenarios. We define four new rankings:

- one for the case where experts miss some of the interdependencies existing among criteria,
- three for the scenarios where experts incorporate too many relations and modify their relative strength.

We will define four new sets of interdependent criteria weights together with their corresponding rankings and compare the latter with the original ones derived from the benchmark framework presented in Section 4. The whole set of calculations describing every step within each new interdependent scenario can be found in the online appendix section.

5.1. Decreasing the number of interdependencies among criteria

The first alternative scenario illustrates the differences between the benchmark framework described in the previous section and a sparser

Table 23
Correlations across the different interdependent scenarios.

			Correlations Lower	Benchmark	Higher	Maximum	Max Equal
Spearman's rho	**Lower**	**Correlation Coefficient**	1.000	0.964**	0.964**	0.879**	0.879**
		Sig. (2-tailed)		0.000	0.000	0.001	0.001
		N	10	10	10	10	10
	Benchmark	**Correlation Coefficient**	0.964**	1.000	1.000**	0.964**	0.964**
		Sig. (2-tailed)	0.000			0.000	0.000
		N	10	10	10	10	10
	Higher	**Correlation Coefficient**	0.964**	1.000**	1.000	0.964**	0.964**
		Sig. (2-tailed)	0.000			0.000	0.000
		N	10	10	10	10	10
	Maximum	**Correlation Coefficient**	0.879**	0.964**	0.964**	1.000	1.000**
		Sig. (2-tailed)	0.001	0.000	0.000		
		N	10	10	10	10	10
	Max Equal	**Correlation Coefficient**	0.879**	0.964**	0.964**	1.000**	1.000
		Sig. (2-tailed)	0.001	0.000	0.000		
		N	10	10	10	10	10

Note: **Correlation is significant at the 0.01 level (2-tailed).

setting missing several interdependencies among a subset of criteria. Consider the three two-way relationships (S and P), (E and I), and (S and R) defined in the benchmark scenario. We now assume that the experts miss some interactions between criteria. That is, these influences become one-way relationships. In this case, P will be assumed to affect S. Still, S will not affect P. This modification could be due to the subjective opinion of an expert who considers that enhancing the process requires safety improvements. In contrast, Safety can be modified without requiring process enhancements. Similarly, E will be assumed to influence I but not the other way around. Finally, S will be assumed to influence R but remain unaffected by it. The corresponding influence-intensity matrix is defined in Table 17.

Note how P is not influenced by any criterion but continues to influence all the other criteria, increasing its relative weight concerning the benchmark scenario. That is, when considering the influence of other criteria on a given criterion, the intensity of the influence is divided as follows: 50 % is assigned to the criterion on itself. In comparison, the other 50 % describes the intensity of the influence received from the other criteria. In this particular case, we have eliminated all the external influence on P, whose influence on itself shifts to 100 %. At the same time, the influence of P on the other criteria has not been modified. As a result, its interdependent weight (and relative importance) increases, as illustrated in Fig. 3. We will elaborate on this result in the next section.

A similar intuition applies to S, R, and I, whose interdependent weights decrease as their influence on the other criteria weakens. Note that the entries composing the normalized influence-intensity matrix determine the value of the interdependent weights when combined with the original independent weights assigned to each criterion. That is, the influence of each criterion on the others conditions its relative importance. These changes in the relative importance and subsequent weights of the different criteria are reflected in the ranking obtained, which is described in Table 18. Note how the ranking presents three modifications with respect to the benchmark scenario, including the first position. The intuition that follows from the analysis will be validated through the remaining scenarios. We will illustrate how the interdependent weights are determined by the influence exerted by each criterion on the others as well as the one received from the other criteria.

5.2. Increasing the number of interdependencies among criteria

As a complementary set of comparative scenarios, we assume that the experts define too many interdependencies across criteria. The subsequent modifications in the project rankings will highlight the importance of both the existing interdependencies among criteria and the capacity of the experts to correctly identify and evaluate them.

The first extension corresponds to the influence-intensity matrix described in Table 19, where the main changes applied have been highlighted. We have extended the model described in Fig. 2, creating three two-way relations out of three one-way relations: R has been assumed to influence E, S influences C, and I influences P. Note that we have added the three influence relations between these criteria assuming a completely symmetric interdependency. This is clearly not a requirement of the model but will be used to generate a consistent framework through the different analyses performed. Thus, the influence relationship between S and C has been assumed to be equal to 2, precisely the same as that between C and S defined in the benchmark framework. The remaining entries are defined in the same way, noticing that the original influence of S on P equals 6.

As a second extension, the same type of interdependence is applied to all the criteria that did not display any influence within the benchmark framework. That is, we are defining the extreme case where all the criteria are related through a two-way relationship. This scenario describes the largest number of relations that can be defined within the current setting. The experts are thus over-identifying relations among criteria, a feature that spreads the relative influence of each criterion across all those being considered, weakening the strength of the initial influence effects.

In the previous scenario, we assumed symmetric relations across a subset of criteria. To be consistent, given that the experts have not defined any of these relations, we have preserved this symmetric quality when defining the matrix described in Table 20.

Finally, note that this latter scenario assumes that the interval limits determining the relative intensities across criteria differ. That is, the influence of the different criteria on Safety ranges from 2 to 9, while the influence of the different criteria on Cost-savings ranges from 2 to 6. These differences emphasize the intuition provided by our model when describing the relative intensity of the interdependencies defined among criteria. Thus, the final scenario presented in Table 21 introduces identical upper and lower influence levels for all criteria while leaving the intermediate values unchanged.

That is, we have shifted the highest column value to 9 and the lowest to 2 – unless these values were already defined in the column –. For instance, the influence effect of Safety on Systems Engineering had a value of 8 in the previous influence-intensity matrix while now equals 9. In this way, the limit values and the subsequent spread of the intervals defining the relative intensity across criteria are identical for all criteria.

Note that, in case of a draw between different column values, we have only increased the value of the influence that was originally defined as the highest one by the experts. For instance, the influence effect of S on R was the highest one in the original influence-intensity matrix, displaying a value of 8. This value has been increased to 9, but not the influence of I on R, which was introduced in Table 20 when assuming a symmetric effect between initially independent criteria.

These modifications highlight one of the main constraints inherent to a direct application of the BWM, where a unique pair of highest and lowest influence values is applied to the vector describing the criteria. Our approach emphasizes the differences in the highest and lowest influence values defined across criteria, which provide essential information to analyze their relative intensity. Together with the potential sets of interdependencies that can be defined among criteria, these differences trigger variations in the resulting rankings, as can be observed in Table 22, which presents the rankings obtained from the three scenarios introduced in the current section.

5.3. Comparing the different interdependent scenarios

In order to evaluate the stability of the results and the variations arising across scenarios, a correlation analysis of the different rankings obtained has been performed. We also analyze the consequences – in terms of criteria weights – from both under-identifying the interdependencies existing across criteria and over-identifying them.

Fig. 3 illustrates the interdependent weights obtained from the different scenarios simulated, namely, lower, benchmark, higher, maximum, and max equal. The first clearly observable quality is the significant difference arising between the lower scenario, where experts under-identify the interdependencies existing across criteria, and the other ones. This feature is particularly relevant when considering the last three criteria, that is, process enhancement, reliability, and implementation.

Note, in particular, the significant increase in the weight of the process enhancement criterion, mainly due to the lack of influence from other criteria within the lower scenario. That is, the weight is concentrated on the influence of the criterion on itself. Note also how the elimination of interdependencies leads the last two criteria to lose importance relative to the benchmark scenario. The four remaining scenarios display similar weight distributions, except when considering the last two criteria, where some unilateral divergences arise. These results highlight the substantial differences arising whenever the influence interactions across criteria are modified.

The intuition derived from the distribution of weights is also observable through the correlation analysis of the rankings presented in Tables 16, 18, and 22. Table 23 illustrates how the differences between the rankings generated by the lower scenario and the maximum and max equal ones are particularly relevant. The benchmarking framework preserves its consistency when basic modifications – such as increasing the number of interdependencies slightly – are introduced, as is the case of the higher scenario.

However, larger differences arise when distorting the scenarios further, that is, when considering the maximum and max equal ones. In this case, unifying the evaluation intervals does not modify the rankings obtained. When all the variables display interdependencies and the limit values are sufficiently close to the actual upper and lower limits, stretching the limits to equate the width of the intervals does not induce a modification in the ranking. As illustrated in Fig. 3, the weights assigned to the criteria differ between both scenarios, though the corresponding modifications are minimal.

All in all, the most relevant modifications arise from the under-identification of the interdependencies or their substantial over-identification, as defined in the maximum and max equal scenarios.

6. Conclusions and future research directions

The traditional assumption of criteria independence used in MCDM makes the models unrealistic and their solutions rather abstract because the decision-maker cannot be sure that the models have considered the complete trade-offs among the decision criteria. In our model, experts consider both the influence of each criterion on the others and the relative intensity of these influences when assigning their evaluations. Intensities are reflected in the domain's width defined by each criterion's relative influence on the other criteria, with wider spreads implying higher degrees of influence. This latter effect is implicit in the comparisons of experts across criteria, though it is generally omitted from the analyses by assuming independent criteria.

We have proposed GBWM to consider the interdependencies and the strength of the dependencies among the decision criteria in MCDM. GBWM is a general form of the BWM that delivers more reliable results than the BWM in problems with interdependencies. GBWM considers the intensity of the dependencies and produces solutions that are equally or more consistent than BWM because it starts with a BWM solution and adjusts this solution with a completely-consistent vector. Unlike the competing hybrid network dependency models, the proposed method is simple to understand and easy to implement. In addition, GBWM produces relative influence-intensity criteria weights that reflect the interdependencies and the intensity of the dependencies among decision criteria. We have also revisited a real-world application to evaluate and prioritize advanced-technology projects at NASA to demonstrate the proposed method's applicability.

Many real-world decision problems involve complex network structures with various interdependencies within a criteria cluster and between criteria clusters. The method proposed in this study could be extended to consider interdependencies within and between criteria clusters. That is, while techniques such as data envelopment analysis have been extended to incorporate interdependencies among variables within their network structures, other MCDM models such as TOPSIS and VIKOR lack a formal environment to incorporate these features. In this regard, the current model can be easily adapted to formalize potential interactions among the criteria when generating the corresponding rankings.

Finally, it has been assumed that a criterion's influence on other criteria is subjectively defined by the experts, as is generally the case in MCDM models. This assumption constitutes a problem from a strategic perspective, as highlighted by Santos-Arteaga et al. (2022). Incorporating into the analysis, the subjectivity inherent to the criteria evaluations and the strategic reporting capacity of experts constitute potential immediate extensions of the current model. Given the significant development of fuzzy MCDM methods in the literature (Grabisch, 1996; Grabisch and Labreuche, 2008; Zhang and Deng, 2019), the same intuition applies to the introduction of fuzzy evaluation frameworks to describe the importance and influence-intensity degrees of criteria.

CRediT authorship contribution statement

Madjid Tavana: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Hassan Mina:** Writing – original draft, Validation, Methodology, Formal analysis. **Francisco J. Santos-Arteaga:** Writing – original draft, Validation, Methodology.

Declaration of Competing Interest

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

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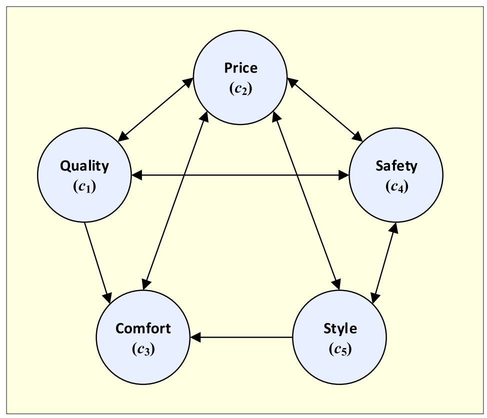
Appendix 1. A comparison between the current, no influence, and extreme scenarios

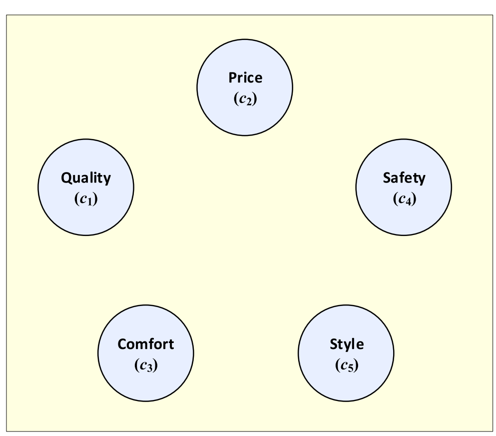
Current scenario

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	0.5	0.146	0.167	0.167	0	0.2105	0.2195	+0.0090	+4.26 %
Price	0.292	0.5	0.208	0.222	0.3	0.4211	0.3564	−0.0647	−15.36 %
Comfort	0	0.084	0.5	0	0	0.1053	0.0880	−0.0173	−16.41 %
Safety	0.208	0.166	0	0.5	0.2	0.2105	0.2295	+0.0190	+9.01 %
Style	0	0.104	0.125	0.111	0.5	0.0526	0.1066	+0.0540	+102.70 %



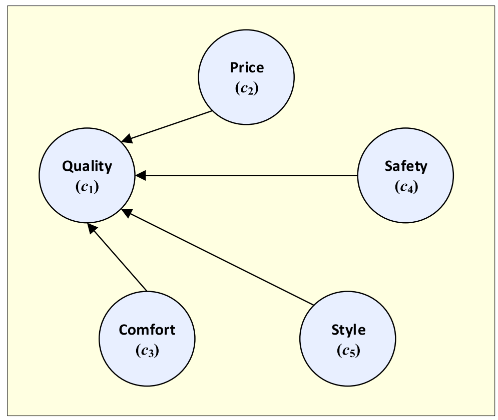
Scenario 1: No influences (BWM)

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	1	0	0	0	0	0.2105	0.2105	0.0000	0.00 %
Price	0	1	0	0	0	0.4211	0.4211	0.0000	0.00 %
Comfort	0	0	1	0	0	0.1053	0.1053	0.0000	0.00 %
Safety	0	0	0	1	0	0.2105	0.2105	0.0000	0.00 %
Style	0	0	0	0	1	0.0526	0.0526	0.0000	0.00 %



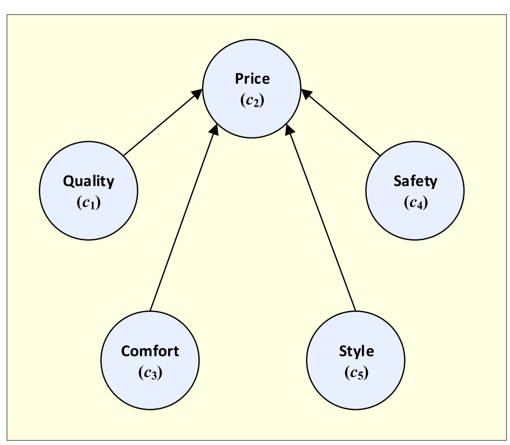
Scenario 2: Equal influence of all criteria on Quality

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	0.5	0	0	0	0	0.2105	0.1053	−0.1053	−50.00 %
Price	0.125	1	0	0	0	0.4211	0.4474	+0.0263	+6.25 %
Comfort	0.125	0	1	0	0	0.1053	0.1316	+0.0263	+24.99 %
Safety	0.125	0	0	1	0	0.2105	0.2368	+0.0263	+12.50 %
Style	0.125	0	0	0	1	0.0526	0.0789	+0.0263	+50.02 %



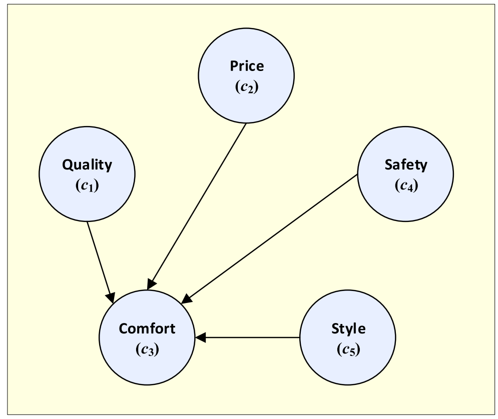
Scenario 3: Equal influence of all criteria on Price

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	1	0.125	0	0	0	0.2105	0.2631	+0.0526	+25.01 %
Price	0	0.5	0	0	0	0.4211	0.2106	−0.2106	−50.00 %
Comfort	0	0.125	1	0	0	0.1053	0.1579	+0.0526	+49.99 %
Safety	0	0.125	0	1	0	0.2105	0.2631	+0.0526	+25.01 %
Style	0	0.125	0	0	1	0.0526	0.1052	+0.0526	+100.07 %



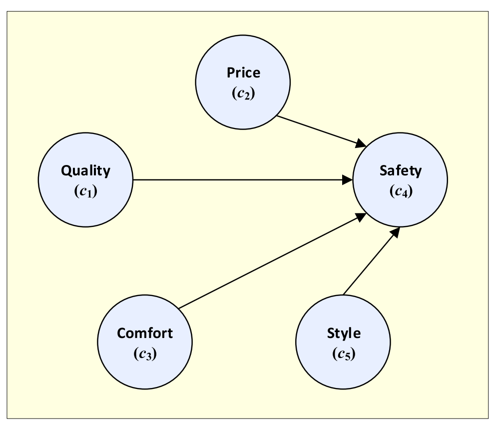
Scenario 4: Equal influence of all criteria on Comfort

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	1	0	0.125	0	0	0.2105	0.2237	+0.0132	+6.25 %
Price	0	1	0.125	0	0	0.4211	0.4343	+0.0132	+3.13 %
Comfort	0	0	0.5	0	0	0.1053	0.0527	−0.0527	−50.00 %
Safety	0	0	0.125	1	0	0.2105	0.2237	+0.0132	+6.25 %
Style	0	0	0.125	0	1	0.0526	0.0658	+0.0132	+25.02 %



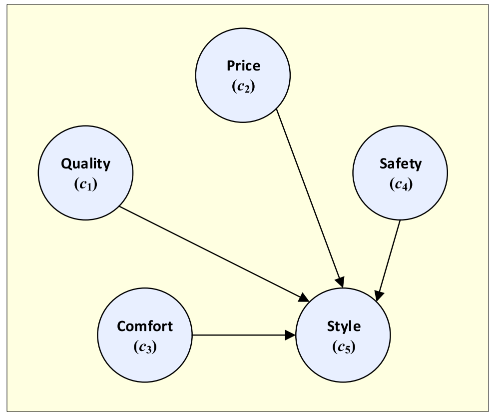
Scenario 5: Equal influence of all criteria on Safety

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	1	0	0	0.125	0	0.2105	0.2368	+0.0263	+12.50 %
Price	0	1	0	0.125	0	0.4211	0.4474	+0.0263	+6.25 %
Comfort	0	0	1	0.125	0	0.1053	0.1316	+0.0263	+24.99 %
Safety	0	0	0	0.5	0	0.2105	0.1053	−0.1053	−50.00 %
Style	0	0	0	0.125	1	0.0526	0.0789	+0.0263	+50.02 %



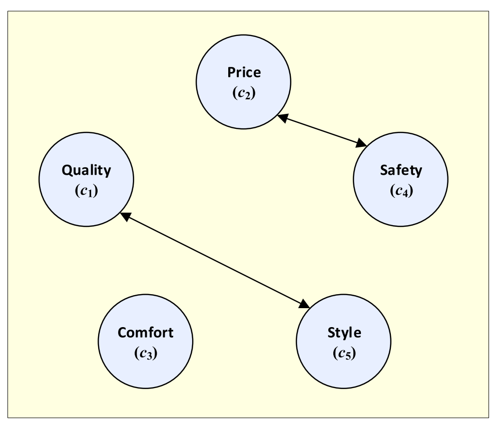
Scenario 6: Equal influence of all criteria on Style

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	1	0	0	0	0.125	0.2105	0.2171	+0.0066	+3.12 %
Price	0	1	0	0	0.125	0.4211	0.4277	+0.0066	+1.56 %
Comfort	0	0	1	0	0.125	0.1053	0.1119	+0.0066	+6.24 %
Safety	0	0	0	1	0.125	0.2105	0.2171	+0.0066	+3.12 %
Style	0	0	0	0	0.5	0.0526	0.0263	−0.0263	−50.00 %



Scenario 7: Equal influence of Price on Safety and Safety on Price and equal influence of Quality on Style and Style on Quality

	Quality	Price	Comfort	Safety	Style	Rezaei (2016)	GBWM	Difference	% Increase or Decrease
Quality	0.5	0	0	0	0.5	0.2105	0.1316	−0.0790	−37.51 %
Price	0	0.5	0	0.5	0	0.4211	0.3158	−0.1053	−25.01 %
Comfort	0	0	1	0	0	0.1053	0.1053	0.0000	0.00 %
Safety	0	0.5	0	0.5	0	0.2105	0.3158	+0.1053	+50.02 %
Style	0.5	0	0	0	0.5	0.0526	0.1316	+0.0790	+150.10 %



Appendix 2. Probabilities of occurrence

Criteria	Sub-criteria		Project									
			Hubble	Photovoltaic	Airlock	Babaloon	Planet-Finder	Nebula	Solar	Truss	Centrifuge	Tether
Safety (S)	S-DSI	Eliminating the possibility of death or serious injury	0.90	0.60	0.30	0.90	0.20	0.80	0.70	0.60	0.90	0.40
	S-LOF	Eliminating the possibility of loss of flight hardware, facility, or GSE	0.30	0.70	0.90	0.70	0.60	0.90	0.70	0.90	1.00	0.50
	S-PID	Eliminating the possibility of personal injury or flight hardware, facility, or GSE damage	0.80	0.20	0.60	1.00	0.70	0.70	0.70	0.70	0.90	1.00
	S-SVS	Eliminating the possibility of a serious violation of safety, health, or environmental federal/state	0.70	0.90	0.80	0.20	0.80	0.90	0.60	1.00	0.30	0.50
	S-DVS	Eliminating the possibility of a de minimus violation of safety, health, or environmental	0.60	0.90	0.30	0.40	1.00	0.60	1.00	0.80	1.00	0.20

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(*continued*)

Criteria	Sub-criteria		Project									
			Hubble	Photovoltaic	Airlock	Babaloon	Planet-Finder	Nebula	Solar	Truss	Centrifuge	Tether
Systems Engineering (E)	E-LSP	Reducing or eliminating the possibility of launch slippage	0.10	0.60	0.00	0.50	0.70	0.50	0.40	0.20	0.10	0.10
	E-NTR	Supporting program for near-term requirements	0.70	0.80	0.70	0.50	0.00	1.00	0.00	0.00	0.00	0.00
	E-ONA	Eliminating occurrence of nonsupport activities	0.30	0.10	0.00	0.40	1.00	0.00	0.40	0.80	0.30	0.30
	E-FAL	Reducing or eliminating a system failure	0.70	1.00	0.00	0.90	0.00	0.30	0.80	0.00	0.00	0.90
	E-OBS	Eliminating reliance on identified obsolete technology	0.10	0.10	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cost-savings (C)	C-LAB	Reducing or eliminating unnecessary labor dollars	0.70	0.30	0.30	0.30	0.30	0.70	0.50	0.50	0.50	0.40
	C-MAT	Reducing or eliminating unnecessary material dollars	0.60	0.60	0.80	0.60	0.90	0.60	0.70	0.60	0.80	0.30
	C-TSI	Utilizing time-sensitive implementation methodology	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
	C-MPC	Meeting the proposed cost	0.60	0.70	0.60	0.40	0.70	0.70	0.60	0.30	0.70	0.20
	C-MPS	Meeting the proposed schedule	0.50	0.50	0.50	0.60	0.50	0.60	0.50	0.50	0.50	0.50
	C-ROM	Reducing operations and maintenance costs	0.70	0.70	0.60	0.80	0.10	0.20	0.10	0.50	0.60	0.60
	C-CON	Meeting contractual obligations	0.70	0.90	1.00	0.80	1.00	0.30	1.00	0.70	1.00	0.80
Process Enhancement (P)	P-LPL	Reducing labor hours used on the launch pad	0.20	0.60	0.70	0.20	0.40	0.20	0.20	0.20	0.20	0.40
	P-LPT	Reducing launch and processing time	0.80	1.00	0.20	0.30	0.60	0.60	0.80	0.40	0.20	0.60
	P-LPA	Improving launch pad accessibility	0.10	0.10	0.30	0.10	0.80	0.10	0.10	0.10	0.30	0.10
	P-LPH	Reducing or eliminating hardware and materials expended on the launch pad	0.10	0.40	1.00	1.00	0.10	0.40	0.10	0.10	0.10	0.20
Reliability (R)	R-SFP	Eliminating critical single failure points (CSFPs)	0.80	0.00	0.90	0.00	0.00	0.90	0.00	0.00	0.70	0.00
	R-CFP	Reducing the possibility of failure propagation to other components or systems	0.90	0.70	0.00	0.80	0.70	0.80	1.00	0.00	0.20	0.00
	R-MTR	Improving mean time to repair (MTTR)	0.70	0.90	0.70	1.00	0.70	0.60	0.40	0.70	0.60	0.30
	R-IFI	Improving Fault Identification and Fault Isolation (FI/FI)	0.70	0.70	0.00	0.80	0.50	0.70	0.70	0.70	0.80	0.00
	R-SIM	Providing for a simpler system	0.80	0.60	0.70	0.00	0.00	0.80	0.60	0.70	0.10	0.70
	R-AMT	Improving access for maintenance tasks	0.60	0.70	0.70	0.90	0.70	0.80	0.80	0.00	0.00	0.60
	R-TBF	Increasing mean time between failures (MTBFs)	0.70	0.40	0.00	0.00	0.30	0.40	0.60	0.70	0.70	0.80
	R-ETT	Reducing support equipment, special tools, and special training requirements	0.00	0.70	0.70	1.00	0.70	0.70	0.70	0.00	0.70	0.70
	R-COT	Providing for the use of standard commercial off-the-shelf (COTS) parts	0.90	0.20	0.70	0.80	0.50	0.20	0.30	0.90	0.10	0.60
	R-EQP	Providing for equipment interchangeability	0.80	0.70	0.80	0.90	0.20	0.00	0.80	0.60	0.80	0.00
Implementation (I)	I-MSA	Reducing or eliminating multisite applicability	0.00	0.80	0.50	0.90	0.50	0.00	0.90	0.80	0.70	0.80
	I-IMI	Reducing or eliminating the possibility of interference in implementation	1.00	0.90	0.50	0.70	0.40	0.90	0.20	0.90	0.80	0.90
	I-FMC	Reducing or eliminating the possibility of flight manifest changes	0.90	0.90	0.50	0.70	0.40	0.80	0.20	0.80	0.40	0.90
	I-MSC	Reducing or eliminating the effects on multisystem configuration systems	0.90	0.80	0.70	0.80	0.80	1.00	0.60	0.60	0.80	0.70
	I-EOH	Reducing or eliminating the possibility of equipment and occupational hazards	1.00	0.50	0.40	0.60	0.50	1.00	0.50	0.80	0.70	0.80
	I-SSR	Reducing or eliminating site-specific restrictions	0.90	0.80	0.50	0.70	0.50	1.00	0.30	0.70	0.60	0.60
	I-TCH	Meeting new technology considerations	0.00	0.30	0.10	0.10	0.10	0.00	0.00	0.10	0.10	0.40

Appendix 3. Developing the case study

See Tables A1-A8

Table A1
Best-to-others vectors (advanced technology and innovation selection problem).

Criteria	Best-to-other vector	Sub-criteria	Best-to-other vector
Safety (S)**	1	S-DSI**	1
		S-LOF	2
		S-PID	4
		S-SVS	7
		S-DVS	8
Systems Engineering (E)	4	E-LSP**	1
		E-NTR	3
		E-ONA	4
		E-FAL	5
		E-OBS	9
Cost-savings (C)	6	C-LAB**	1
		C-MAT	2
		C-TSI	3
		C-MPC	4
		C-MPS	5
		C-ROM	8
		C-CON	9
Process Enhancement (P)	7	P-LPL**	1
		P-LPT	2
		P-LPA	4
		P-LPH	9
Reliability (R)	4	R-SFP**	1
		R-CFP	2
		R-MTR	3
		R-IFI	4
		R-SIM	5
		R-AMT	6
		R-TBF	6
		R-ETT	7
		R-COT	8
		R-EQP	9
Implementation (I)*	8	I-MSA**	1
		I-IMI	3
		I-FMC	4
		I-MSC	5
		I-EOH	7
		I-SSR	8
		I-TCH	9

**Best criterion/sub-criterion.

Table A2
Others-to-worst vectors (advanced technology and innovation selection problem).

Criteria	Others-to-worst vector	Sub-criteria	Others-to-worst vector
Safety (S)	8	S-DSI	8
		S-LOF	4
		S-PID	2
		S-SVS	1
		S-DVS*	1
Systems Engineering (E)	2	E-LSP	9
		E-NTR	4
		E-ONA	3
		E-FAL	2
		E-OBS*	1
Cost-savings (C)	2	C-LAB	9
		C-MAT	5
		C-TSI	4
		C-MPC	3
		C-MPS	3
		C-ROM	1
		C-CON*	1
Process Enhancement (P)	1	P-LPL	9
		P-LPT	4
		P-LPA	2
		P-LPH*	1

(continued on next page)

Table A2 (*continued*)

Criteria	Others-to-worst vector	Sub-criteria	Others-to-worst vector
Reliability (R)	2	R-SFP	9
		R-CFP	6
		R-MTR	5
		R-IFI	5
		R-SIM	4
		R-AMT	2
		R-TBF	2
		R-ETT	2
		R-COT	1
		R-EQP*	1
Implementation (I)*	1	I-MSA	9
		I-IMI	7
		I-FMC	6
		I-MSC	5
		I-EOH	2
		I-SSR	1
		I-TCH*	1

* Worst criterion/sub-criterion

Table A3
Independent local criteria and sub-criteria weights (advanced technology and innovation selection problem).

Criteria	Independent local weights ($\delta^* = 0.030$)	Sub-criteria	Independent local weights
Safety (S) ($\delta^* = 0.007$)	0.506	S-DSI	0.493
		S-LOF	0.250
		S-PID	0.125
		S-SVS	0.069
		S-DVS	0.062
Systems Engineering (E) ($\delta^* = 0.032$)	0.134	E-LSP	0.516
		E-NTR	0.183
		E-ONA	0.137
		E-FAL	0.110
		E-OBS	0.054
Cost-savings (C) ($\delta^* = 0.033$)	0.089	C-LAB	0.380
		C-MAT	0.206
		C-TSI	0.138
		C-MPC	0.103
		C-MPS	0.083
		C-ROM	0.052
		C-CON	0.039
Process Enhancement (P) ($\delta^* = 0.015$)	0.077	P-LPL	0.538
		P-LPT	0.262
		P-LPA	0.138
		P-LPH	0.062
Reliability (R) ($\delta^* = 0.051$)	0.134	R-SFP	0.303
		R-CFP	0.177
		R-MTR	0.118
		R-IFI	0.089
		R-SIM	0.071
		R-AMT	0.059
		R-TBF	0.059
		R-ETT	0.051
		R-COT	0.044
		R-EQP	0.028
Implementation (I) ($\delta^* = 0.092$)	0.060	I-MSA	0.423
		I-IMI	0.171
		I-FMC	0.129
		I-MSC	0.103
		I-EOH	0.073
		I-SSR	0.064
		I-TCH	0.037

Table A4
Influence-intensity of the most influential-to-others vectors (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	N	N	-***	8/8	9/9
Systems engineering (E)	8/8	–	6/6	N	8/7	9/7
Cost-savings (C)	8/2	N	–	N	8/5	9/4
Process enhancement (P)	8/3	3/2	6/3	–	8/3	9/3
Reliability (R)	8/4	N	N	N	–	9/8
Implementation (I)	N	3/3	N	N	N	–

Note: Process enhancement is a single-influenced factor (only influenced by Safety) and has no vector calculations.

Table A5
Influence-intensity of the others-to-least influential vectors (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	–	N	N	-***	8/3	9/3
Systems engineering (E)	8/2	–	6/3	N	7/3	7/3
Cost-savings (C)	2/2	N	–	N	5/3	4/3
Process enhancement (P)	3/2	2/2	3/3	–	3/3	3/3
Reliability (R)	4/2	N	N	N	–	8/3
Implementation (I)	N	3/2	N	N	N	–

Note: Process enhancement is a single-influenced factor (only influenced by Safety) and has no vector calculations.

Table A6
Relative influence-intensity weights (advanced technology and innovation selection problem).

Criteria	Safety (S) ($\delta^* = 0$)	Systems engineering (E) ($\delta^* = 0$)	Cost-saving (C) ($\delta^* = 0$)	Process enhancement (P) ($\delta^* = 0$)	Reliability (R) ($\delta^* = 0$)	Implementation (I) ($\delta^* = 0$)
Safety (S)	–	N	N	-***	0.348	0.290
Systems engineering (E)	0.471	–	0.667	N	0.304	0.226
Cost-savings (C)	0.118	N	–	N	0.217	0.129
Process enhancement (P)	0.176	0.400	0.333	–	0.130	0.097
Reliability (R)	0.235	N	N	N	–	0.258
Implementation (I)	N	0.600	N	N	N	–

Table A7
Relative influence-intensity matrix (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	1	0	0	1*	0.348	0.290
Systems engineering (E)	0.471	1	0.667	0	0.304	0.226
Cost-savings (C)	0.118	0	1	0	0.217	0.129
Process enhancement (P)	0.176	0.400	0.333	1	0.130	0.097
Reliability (R)	0.235	0	0	0	1	0.258
Implementation (I)	0	0.600	0	0	0	1

Table A8
Normalized relative influence-intensity matrix (advanced technology and innovation selection problem).

Criteria	Safety (S)	Systems engineering (E)	Cost-saving (C)	Process enhancement (P)	Reliability (R)	Implementation (I)
Safety (S)	0.500	0	0	0.500	0.174	0.145
Systems engineering (E)	0.236	0.500	0.334	0	0.152	0.113
Cost-savings (C)	0.059	0	0.500	0	0.109	0.065
Process enhancement (P)	0.088	0.200	0.167	0.500	0.065	0.049
Reliability (R)	0.118	0	0	0	0.500	0.129
Implementation (I)	0	0.300	0	0	0	0.500

Appendix 4. Project success factors (advanced technology and innovation selection problem)

Sub-criteria	Global influence-intensity weights	Project									
		Hubble	Photovoltaic	Airlock	Babaloon	Planet-Finder	Nebula	Solar	Truss	Centrifuge	Tether
S-DSI	0.1597	0.90	0.60	0.30	0.90	0.20	0.80	0.70	0.60	0.90	0.40
S-LOF	0.0810	0.30	0.70	0.90	0.70	0.60	0.90	0.70	0.90	1.00	0.50
S-PID	0.0405	0.80	0.20	0.60	1.00	0.70	0.70	0.70	0.70	0.90	1.00
S-SVS	0.0224	0.70	0.90	0.80	0.20	0.80	0.90	0.60	1.00	0.30	0.50
S-DVS	0.0201	0.60	0.90	0.30	0.40	1.00	0.60	1.00	0.80	1.00	0.20
E-LSP	0.1254	0.10	0.60	0.00	0.50	0.70	0.50	0.40	0.20	0.10	0.10
E-NTR	0.0445	0.70	0.80	0.70	0.50	0.00	1.00	0.00	0.00	0.00	0.00
E-ONA	0.0333	0.30	0.10	0.00	0.40	1.00	0.00	0.40	0.80	0.30	0.30
E-FAL	0.0267	0.70	1.00	0.00	0.90	0.00	0.30	0.80	0.00	0.00	0.90
E-OBS	0.0131	0.10	0.10	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C-LAB	0.0353	0.70	0.30	0.30	0.30	0.30	0.70	0.50	0.50	0.50	0.40
C-MAT	0.0192	0.60	0.60	0.80	0.60	0.90	0.60	0.70	0.60	0.80	0.30
C-TSI	0.0128	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
C-MPC	0.0096	0.60	0.70	0.60	0.40	0.70	0.70	0.60	0.30	0.70	0.20
C-MPS	0.0077	0.50	0.50	0.50	0.60	0.50	0.60	0.50	0.50	0.50	0.50
C-ROM	0.0048	0.70	0.70	0.60	0.80	0.10	0.20	0.10	0.50	0.60	0.60
C-CON	0.0036	0.70	0.90	1.00	0.80	1.00	0.30	1.00	0.70	1.00	0.80
P-LPL	0.0732	0.20	0.60	0.70	0.20	0.40	0.20	0.20	0.20	0.20	0.40
P-LPT	0.0356	0.80	1.00	0.20	0.30	0.60	0.60	0.80	0.40	0.20	0.60
P-LPA	0.0188	0.10	0.10	0.30	0.10	0.80	0.10	0.10	0.10	0.30	0.10
P-LPH	0.0084	0.10	0.40	1.00	1.00	0.10	0.40	0.10	0.10	0.10	0.20
R-SFP	0.0406	0.80	0.00	0.90	0.00	0.00	0.90	0.00	0.00	0.70	0.00
R-CFP	0.0237	0.90	0.70	0.00	0.80	0.70	0.80	1.00	0.00	0.20	0.00
R-MTR	0.0158	0.70	0.90	0.70	1.00	0.70	0.60	0.40	0.70	0.60	0.30
R-IFI	0.0119	0.70	0.70	0.00	0.80	0.50	0.70	0.70	0.70	0.80	0.00
R-SIM	0.0095	0.80	0.60	0.70	0.00	0.00	0.80	0.60	0.70	0.10	0.70
R-AMT	0.0079	0.60	0.70	0.70	0.90	0.70	0.80	0.80	0.00	0.00	0.60
R-TBF	0.0079	0.70	0.40	0.00	0.00	0.30	0.40	0.60	0.70	0.70	0.80
R-ETT	0.0068	0.00	0.70	0.70	1.00	0.70	0.70	0.70	0.00	0.70	0.70
R-COT	0.0059	0.90	0.20	0.70	0.80	0.50	0.20	0.30	0.90	0.10	0.60
R-EQP	0.0038	0.80	0.70	0.80	0.90	0.20	0.00	0.80	0.60	0.80	0.00
I-MSA	0.0296	0.00	0.80	0.50	0.90	0.50	0.00	0.90	0.80	0.70	0.80
I-IMI	0.0120	1.00	0.90	0.50	0.70	0.40	0.90	0.20	0.90	0.80	0.90
I-FMC	0.0090	0.90	0.90	0.50	0.70	0.40	0.80	0.20	0.80	0.40	0.90
I-MSC	0.0072	0.90	0.80	0.70	0.80	0.80	1.00	0.60	0.60	0.80	0.70
I-EOH	0.0051	1.00	0.50	0.40	0.60	0.50	1.00	0.50	0.80	0.70	0.80
I-SSR	0.0045	0.90	0.80	0.50	0.70	0.50	1.00	0.30	0.70	0.60	0.60
I-TCH	0.0026	0.00	0.30	0.10	0.10	0.10	0.00	0.00	0.10	0.10	0.40
Project success factor		**0.5449**	**0.5928**	**0.4446**	**0.5789**	**0.4713**	**0.6088**	**0.5199**	**0.4626**	**0.5124**	**0.3889**

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.08.036.

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