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ORIGINAL RESEARCH

Combining fuzzy MCDM with Kano model and FMEA: a novel 3-phase MCDM method for reliable assessment

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Abstract

In the circular economy era, this study addresses sustainable business management for high-investment and long-life cycle projects, where accurate and reliable assessments are crucial to ensuring successful outcomes. The objective is to elevate the reliability of assessments by introducing a novel decision-making method that, for the first time, integrates time-based satisfaction and risk factors simultaneously. We propose a 3-phase multi-criteria decision-making (MCDM) method, which combines fuzzy MCDM comprising fuzzy analytic hierarchy process and fuzzy technique for order preference by similarity to ideal situation (TOPSIS), Kano model, and failure mode and effects analysis (FMEA) techniques, to handle reliable assessments effectively. Our method is distinct in its incorporation of time-based satisfaction weights derived from Kano model, emphasising decision-makers' criteria preferences in short, medium, and long terms. Furthermore, we introduce risk-discounted weights by using FMEA to tune criteria scores. The method is validated via a numerical example case, assessing and selecting the most appropriate hydrogen storage method for lightweight vehicles. The results suggest that cryo-compressed hydrogen tank with 250–350 bar and at cryogenic temperature is the most suitable storage method. Health & safety with a weight of 0.5318 emerges as the most important main criterion, and permeation & leakage with a weight of 0.4008 is the most important sub-criterion. To bridge the gap between theoretical research and practical application, we transform the new method into a user-friendly web

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application with graphical user interface (GUI). End-users can conduct reliable assessments and foster sustainable business management through informed decision-making.

Keywords Fuzzy MCDM · Kano model · FMEA · Reliable assessment · High-investment and long-life cycle projects · Web application with GUI

1 Introduction

The fuzzy multi-criteria decision-making (MCDM) methods have been widely used on evaluation and selection problems with uncertainty (Mardani et al., 2015) such as supplier selection (Chai et al., 2013), site selection (Yap et al., 2019; Deveci et al., 2021), service selection (Masdari & Khezri, 2021), healthcare technology selection (Mardani et al., 2019; Deveci, 2023), circular economy assessment (dos Santos Gonçalves & Campos, 2022; Bai et al., 2022; Lee et al., 2023), energy policymaking (Kaya et al., 2019), urban transport policymaking (Deveci et al., 2023a, b, c; Jeevaraj et al., 2023; Mishra et al., 2023), construction management (Chen & Pan, 2021). Notably, the pursuit of reliability in assessment and selection methods increases particularly for high-investment and long-life cycle projects (Önüt et al., 2009; He et al., 2016; Escrig-Olmedo et al., 2017; Wu et al., 2018; Kaya et al., 2019; Pouyakian et al., 2022). The nature of such projects motivates managers to commit to the choices of suppliers, sites, technologies, or strategies for the long haul. Switching to alternative options halfway could incur significant costs or environmental harm. Therefore, the choices made initially should be forward-looking and reliable enough to accommodate the projects with costly and long-term features. For example, a manufacturing project of lightweight vehicles powered by hydrogen fuel cells with hydrogen storage challenges has the feature of high-investment and long-life cycle. Such a hydrogen vehicle can cost around USD 80k. Once the hydrogen storage method is chosen and determined, this technology could be applied to several models, and probably would not be replaced easily during the 20-year lifespan of vehicles. Furthermore, the life of vehicles can be prolonged by applying the circular economy principles that are being widely popularised (Aguilar Esteva et al., 2021). The hydrogen storage tanks can be refurbished to extend their use and the components can be reused within the same type of vehicles.

However, there are no sufficient studies that improved the conventional fuzzy MCDM methods, particularly in response to the need for long-lasting choices. The two essential factors that ensure a reliable assessment, i.e., the satisfaction with the choice and the risk of failure, have yet to be considered at the same time in MCDM. Either the satisfaction (Ghorbani et al., 2013; Avikal et al., 2014) or the risk analysis (Li & Zeng, 2016; Liu et al., 2019) was individually applied to strengthen an assessment in fuzzy MCDM. This gap in research motivates us to originate and develop a new fuzzy MCDM method in this paper to enhance the reliability of assessments to guarantee the results are applicable and effective over a long period.

We innovatively introduce a 'time-based' satisfaction weight for the decision criteria, which incorporates decision-makers' satisfaction with criteria over different project time horizons—short, medium, and long terms. As per our knowledge, our approach is the first one that differentiates and quantifies decision-makers' perceptions across various stages of a project. It is achieved by involving a time dimension in the commonly used Kano model (Kano, 1984; Berger et al., 1993), which effectively attaches enough importance to the satisfaction level that is likely to vary throughout the project lifecycle. The integration of this time-based satisfaction weight can increase the reliability of assessments in high-investment and long-life cycle projects. Simultaneously, a risk discounted weight is used to raise the reliability of the assessment by tuning the performance of decision criteria based on the failure mode and effects analysis (FMEA) method (Li & Zeng, 2016). This addition is critical given the intricate risk profiles are typically associated with high-investment and long-life cycle projects. There is a high possibility that the risks will affect the actual performance of criteria and cause them to deviate significantly from the anticipated outcomes. Proactively incorporating the risk factor into assessments can diminish the possibility of such deviations.

Since it is our initiation to include the time-based satisfaction and risk factors in the assessment method to strengthen the reliability, there are no existing MCDM methods that can be directly referred to technically develop this new conception. Thus, in our assessment method, as we will utilise the Kano model for the time-based satisfaction factor, and the FMEA for risk factor as the underpinning, we integrate the three approaches for the first time, i.e., Kano model, FMEA, and fuzzy MCDM consisting of fuzzy analytic hierarchy process (AHP) and fuzzy technique for order preference by similarity to the ideal situation (TOPSIS). Inventively, three phases are specifically designed for this novel MCDM method, where Phase I applies the fuzzy AHP and Kano model for weight determination of the decision criteria; Phase II is based on the FMEA for risk assessment on the criteria for alternatives; and finally, Phase III uses the fuzzy TOPSIS to determine scores for alternatives. An elaborative framework of the proposed 3-phase MCDM method is illustrated in Fig. 1.

Taking a step further in examining the practical applications of the MCDM methods, only a handful of literature such as (Hamdan & Cheaitou, 2017; Grazioso et al., 2017) created the software implementations with practical, hands-on software with GUIs. Therefore, we are inspired to transfer the proposed 3-phase MCDM method to a free, interactive web application with graphical user interface (GUI), especially for evaluating different hydrogen supply chain stakeholders. It is built in the HyChain (accessible via https://hychain.co.uk/), which is a smart hub founded by us to provide hydrogen supply chain solutions and knowledge to diverse audiences, including industry professionals, academics, and the general public. Creative efforts are invested into the GUI design, ensuring an intuitive and engaging user experience. This first-of-its-kind web application extends the reach of our 3-phase MCDM method beyond the academic domain. It enables any users to effortlessly apply it to real-world assessments of hydrogen supply chains, or more broadly, to any high-investment and long-life cycle projects. The tool can provide the facility to replicate the example case detailed in the paper to select the best hydrogen storage method for lightweight vehicles.

The contributions of this paper are summarised as follows:

1. The implementation of reliable assessment through a novel MCDM method that considers the time-based satisfaction and risk factors simultaneously.
2. The technical development of a 3-phase MCDM method combining fuzzy MCDM with Kano model and FMEA.
3. The web application development of the proposed MCDM method that pertains hydrogen supply chain stakeholder assessment.

The remainder of the paper is organised as follows. Section 2 reviews the literature on reliability-oriented methods in fuzzy MCDM. Section 3 develops a novel 3-phase MCDM method for reliable assessment, which combines the Kano model, FMEA, fuzzy AHP, and fuzzy TOPSIS. In Sect. 4, an example case of hydrogen storage method selection for lightweight vehicles is applied to demonstrate step by step the proposed 3-phase MCDM method. Section 5 introduces the MCDM web application design and interface. The potential policy implications on business management are also discussed. Section 6 in the end summarises this research and provides insights on future directions.

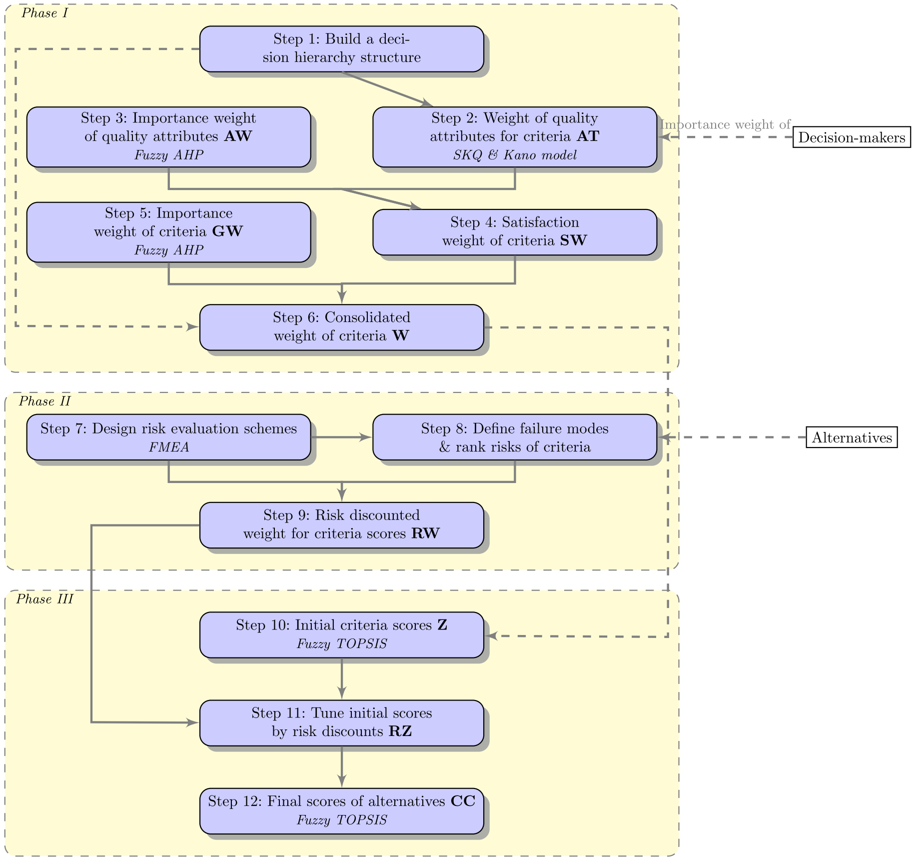

Fig. 1 Framework of the proposed 3-phase MCDM method for reliable assessment

2 Literature review

The fuzzy MCDM, based on the fuzzy set theory (Zadeh, 1965), is a systematic decision-making tool for evaluating the alternatives and choosing the best option in uncertain and ambiguous environments where linguistic variables need to be well defined (Kahraman et al., 2015; Mardani et al., 2015). In this section, we first review the literature that used reliability-oriented methods in fuzzy MCDM as summarised in Table 1, referring to the studies for improving the reliability of assessment and selection problems. The purposes of employing these methods are interpreted in Column 4 of the table. Regardless of the different application contexts, the so-called reliability of assessment is mainly manifested through considerations of stakeholder voices or satisfaction, risk, quality, and psychological behaviours. Based on the practical needs of targeting a reliable assessment method for high-investment and long-life cycle projects, we identify that satisfaction and risk are two imperative, effective factors to be simultaneously considered for this type of project. However, these two factors have not yet been taken into account at the same time. This gap gives us space to propose a new method that not only incorporates both the factors but furthermore reinforces the satisfaction factor to feature the time effects (see the last row in Table 1). Appropriate technical methods can then be correspondingly determined, i.e., the Kano model for satisfaction measurement and FMEA for risk analysis. Both of them would be integrated with two typical fuzzy MCDM methods, i.e., fuzzy AHP (Liu et al., 2020; Pereira & Bamel, 2023) and fuzzy TOPSIS (Salih et al., 2019) (like most of the literature in Table 1 have done so and validated the suitability of adopting fuzzy AHP and fuzzy TOPSIS as the representatives of fuzzy MCDM) to generate a new MCDM method in this paper.

The Kano model is used in the proposed MCDM method for satisfaction measurement. It is a tool initially proposed by Kano (1984) in 1984 to classify the product requirements into different dimensional quality attributes, i.e., must-be, one-dimensional, and attractive attributes. The quality attributes depict different linear or nonlinear relationships between product performance and customer satisfaction. The original Kano model has been extended to different variations over the years (Shahin et al., 2013). The main advantage of using the Kano model in our MCDM as the basis to express the time-based satisfaction of decision-makers with criteria is that through a better understanding of the characteristics of criteria, we can recognise the criteria with higher weights in satisfaction. They will drive greater influence on the performance evaluation of alternatives. By this means, guided by the differentiated satisfaction levels in short, medium, and long terms, the assessment results would be reliable, even for a long-term period.

The FMEA is also employed in the proposed MCDM method for risk analysis. FMEA was created in 1949 for the US Department of Defence (Stamatis, 2003), and has been widely combined with different sorts of MCDM methods and applied in various industries (Liu et al., 2019; Huang et al., 2020). It is a powerful risk and reliability management approach to proactively identifying failure modes and their effects, causes, and control mechanisms, and ranking the failure modes in these three aspects to obtain the severity, likelihood and control scores. Traditionally, the numeric scores can be multiplied together to form a risk priority number (RPN) for each failure mode. However, the traditional RPN was criticised due to its shortcomings as summarised in Liu et al. (2013). Therefore, we use an improved format of RPN as suggested in Li and Zeng (2016) for our MCDM to examine the potential risks of criteria to make the assessment more reasonable and reliable.

Since it is the first time that the Kano model and FMEA will be integrated into fuzzy MCDM (specifically fuzzy AHP and fuzzy TOPSIS) in the proposed method, we refer to the existing four studies in the field that incorporated Kano and FMEA from the technical point of view even though they were not used in fuzzy MCDM.

An approach to enhance FMEA capabilities was proposed in Shahin (2004) through its integration with Kano model. The traditional ways of deciding the severity score for an effect of failure mode, as well as defining the RPN in FMEA were modified by classifying severity from customers' perceptions, rather than managers' eyes. The Kano model was used to picture the relationship between the frequency and severity of the effect of failure mode. A new index called correction ratio was proposed as a failure prioritisation to replace RPN. This approach enables managers to prevent failures at the early stage of design and can be used before and after the production stages.

With the same goal in mind of developing a customer-oriented FMEA, another new FMEA was designed in Koomsap and Charoenchokdilok (2018) to improve the earlier work (Shahin, 2004) by getting a better reflection of customer voices. Kano model was applied to identify how customers perceive failure mode effects. Customer dissatisfaction was integrated into this approach, where severity and likelihood were viewed as the factors influencing customer dissatisfaction. Similarly, a new PRN was developed. In contrast to the approach in Shahin (2004) and traditional FMEA, this new customer-oriented FMEA proved that how customers perceive the failure mode effects has the greatest impact on prioritisation.

Table 1 Literature of reliability-oriented methods used in fuzzy MCDM

References	Methods towards reliability	Fuzzy MCDM methods	Purposes
Ghorbani et al. (2013) and Avikal et al. (2014)	Kano model	Fuzzy AHP, fuzzy TOPSIS	Deploying voice of stakeholders, criteria classification
Li and Zeng (2016)	FMEA	Fuzzy AHP, fuzzy TOPSIS	Risk analysis
Tian et al. (2018)	QFD	BWM, fuzzy MDM, fuzzy MULTIMOORA	Transforming customer voices to technical requirements to plan products or services
Liu et al. (2019)	FMEA	Fuzzy MCDM	Risk assessment and reliability analysis
Pourmadadkar et al. (2020)	FMEA, QFD	Fuzzy AHP, fuzzy TOPSIS	Risk assessment and service quality enhancement
Wang et al. (2019)	FMEA, prospect theory	Fuzzy TODIM	Considering interactions between risk indicators and psychological behaviours of decision-makers
Sagnak et al. (2020)	FMEA, prospect theory	Fuzzy TODIM, fuzzy AHP	Integrating decision-makers' risk attitudes into risk evaluation
Tian et al. (2021)	Prospect theory	TODIM	Considering psychological behaviours of decision-makers
Erol et al. (2022)	QFD	HFLTS-ANP, HFLTS-TOPSIS	Transforming customer voices to technical requirements to plan products or services
This paper	Kano model with time effects, FMEA	Fuzzy AHP, fuzzy TOPSIS	Considering time-based satisfaction and risk factors in assessment for high-investment and long-life cycle projects

[1] Among the references, Liu et al. (2019) and Tian et al. (2021) are literature reviews, in which more evidence with the same characteristics can be found
[2] QFD—quality function deployment, BWM—best-worst method, MDM—maximizing deviation method, MULTIMOORA—multi-objective optimization by ratio analysis plus the full multiplicative form, TODIM—an acronym in Portuguese of interactive MCDM, and HFLTS—hesitant fuzzy linguistic term sets

A more precise method for determining categories of requirements was designed in Madzík and Kormanec (2020) by using requirement curves. It mainly addressed three improvements compared with the previous Kano model and FMEA integration work (Shahin, 2004)—requirement categorisation to eliminate imprecision, RPN calculation including the effect of the characteristics of requirements, and prioritisation of preventive measures to reduce the risk of dissatisfaction.

Apart from the three studies above which do not combine with MCDM methods, a recent research integrating Kano model and FMEA into a non-fuzzy MCDM called VIKOR (an acronym in Serbian of multicriteria optimization and compromise solution) was presented in Hettiarachchi et al. (2022). VIKOR was integrated with a power law-based customer-oriented FMEA to achieve more logical and reliable prioritisation in comparison with other customer-oriented FMEAs.

There are only limited studies combining Kano model with FMEA, while no one has applied both of them to fuzzy MCDM. Hence, this technical gap motivates us to develop a novel MCDM method containing three phases for blending fuzzy MCDM with Kano model and FMEA as shown in Fig. 1.

3 3-phase MCDM method for reliable assessments

The proposed MCDM method is developed to evaluate and select alternatives reliably for high-investment and long-life cycle projects in three phases, namely (1) weight determination of the decision criteria, (2) risk assessment on the criteria for alternatives, and (3) score assessment for alternatives. The framework of this 3-phase structure is given in Fig. 1. In the following subsections, we will develop the 3-phase MCDM method step by step.

3.1 Phase I: Weight determination of the decision criteria

Phase I (6 steps) is for weight determination of the decision criteria. A team of k_1 decision-makers[1] is established for the assessment of alternatives in a high-investment and long-life cycle project.

3.1.1 Building decision hierarchy structure

The decision-maker panel first determines a comprehensive decision hierarchy structure with a goal to assess k_2 alternatives based on k_3 main criteria and k_4 sub-criteria. Each sub-criterion is subordinate to a main criterion.

3.1.2 Identifying weight of quality attributes for criteria by Kano model

The original Kano model (Kano, 1984) used functional and dysfunctional Kano Questionnaire (KQ) and a 5-by-5 evaluation table to classify the quality attributes of a product (Berger et al., 1993). This paper proposes a Staged Kano Questionnaire (SKQ) to determine the quality attributes of the decision criteria. Compared with the KQ, the SKQ takes the time factor into consideration as the criteria may perform differently in different stages of the project life cycle,

[1] The importance weight of decision-maker DM_p^{weight} is rated on a 5-point scale, where 1—not important, 2—slightly important, 3—moderately important, 4—important, and 5—very important.

which is a key improvement in the evaluation of alternatives in high-investment and long-life cycle projects. The SKQ contains three pairs of functional (f.1–f.3) and dysfunctional questions (d.1–d.3) for the short, medium, and long term of each criterion x as follows:

(f.1) If the criterion x works well in the short term, how do you feel?
(d.1) If the criterion x does not work well in the short term, how do you feel?
(f.2) If the criterion x works well in the medium term, how do you feel?
(d.2) If the criterion x does not work well in the medium term, how do you feel?
(f.3) If the criterion x works well in the long term, how do you feel?
(d.3) If the criterion x does not work well in the long term, how do you feel?

The 5-by-5 evaluation table known as Kano evaluation Table (in Table 2), categorises the quality attributes into the following six types based on five-dimensional answers,[2] (Berger et al., 1993):

1. Attractive attribute (A): refers to sufficient quality attributes leading to customer satisfaction and excitement, and absence does not lead to customer dissatisfaction.
2. Must-be attribute (M): refers to quality attributes that are not mentioned unless not included, sufficiency will not result in more satisfaction but insufficiency will lead to strong dissatisfaction.
3. One-dimensional attribute (O): refers to sufficient quality attributes leading to customer satisfaction, and insufficiency leading to customer dissatisfaction.
4. Questionable attribute (Q): refers to quality attributes that the customer probably does not understand.
5. Indifferent attribute (I): refers to quality attributes that sufficiency or insufficiency will not affect customer satisfaction.
6. Reverse attribute (R): refers to sufficient quality attributes leading to customer dissatisfaction or vice-versa.

Each decision-maker DM_p needs to answer the SKQ, and to weight the importance of short (ws_p), medium (wm_p) and long (wl_p) term effects with regard to the criteria performance, where $ws_p + wm_p + wl_p = 1$, for all $p = 1, \ \ldots, \ k_1$. In terms of the way to answer the SKQ, each of the six questions should come back with a degree of agreement[3] on the five-dimensional answers from Kano evaluation Table, denoted as mP_r^q for functional questions f.1-f.3 or mN_r^q for dysfunctional questions d.1-d.3, where r refers to the corresponding five-dimensional answers, and q refers to the short, medium and long terms. An example of a decision-maker's answer to the SKQ for one criterion is given in Table 3. For instance, $mN_2^{short} = 0$ means that when being asked the question d.1, the decision-maker feels that it 'not at all' must be that way, while $mP_1^{mid} = 4$ means that the decision-maker 'strongly' like it that way for the question f.2.

The degree of agreement with the answers for each time stage can be normalised by $mP^q = mP_r^q / \sum_{r=1}^{5} mP_r^q$ and $mN^q = mN_r^q / \sum_{r=1}^{5} mN_r^q$. For instance, the two normalised degree vectors for the long term can be calculated from Table 3 as,

$$\mathbf{mP}^{long} = (0.5, 0.25, 0.125, 0.125, 0) \,,$$
$$\mathbf{mN}^{long} = (0, 0, 0.25, 0.25, 0.5) \,.$$

[2] Answers are (1) 'I like it that way', (2) 'It must be that way', (3) 'I am neutral', (4) 'I can live with it that way', and (5) 'I dislike it that way'.

[3] The degree is rated on six levels, varying from 0—'not at all', 1—'very slightly', 2—'slightly', 3—'moderately', 4—'strongly' to 5—'very strongly'.

Table 2 Kano evaluation table (Berger et al., 1993)

Customer requirements	Dysfunctional question				
	(1) I like it that way	(2) It must be that way	(3) I am neutral	(4) I can live with it that way	(5) I dislike it that way
Functional question					
(1) I like it that way	Q	A	A	A	O
(2) It must be that way	R	I	I	I	M
(3) I am neutral	R	I	I	I	M
(4) I can live with it that way	R	I	I	I	M
(5) I dislike it that way	R	R	R	R	Q

A—attractive attribute, M—must-be attribute, O—one-dimensional attribute, Q—questionable attribute, I—indifferent attribute, and R—reverse attribute

Table 3 An example of a decision-maker's answer to the SKQ for one criterion

	(1) I like it that way	(2) It must be that way	(3) I am neutral	(4) I can live with it that way	(5) I dislike it that way
Short					
Functional	$mP_1^{short} = 4$	$mP_2^{short} = 1$	$mP_3^{short} = 2$	$mP_4^{short} = 2$	$mP_5^{short} = 0$
Dysfunctional	$mN_1^{short} = 0$	$mN_2^{short} = 0$	$mN_3^{short} = 2$	$mN_4^{short} = 2$	$mN_5^{short} = 1$
Medium					
Functional	$mP_1^{mid} = 4$	$mP_2^{mid} = 1$	$mP_3^{mid} = 2$	$mP_4^{mid} = 2$	$mP_5^{mid} = 0$
Dysfunctional	$mN_1^{mid} = 0$	$mN_2^{mid} = 0$	$mN_3^{mid} = 2$	$mN_4^{mid} = 2$	$mN_5^{mid} = 1$
Long					
Functional	$mP_1^{long} = 4$	$mP_2^{long} = 2$	$mP_3^{long} = 1$	$mP_4^{long} = 1$	$mP_5^{long} = 0$
Dysfunctional	$mN_1^{long} = 0$	$mN_2^{long} = 0$	$mN_3^{long} = 1$	$mN_4^{long} = 1$	$mN_5^{long} = 2$

By comparing the 5×5-matrix $\mathbf{S}^q = (\mathbf{mP}^q)^T \times \mathbf{mN}^q$ with the Kano evaluation Table in Table 2, we can add up the degree values in $\mathbf{S}^q$ with the same quality attribute to generate a quality attribute weight vector $\mathbf{T}^q$ for each criterion. To continue the example above,

$$\mathbf{S}^{long} = (\mathbf{mP}^{long})^T \times \mathbf{mN}^{long} = \begin{pmatrix} 0 & 0 & 0.125 & 0.125 & 0.25 \\ 0 & 0 & 0.063 & 0.063 & 0.125 \\ 0 & 0 & 0.031 & 0.031 & 0.063 \\ 0 & 0 & 0.031 & 0.031 & 0.063 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}.$$

As there are three A—attractive attribute in Kano evaluation Table, we add up the values in the corresponding rows and columns in $\mathbf{S}^{long}$, i.e., $s_{1,2}^{long} = 0$, $s_{1,3}^{long} = 0.125$ and $s_{1,4}^{long} = 0.125$, and get the sum as $t^{long,A} = 0.25$. Thereby, the weight of quality attributes for the long term is as,

$$\mathbf{T}^{long} = \left(t^{long,A}, t^{long,M}, t^{long,O}, t^{long,Q}, t^{long,I}, t^{long,R}\right) = (0.25, 0.25, 0.25, 0, 0.25, 0).$$

Combining the three-time stages, the weight of quality attributes $\mathbf{ST}_p$ that the decision-maker DM_p evaluates on one criterion can be obtained as,

$$\mathbf{ST}_p = ws_p \cdot \mathbf{T}_p^{short} + wm_p \cdot \mathbf{T}_p^{mid} + wl_p \cdot \mathbf{T}_p^{long}. \tag{1}$$

We then aggregate all k_1 decision-makers' $\mathbf{ST}_p$ to calculate the weighted average of the weight of quality attributes on one criterion, i.e., $\mathbf{AT} = (at_A, at_M, at_O, at_Q, at_I, at_R)$, based on the importance weight of decision-makers DM_p^{weight} as,

$$\mathbf{AT} = \frac{\sum_p^{k_1} DM_p^{weight} \cdot \mathbf{ST}_p}{\sum_p^{k_1} DM_p^{weight}}. \tag{2}$$

3.1.3 Determining importance weight of quality attributes by fuzzy AHP

The fuzzy AHP method can capture imprecise human qualitative judgements by using linguistic variables. The decision-makers define a 5-level linguistic scale based on triangular fuzzy numbers as the relative importance scale (see Table 4). It is used in a fuzzy pairwise comparison matrix $\widetilde{\mathbf{AP}} = (l_{ij}, m_{ij}, u_{ij})_{n\times n}$ for scoring the relative importance of the six quality attributes, i.e., A, M, O, Q, I, and R (here $n = 6$). Before accepting the pairwise comparison matrix $\widetilde{\mathbf{AP}}$, it is required to pass the consistency check. First, the fuzzy matrix $\widetilde{\mathbf{AP}}$ should be converted to a crisp one by $\mathbf{AP}^{crisp} = (1/6 \cdot l_{ij} + 2/3 \cdot m_{ij} + 1/6 \cdot u_{ij})_{n\times n}$, (Yu & Hua, 2003).

Then, the consistency ratio CR[4] needs to be verified for $\mathbf{AP}^{crisp}$.

[4] $CR = CI/RI$, $CI = (\lambda_{max} - n)/(n-1)$, where for the consistency index CI, λ_{max} is the maximum eigenvalue of the matrix $\mathbf{AP}^{crisp}$, and RI is the random consistency index as shown in Table 5. If $CR > 0.2$, the values in the matrix need to be modified until $CR \leq 0.2$ (Zhong et al., 2020).

Table 4 Relative importance scale for pairwise comparison matrix

Linguistic variable	Triangular fuzzy number
Equally important	(1,1,3)
Moderately more important	(1,3,5)
Strongly more important	(3,5,7)
Very strongly more important	(5,7,9)
Extremely more important	(7,9,9)

Table 5 Random consistency index (RI) (Avikal et al., 2014)

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45

Next, the fuzzy synthetic extent $\widetilde{AS}_i$[5], for A, M, O, Q, I, R where $i = 1, \ldots, 6$, can be calculated from the pairwise comparison matrix $\widetilde{\mathbf{AP}}$ as,

$$\widetilde{AS}_i = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right) \bigotimes \left(\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} u_{ij}}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} m_{ij}}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} l_{ij}}\right), \tag{3}$$

and the degree of possibility of one fuzzy synthetic extent larger than the other, e.g., $\widetilde{AS}_1 = (l_1, m_1, u_1) \geq \widetilde{AS}_2 = (l_2, m_2, u_2)$ can be computed as,

$$\text{Pos}\,(\widetilde{AS}_1 \geq \widetilde{AS}_2) = \begin{cases} 1, & \text{if } m_1 \geq m_2 \\ \dfrac{u_1 - l_2}{(u_1 - m_1) + (m_2 - l_2)}, & \text{if } u_1 \geq l_2 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

On this base, the degree of possibility of $\widetilde{AS}_i$ larger than all the other fuzzy synthetic extents is given by,

$$\text{Pos}\,(\widetilde{AS}_i \geq \widetilde{AS}_j | j = 1, \ldots, n;\ j \neq i) = \min_{j \in \{1,\ldots,n,\, j \neq i\}} \text{Pos}\,(\widetilde{AS}_i \geq \widetilde{AS}_j), \quad i = 1, \ldots, n. \tag{5}$$

Thus, the importance weight vector $\mathbf{AW} = (aw_1, \ldots, aw_n)^T$ can be calculated, where each

$$aw_i = \frac{\text{Pos}\,(\widetilde{AS}_i \geq \widetilde{AS}_j | j = 1, \ldots, n;\ j \neq i)}{\sum_{k=1}^{n} \text{Pos}\,(\widetilde{AS}_k \geq \widetilde{AS}_j | j = 1, \ldots, n;\ j \neq k)}. \tag{6}$$

3.1.4 Calculating satisfaction weight of criteria

Integrating the weight of quality attributes for all k_4 criteria **AT** (a $k_4 \times 6$ matrix) with the importance weight of quality attributes themselves **AW**, we can obtain a satisfaction weight of all criteria $\mathbf{SW} = (sw_1, \ldots, sw_{k_4})^T$, where

$$sw_v = \sum_{i=1}^{6} at_{vi} \cdot aw_i, \quad v = 1, \ldots, k_4. \tag{7}$$

[5] The symbol $\bigotimes$ represents the multiplication operator of fuzzy numbers, i.e., $\tilde{a} \bigotimes \tilde{b} = (a_1, a_2, a_3) \bigotimes (b_1, b_2, b_3) = (a_1 \cdot b_1, a_2 \cdot b_2, a_3 \cdot b_3)$, and $\tilde{a} \bigotimes b = (a_1, a_2, a_3) \bigotimes b = (a_1 \cdot b, a_2 \cdot b, a_3 \cdot b)$.

The satisfaction weight is newly proposed in our method. It measures how well the decision criteria can satisfy the decision-maker's needs in short, medium and long terms, which is a critical factor to be taken into account for high-investment and long-life cycle projects. The satisfaction weight of criteria will be incorporated with the conventional importance weight to define a more comprehensive weight for decision criteria.

3.1.5 Determining importance weight of criteria by fuzzy AHP

By using the same fuzzy AHP approach to determining the importance weight of quality attributes in Sect. 3.1.3, the decision-makers can obtain the traditional importance weight of criteria. Since there are k_3 main criteria containing k_4 sub-criteria, one fuzzy pairwise comparison matrix for all the main criteria, and k_3 number of comparison matrices for all the groups of sub-criteria should be developed. For each of these fuzzy pairwise comparison matrices, we can get an importance local weight vector **LW**. Combining **LW** of the main and sub-criteria based on hierarchy structure, a normalised importance weight vector of all the criteria can be produced as $\mathbf{GW} = (gw_1, \ldots, gw_{k_4})^T$.

3.1.6 Integrating satisfaction and importance weight for consolidated weight

Eventually, a consolidated weight **CW** can be established based on the outputs of the two steps above as,

$$\mathbf{CW} = \mathbf{SW} \cdot \mathbf{GW}, \tag{8}$$

and then normalised to $\mathbf{W} = (w_1, \ldots, w_{k_4})^T$. The consolidated weight of criteria **W** jointly evaluates the satisfaction and importance factors of all decision criteria. It is the final outcome of Phase I of our 3-phase MCDM method.

3.2 Phase II: Risk assessment on the criteria for alternatives

Phase II (3 steps) is for risk assessment on the decision criteria for all the alternatives. The comprehensive analysis of risks reduces the gap with the expected performance of criteria, which can make the final assessment results more reliable. This is particularly crucial for the high-investment and long-life cycle projects. This risk assessment phase employs the FMEA method (Li & Zeng, 2016), which contains three steps as follows.

3.2.1 Designing FMEA evaluation schemes

For each of the k_4 number of decision criteria, the decision-maker panel needs to define a specific FMEA evaluation scheme, i.e., depict a series of potential risk situations in the three risk dimensions (likelihood, severity and control), and map the risk situations to a 10-point scale (larger points indicate higher risks). For instance, a generic FMEA evaluation scheme is illustrated in Table 6 for one criterion (Li & Zeng, 2016). The k_4 FMEA evaluation schemes will later be used to rank the failure modes of criteria for the alternatives.

3.2.2 Defining failure modes and ranking risks of criteria for alternatives

The decision-maker panel defines one or more failure modes under each criterion for each alternative. More than one set of the effects with severity ranks, the causes with likelihood

Table 6 Generic FMEA evaluation scheme (Li & Zeng, 2016)

Rank	Likelihood	Severity	Control
9–10	Very high and inevitable	Fail to meet safety and/or regulatory requirements	No detection opportunity
7–8	High and uncertain	Loss or degradation of primary function	Possibly detected by offline testing
5–6	Moderate	Loss or degradation of secondary function	Possibly detected by online planned testing
2–4	Low	Annoying effects	Possibly detected by online automatic continuous testing
1	Very low	No discernible effects	Highly noticeable in regular operations

ranks, and the detection or control approaches with control ranks can be recognised for each failure mode. The designed FMEA evaluation schemes from the previous step are used to rate the severity, likelihood and control levels. Thus, all the failure modes of criteria, along with the ranks in three dimensions compose an FMEA document for each alternative.

A partial FMEA document, which is an example of two failure modes of one criterion 'storage system cost' for one alternative 'hydrogen storage method A' is illustrated in Table 7.

3.2.3 Calculating risk discounted weight for criteria scores

Based on the severity (S), likelihood (L), and control (C) ranks in the FMEA documents, a risk discount can be generated for each criterion of every alternative (Li & Zeng, 2016). The risk discounts will be used to tune the initial assessment scores on the criteria of alternatives, which can add the risk impacts to the final scores.

In order to calculate the risk discounts, first, a risk number RN can be defined by combining the risk severity and likelihood in a failure mode as $RN = S \times L$, where $1 \leq RN \leq 100$. Then, an original risk discount can be formulated as $od = (RN - 1)/99$, where $0 \leq od \leq 1$. The lower the risk RN, the smaller the risk discount od. The original risk discount od is adjusted via an exponent ep,

$$d = od^{ep} = \left(\frac{S \times L - 1}{99}\right)^{ep}, \tag{9}$$

where $ep = -0.1C + 1.55$, as the risk control C stands for the capability to detect and reduce the risk. The two parameter values in ep are tailored specifically for this paper due to the 10-point scale used in the FMEA evaluation schemes. We can find that $ep = 1, d = od$ when $C = 5.5$, i.e., the median of C range. Finally, we calculate the mean $\bar{d}$ if there are more than one failure mode under each criterion. Taking the example in Table 7, the risk discount of the criterion 'storage system cost' $\bar{d} = \{[(2 \times 2 - 1)/99]^{-0.1\times2+1.55} + [(1 \times 1 - 1)/99]^{-0.1\times2+1.55}\}/2 = 0.0045$.

The risk discounts $\bar{d}$ will be used for tuning purposes in Phase III. Those criteria which will be heavily discounted (i.e., with large risk discounts) indicate high risks in performance attainment and vice versa. A risk discounted weight $rw = 1 - \bar{d}$ should be multiplied on the initial assessment score of each criterion. For the example above, the risk discounted weight of the criterion 'storage system cost' $rw = 1 - 0.0045 = 0.9955$. The risk discounted

Table 7 Example failure modes of one criterion ‘storage system cost’ for one alternative ‘hydrogen storage method A’

Criterion	Failure modes	Effects	*S*	Causes	*L*	Control	*C*
Storage system cost	Too expensive comparing with battery	Profit declines	2	Fuel cost and material price increase	2	Forecast policy of fuel	2
	Double price as battery	Rejected by market	1	Electricity cost increase and the cost of relevant materials increase	1	Forecast policy of fuel prediction on raw material market	2

S—severity rank, *L*—likelihood rank, and *C*—control rank

Table 8 Criteria performance scale for rating alternatives

Linguistic variable	Triangular fuzzy number
Bad (B)	(1,1,3)
Fair (F)	(1,3,5)
Average (A)	(3,5,7)
Good (G)	(5,7,9)
Excellent (E)	(7,9,9)

weight of all the criteria for all the alternatives can form a risk discounted weight matrix as $\mathbf{RW} = (rw_{hv})_{k_2 \times k_4}$, which is the outcome of Phase II.

3.3 Phase III: Score assessment for alternatives

Phase III (3 steps) is to assess the scores for all alternatives by combining the outcomes of Phases I (consolidated weight of criteria $\mathbf{W}$) and II (risk discounted weight of criteria $\mathbf{RW}$). Thereby, the final assessment scores fully take the decision criteria's satisfaction, importance, and risk factors into consideration. This phase fundamentally builds on the fuzzy TOPSIS approach (Hwang & Yoon, 1981) to score the alternatives.

3.3.1 Calculating initial criteria scores for alternatives by fuzzy TOPSIS

Each of the k_1 decision-makers needs to grade all the k_2 potential alternatives with respect to the performance of the k_4 decision criteria, by using a 5-level linguistic scale based on triangular fuzzy numbers as defined in Table 8.

This fuzzy criteria performance rating is denoted as $\widetilde{\mathbf{CP}} = (a_{hvp}, b_{hvp}, c_{hvp})_{k_2 \times k_4 \times k_1}$. Consolidating all the decision-makers' ratings, an aggregated fuzzy criteria performance rating $\widetilde{cp}_{hv} = (a_{hv}, b_{hv}, c_{hv})$ can be obtained, where

$$a_{hv} = \min_{p \in k_1}\{a_{hvp}\},\ \ b_{hv} = \frac{1}{k_1}\sum_{p=1}^{k_1} b_{hvp},\ \ c_{hv} = \max_{p \in k_1}\{c_{hvp}\}. \tag{10}$$

A normalised fuzzy score matrix can then be established as $\widetilde{\mathbf{R}} = (\widetilde{r}_{hv})_{k_2 \times k_4}$, where

$$\begin{aligned} \widetilde{r}_{hv} &= \left(\frac{a_{hv}}{c_v^*}, \frac{b_{hv}}{c_v^*}, \frac{c_{hv}}{c_v^*}\right) \text{ and } c_v^* = \max_{h \in k_2} c_{hv},\ v \in SBC \\ \widetilde{r}_{hv} &= \left(\frac{a_v^-}{c_{hv}}, \frac{a_v^-}{b_{hv}}, \frac{a_v^-}{a_{hv}}\right) \text{ and } a_v^- = \min_{h \in k_2} a_{hv},\ v \in SCC \end{aligned} \tag{11}$$

where SBC and SCC are the sets of benefit criteria and cost criteria, respectively. The benefit criteria refer to those the larger the better, while the cost criteria mean those the smaller the better. Thus, the weighted normalised fuzzy score matrix $\widetilde{\mathbf{Z}} = (\widetilde{z}_{hv})_{k_2 \times k_4}$ is calculated by aggregating the consolidated weight of criteria $\mathbf{W}$ got from Phase I as,

$$\widetilde{z}_{hv} = \widetilde{r}_{hv} \bigotimes w_v. \tag{12}$$

$\widetilde{\mathbf{Z}}$ are regarded as the initial assessment scores of criteria, which will be adjusted by the risk discounted weight in the next step.

3.3.2 Tuning initial criteria scores by risk discounted weight

A risk-tuned fuzzy score matrix $\widetilde{\mathbf{RZ}} = (\widetilde{rz}_{hv})_{k_2 \times k_4}$ is calculated by assigning the risk discounted weight $\mathbf{RW}$ obtained from Phase II to the weighted normalised fuzzy score matrix $\widetilde{\mathbf{Z}}$ as

$$\widetilde{rz}_{hv} = \widetilde{z}_{hv} \bigotimes rw_{hv}. \tag{13}$$

3.3.3 Determining final scores of alternatives by fuzzy TOPSIS

Continuing with the fuzzy TOPSIS approach, it computes in this step the fuzzy positive ideal solution (FPIS, $\mathbf{A}^*$) and fuzzy negative ideal solution (FNIS, $\mathbf{A}^-$) as,

$$\begin{aligned} \mathbf{A}^* &= (\widetilde{rz}_1^*, \ldots, \widetilde{rz}_{k_4}^*), \text{where } \widetilde{rz}_v^* = (1, 1, 1) \text{ for } v \in SBC, \\ &\quad \text{and } \widetilde{rz}_v^* = (0, 0, 0) \text{ for } v \in SCC, \\ \mathbf{A}^- &= (\widetilde{rz}_1^-, \ldots, \widetilde{rz}_{k_4}^-) \text{where } \widetilde{rz}_v^- = (0, 0, 0) \text{ for } v \in SBC, \\ &\quad \text{and } \widetilde{rz}_v^- = (1, 1, 1) \text{ for } v \in SCC. \end{aligned} \tag{14}$$

Then the distances between the risk-tuned fuzzy scores $\widetilde{\mathbf{RZ}}$ and FPIS or FNIS for each alternative are defined respectively as,

$$\begin{aligned} fd_h^+ &= \sum\nolimits_{v=1}^{k_4} dis(\widetilde{rz}_{hv}, \widetilde{rz}_v^*), \\ fd_h^- &= \sum\nolimits_{v=1}^{k_4} dis(\widetilde{rz}_{hv}, \widetilde{rz}_v^-), \end{aligned} \tag{15}$$

where dis states the distance between two fuzzy variables as,

$$dis(\widetilde{x}, \widetilde{y}) = \sqrt{\frac{1}{3}\left[(a_x - a_y)^2 + (b_x - b_y)^2 + (c_x - c_y)^2\right]}. \tag{16}$$

Lastly, the closeness coefficient of each alternative CC_h considers the distances from $\widetilde{\mathbf{RZ}}$ to FPIS and FNIS simultaneously, which is formulated as,

$$CC_h = \frac{fd_h^-}{fd_h^- + fd_h^+}. \tag{17}$$

Up to here, the final scores of alternatives CC_h have been obtained. The alternatives can be ranked from the best to worst based on CC_h values in descending order, for decision-makers' convenience to further select the best option.

4 Application of 3-phase MCDM method: Hydrogen storage method selection for lightweight vehicles

Sustainable transport contributes to the reduction of carbon emissions. Some countries provide incentives to shift petroleum-fueled vehicles to hydrogen vehicles in order to mitigate environmental damage caused by the widespread use of gasoline and diesel fuel. The ensuing need for reliable decision mechanisms for automotive companies to assess the hydrogen-related alternatives and select the best option can be met by the proposed 3-phase MCDM method.

In this section, we use a numerical example case of hydrogen storage method selection for lightweight vehicles, which has the characteristics of high investment and long-life cycle.

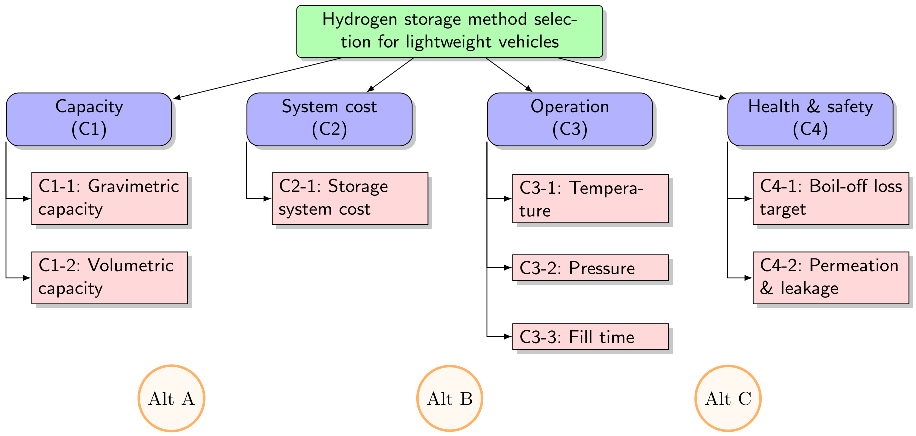

Fig. 2 Decision hierarchy structure of hydrogen storage method selection (Alternative A, B and C) for lightweight vehicles

Our 3-phase MCDM method is demonstrated according to Sect. 3 on the assessment and selection of hydrogen storage methods.

4.1 Phase I: Weight determination of the decision criteria

Phase I mainly applies the fuzzy AHP and modified Kano model. A team of $k_1 = 3$ decision-makers is established, containing a chief technology officer (CTO) of a hydrogen storage tank manufacturer (DM_1), a chief financial officer (CFO) of a hydrogen storage tank manufacturer (DM_2), and an automotive manufacturer (DM_3). The importance weights of the three decision-makers are rated as 5, 4, and 3, respectively, as per their dominance in the decision-making.

4.1.1 Building decision hierarchy structure

The three decision-makers determine a decision hierarchy structure (see Fig. 2). It includes $k_3 = 4$ main decision criteria, namely capacity, system cost, operation, and health & safety. $k_4 = 8$ sub-criteria in total can be found under all the main criteria. $k_2 = 3$ alternatives of hydrogen storage methods will be assessed for selection. The hydrogen storage alternative A uses a compressed gaseous hydrogen tank (type IV hydrogen tank at 700 bar and atmospheric temperature), the hydrogen storage alternative B uses a liquid hydrogen tank (atmospheric pressure and -253°C), while the hydrogen storage alternative C uses cryo-compressed hydrogen tank (250–350 bar and at cryogenic temperature).

4.1.2 Identifying weight of quality attributes for criteria by Kano model

Eight sets of SKQs for the eight criteria, each of which consists of functional questions f.1-f.3 and dysfunctional questions d.1-d.3 are distributed to every decision-maker to collect answers. Here we present the example answers from DM_1 in Table 9 and omit the answers from DM_2 and DM_3. Table 3 in the last section illustrated answers from hydrogen storage tank manufacturer (DM_2) to the SKQ for criterion boil-off loss target (C4-1). The answers to each SKQ are compared with Table 2 for calculating the weight of quality attributes for all the eight criteria **AT**. Combining with the decision-makers' weighting on the importance of short, medium and long-term effects,[6] the results of **AT** are shown in Table 10.

4.1.3 Determining importance weight of quality attributes by fuzzy AHP

A fuzzy pairwise comparison matrix $\widetilde{\mathbf{AP}}$ can be obtained by scoring the relative importance between the six quality attributes as illustrated in Table 11. The importance weight vector of the quality attributes can be calculated as $\mathbf{AW} = (0.3875, 0.4677, 0.1384, 0.0055, 0.0005, 0.0005)^T$, which indicates that the 'must-be' attribute is the most important one.

4.1.4 Calculating satisfaction weight of criteria

The satisfaction weight of all the eight criteria **SW** integrates the weight of quality attributes **AT** and the importance weight of quality attributes **AW**. The result of $\mathbf{SW} = (0.2342, 0.2276, 0.2300, 0.2118, 0.2021, 0.1736, 0.2143, 0.2813)^T$.

4.1.5 Determining importance weight of criteria by fuzzy AHP

By using fuzzy pairwise comparison to score the relative importance between the four main criteria (see Table 12), as well as the sub-criteria[7] under each main criterion, the importance local weight vectors **LW** can be computed. As shown in Column 2 of Table 13, the importance weight of the four main criteria $\mathbf{LW} = (0.3504, 0.0005, 0.1561, 0.4929)^T$. The results of the importance weight vectors of the sub-criteria under the four main criteria are in Column 4. Column 5 refers to the normalised importance weight vector of all the eight sub-criteria **GW**.

4.1.6 Integrating satisfaction and importance weight for consolidated weight

The consolidated weight of all the eight criteria **W** is obtained by combining the satisfaction weight **SW** with the importance weight **GW**. As the final outcome of the Phase I, $\mathbf{W} = (0.1695, 0.1648, 0.0005, 0.0683, 0.0651, 0.0001, 0.1310, 0.4008)$, where C4-2 (permeation & leakage) is the most important sub-criterion, and C4 (health & safety) is the most important main criterion.

4.2 Phase II: Risk assessment on the criteria for alternatives

Phase II is based on the FMEA method, which comprises the following three steps.

4.2.1 Designing FMEA evaluation schemes

The decision-maker panel defines the FMEA evaluation schemes in view of severity (Table 14), likelihood (Table 15), and control (Table 16) dimensions, respectively, for all the eight criteria.

[6] DM_1 weights $ws_1 = 0.5,\ wm_1 = 0.3,\ wl_1 = 0.2$, DM_2 weights $ws_2 = 0.1,\ wm_2 = 0.2,\ wl_2 = 0.7$, and DM_3 weights $ws_3 = 0.5,\ wm_3 = 0.6,\ wl_3 = 0.3$.

[7] Three fuzzy pairwise comparison matrices for sub-criteria are omitted, but decision-making team's answers are C1-1 is equally important with C1-2; C3-1 and C3-2 are strongly more important than C3-3, while C3-1 and C3-2 are equally important; C4-2 is moderately more important than C4-1.

Table 9 CTO's (DM_1) answer to the SKQ for all criteria

Criteria	Stages	Questions	Answers				
			(1) I like it that way	(2) It must be that way	(3) I am neutral	(4) I can live with it that way	(5) I dislike it that way
	Short	Functional	5	5	2	2	0
		Dysfunctional	0	0	2	3	5
C1-1: Gravimetric	Medium	Functional	5	5	3	3	0
capacity		Dysfunctional	0	0	2	3	5
	Long	Functional	5	4	4	4	1
		Dysfunctional	1	3	4	5	3
	Short	Functional	5	5	2	2	0
		Dysfunctional	0	0	2	3	5
C1-2: Volumetric	Medium	Functional	5	5	4	5	1
capacity		Dysfunctional	1	1	3	4	5
	Long	Functional	5	4	4	3	1
		Dysfunctional	1	3	3	4	3
	Short	Functional	5	3	3	2	1
		Dysfunctional	2	1	2	3	5
C2-1: Storage	Medium	Functional	3	2	4	4	1
system cost		Dysfunctional	2	1	2	2	1
	Long	Functional	3	1	4	4	3
		Dysfunctional	3	4	3	2	3
	Short	Functional	5	4	3	0	0
		Dysfunctional	0	0	0	0	4
C3-1: Temperature	Medium	Functional	5	3	2	0	0
		Dysfunctional	4	5	1	2	3
	Long	Functional	5	3	2	1	0
		Dysfunctional	4	5	1	1	2

Table 9 continued

Criteria	Stages	Questions	Answers				
			(1) I like it that way	(2) It must be that way	(3) I am neutral	(4) I can live with it that way	(5) I dislike it that way
	Short	Functional	5	4	3	0	0
		Dysfunctional	0	0	1	0	4
C3-2: Pressure	Medium	Functional	5	4	3	3	2
		Dysfunctional	2	2	4	4	3
	Long	Functional	5	2	3	3	2
		Dysfunctional	1	2	3	2	2
	Short	Functional	4	3	3	3	2
		Dysfunctional	1	1	2	3	3
C3-3: Fill time	Medium	Functional	3	3	3	3	2
		Dysfunctional	2	2	3	3	3
	Long	Functional	4	3	3	3	3
		Dysfunctional	2	2	2	3	3
	Short	Functional	5	3	2	1	1
		Dysfunctional	1	1	1	2	3
C4-1: Boil-off	Medium	Functional	5	3	2	2	1
loss target		Dysfunctional	1	1	1	2	3
	Long	Functional	4	2	2	2	2
		Dysfunctional	4	2	1	1	2
	Short	Functional	5	5	1	0	0
		Dysfunctional	0	0	0	0	5
C4-2: Permeation	Medium	Functional	5	5	1	0	0
& leakage		Dysfunctional	0	0	1	0	5
	Long	Functional	5	4	1	1	0
		Dysfunctional	1	0	1	0	4

Table 10 Weight of quality attributes for all criteria

Criteria	Quality attributes A	M	O	Q	I	R
C1-1	0.1851	0.2995	0.1609	0.0023	0.3450	0.0072
C1-2	0.1826	0.2899	0.1525	0.0073	0.3498	0.0180
C2-1	0.1158	0.3241	0.2400	0.0349	0.2018	0.0835
C3-1	0.2170	0.2252	0.1587	0.0451	0.2941	0.0599
C3-2	0.2246	0.2050	0.1359	0.0296	0.3408	0.0641
C3-3	0.2466	0.1409	0.0843	0.0382	0.4010	0.0889
C4-1	0.2113	0.2137	0.2317	0.0409	0.2363	0.0661
C4-2	0.0949	0.4155	0.3620	0.0063	0.1136	0.0076

Table 11 Fuzzy pairwise comparison matrix of quality attributes

	A	M	O	Q	I	R
A	(1,1,1)	(1,1,3)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,9)
M	(1/3,1,1)	(1,1,1)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)
O	(1/9,1/7,1/5)	(1/9,1/7,1/5)	(1,1,1)	(1,3,5)	(1,3,5)	(7,9,9)
Q	(1/5,1/3,1)	(1/9,1/7,1/5)	(1/5,1/3,1)	(1,1,1)	(1,1,3)	(7,9,9)
I	(1/9,1/7,1/5)	(1/9,1/9,1/7)	(1/5,1/3,1)	(1/3,1,1)	(1,1,1)	(5,7,9)
R	(1/9,1/9,1/7)	(1/9,1/9,1/7)	(1/9,1/9,1/7)	(1/9,1/9,1/7)	(1/9,1/7,1/5)	(1,1,1)

$CR = 0.1746$

Table 12 Fuzzy pairwise comparison matrix of main criteria

	C1	C2	C3	C4
C1	(1,1,1)	(3,5,7)	(1,3,5)	(1/5,1/3,1)
C2	(1/7,1/5,1/3)	(1,1,1)	(1/5,1/3,1)	(1/9,1/7,1/5)
C3	(1/5,1/3,1)	(1,3,5)	(1,1,1)	(1/7,1/5,1/3)
C4	(1,3,5)	(5,7,9)	(3,5,7)	(1,1,1)

$CR = 0.1113$

4.2.2 Defining failure modes and ranking risks of criteria for alternatives

For each alternative, the decision-maker panel develops an FMEA document, which is composed of failure modes with the effects, causes and control approaches for all the eight criteria, as well as the ranks in severity (S), likelihood (L) and control (C) dimensions based on the defined FMEA evaluation schemes. The FMEA documents for all three alternatives are combined and given in Table 17.

4.2.3 Calculating risk discounted weight for criteria scores

The risk discounted weight of all the eight criteria **RW** is calculated for all three alternatives based on the FMEA documents Table 17. **RW** is the final outcome of Phase II, the values of which can be found in the square brackets in Table 18.

Table 13 Importance weight of criteria

Main criteria	**LW** of main criteria	Sub-criteria	**LW** of sub-criteria	**GW** of sub-criteria
C1: Capacity	0.3504	C1-1: Gravimetric capacity	0.5000	0.1752
		C1-2: Volumetric capacity	0.5000	0.1752
C2: System cost	0.0005	C2-1: Storage system cost	1.0000	0.0005
C3: Operation	0.1561	C3-1: Temperature	0.4998	0.0780
		C3-2: Pressure	0.4998	0.0780
		C3-3: Fill time	0.0005	0.0001
C4: Health & safety	0.4929	C4-1: Boil-off loss target	0.3003	0.1480
		C4-2: Permeation & leakage	0.6997	0.3449

Table 14 FMEA evaluation scheme for risk severity (S) for all criteria

Rank of S	Gravimetric capacity	Volumetric capacity[a]	Storage system cost	Temperature	Pressure	Fill time	Boil-off loss target	Permeation & leakage
9–10	Driving distance < 80 miles	159 L H_2 tank at 75 MPa	7 gal gasoline equivalent[b]	Cause tank failure	Cause tank failure	Fail to meet filling target	Fail to meet safety target	In explosion range
7–8	Driving distance < 100 miles	145 L H_2 tank at 75 MPa	6 gal gasoline equivalent	Cause serious leak and tank cracking	Cause leak	Serious blockage or leakage	Degradation of primary function	In flammable range
5–6	Driving distance < 150 miles	130 L H_2 tank at 75 MPa	5 gal gasoline equivalent	Lose hydrogen	Lose hydrogen	Blockage or lower pressure on refuelling station	Small leakage	Annoying effects
2–4	Driving distance < 200 miles	117 L H_2 tank at 75 MPa	4 gal gasoline equivalent	Over 7% maximum operation pressure	Over 7% maximum operation pressure	Annoying effects	Annoying effects	Acceptable
1	Driving distance about 300 miles	106 L H_2 tank at 75 MPa	3 gal gasoline equivalent	No discernible effects	No discernible effects	No discernible effects	No discernible effects	No discernible effects

[a] Assume 300 L volume for a private car
[b] Gal is the abbreviation for the gallon

Table 15 FMEA evaluation scheme for risk likelihood (L) for all criteria

Rank of L	Gravimetric capacity	Volumetric capacity	Storage system cost	Temperature	Pressure	Fill time	Boil-off loss target	Permeation & leakage
9–10	2.5 wt.% for very low energy capacity	0.03 kg/L for very low energy capacity	10 $/kWh net H_2	Over 20% of standard temperature	Over 20% of standard pressure	25 min	50% boil-off loss after 30 days	5% (H_2/air during 10 days)
7–8	3.5 wt.% for low energy capacity	0.04 kg/L for low energy capacity	9 $/kWh net H_2	Over 15% of standard temperature	Over 15% of standard pressure	20 min	40% boil-off loss after 30 days	4% (H_2/air during 10 days)
5–6	4.5 wt.% moderate and achievable	0.05 kg/L moderate and achievable	8 $/kWh net H_2	Over 10% of standard temperature	Over 10% of standard pressure	15 min	30% boil-off loss after 30 days	3% (H_2/air during 10 days)
2–4	5.5 wt.% for high energy capacity	0.06 kg/L for high energy capacity	7 $/kWh net H_2	Over 5% of standard temperature	Over 5% of standard pressure	10 min	20% boil-off loss after 30 days	2% (H_2/air during 10 days)
1	6.5 wt.% for very high energy capacity	0.07 kg/L for very high energy capacity	6 $/kWh net H_2	Over 1% of standard temperature	Over 1% of standard pressure	6 min	10% boil-off loss after 30 days	1% (H_2/air during 10 days)

Table 16 FMEA evaluation scheme for risk control (C) for all criteria

Rank of C	Gravimetric capacity	Volumetric capacity	Storage system cost	Temperature	Pressure	Fill time	Boil-off loss target	Permeation & leakage
9–10	Inner city travel, close to refuelling station	Over half space of car boots	Hybrid system with petrol	Cool down immediately	No detection opportunity	Full service is required	No detection opportunity	Vacate car and space
7–8	Cross city travel with refuelling station nearby	48% car boot space	Hybrid system with battery	Hybrid system with battery	Release pressure	Possibly detected by planned testing	Possibly detected by offline planned testing	Detected by alarm
5–6	Regional travel	40% car boot space	Tax subsidies	Stop charging or discharging immediately	Stop charging or discharging immediately	Check refuelling station capacity and check any blockage on system	Detected by Hydrogen alarm	Detected by vehicle
2–4	Cross regional travel	35% car boot space	Carbon tax reduce the gap between hydrogen and fossil fuel	Stop charging as soon as possible; detect and monitor temperature change	Stop charging as soon as possible; detect and monitor temperature change	Possibly detected by online automatic monitor	Possibly detected by online automatic monitor	Noticeable
1	National travel, identification of refuel station	30% car boot space or compact under seat area	Lightly noticeable	Detect and monitor temperature change	Noticeable before discharging hydrogen	Noticeable	Noticeable	Not noticeable

Table 17 FMEA document for all alternatives

Criteria	Failure modes	Effects	*S*			Causes	*L*			Control	*C*		
			Alt A	Alt B	Alt C		Alt A	Alt B	Alt C		Alt A	Alt B	Alt C
C1-1: Gravimetric capacity	Low capacity of tank	Limit travel distance	3	2	3	Design of tank	2	2	2	Maximise design	1	1	1
C1-2: Volumetric capacity	Large size of tank	Occupation of car space	3	2	3	Design of tank	2	2	2	Optimise design	1	1	1
C2-1: Storage system cost	Too expensive comparing with battery	Profit declines	2	4	5	Fuel cost and material price increase	2	2	2	Forecast policy of fuel	2	2	2
	Double price as battery	Rejected by market	1	3	2	Electricity cost increase and cost of relevant materials increase	1	2	2	Forecast policy of fuel prediction on raw material market	2	2	2
C3-1: Temperature	Elevated temperature	Over temperature, cause failure of tank	7	8	5	Poor quality control	2	3	2	Cooling system temperature monitoring	2	2	2

Table 17 continued

Criteria	Failure modes	Effects	S			Causes	L			Control	C		
			Alt A	Alt B	Alt C		Alt A	Alt B	Alt C		Alt A	Alt B	Alt C
C3-2: Pressure	Over 10% maximum allowed pressure	Cause leak and failure of tank	7	8	6	Overfill or temperature increase	2	3	2	Pressure monitoring; pressure release valve	1	1	1
C3-3: Fill time	Too long	Waiting time	2	2	2	Blockage or low pressure of refuelling station	1	5	3	Annual planned service	1	1	1
C4-1: Boil-off loss target	Loss of hydrogen due to boiling off	Loss of hydrogen capacity	2	2	2	Poor quality or out of life time	1	1	3	Annual check	2	2	2
C4-2: Permeation & leakage	Poor quality or out of life time	Fail to meet safety code	2	2	2	Poor quality or out of life time	1	1	3	Hydrogen alarm and annual service	2	2	2

S—severity rank, L—likelihood rank, and C—control rank

Table 18 Weighted normalised fuzzy scores $\widetilde{\mathbf{Z}}$ and risk discounted weight $\mathbf{RW}$ of all criteria for all alternatives

	Hydrogen storage alternative A	Hydrogen storage alternative B	Hydrogen storage alternative C
C1-1	(0.0565, 0.0942, 0.1319) [0.9868]	(0.0942, 0.1444, 0.1695) [0.9937]	(0.0565, 0.1193, 0.1695) [0.9868]
C1-2	(0.0549, 0.0915, 0.1281) [0.9868]	(0.1281, 0.1648, 0.1648) [0.9937]	(0.0915, 0.1281, 0.1648) [0.9868]
C2-1	(0.0001, 0.0001, 0.0005) [0.9955]	(0.0002, 0.0005, 0.0005) [0.9771]	(0.0002, 0.0005, 0.0005) [0.9759]
C3-1	(0.0076, 0.0158, 0.0683) [0.9355]	(0.0228, 0.0683, 0.0683) [0.8606]	(0.0137, 0.0228, 0.0683) [0.9607]
C3-2	(0.0072, 0.0169, 0.0362) [0.9473]	(0.0072, 0.0410, 0.0651) [0.8795]	(0.0072, 0.0314, 0.0507) [0.9587]
C3-3	(0.0000, 0.0000, 0.0000) [0.9987]	(0.0000, 0.0000, 0.0001) [0.9691]	(0.0000, 0.0000, 0.0001) [0.9868]
C4-1	(0.0146, 0.0231, 0.0437) [0.9980]	(0.0437, 0.1310, 0.1310) [0.9980]	(0.0187, 0.0357, 0.1310) [0.9822]
C4-2	(0.0573, 0.1093, 0.4008) [0.9980]	(0.0573, 0.1093, 0.4008) [0.9980]	(0.0573, 0.0925, 0.4008) [0.9822]

Table 19 Fuzzy criteria performance rating

Panel	Alternative	C1-1	C1-2	C2-1	C3-1	C3-2	C3-3	C4-1	C4-2
	Alt A	A	A	A	F	F	G	G	A
DM_1	Alt B	E	E	B	B	G	A	B	F
	Alt C	G	G	B	F	A	A	A	A
	Alt A	A	A	A	G	B	G	A	B
DM_2	Alt B	G	E	B	B	F	A	B	F
	Alt C	G	G	B	F	F	A	F	F
	Alt A	A	A	F	F	F	G	A	A
DM_3	Alt B	G	E	B	B	G	A	B	A
	Alt C	A	G	B	F	A	A	F	A

Ratings: B—Bad, F—Fair, A—Average, G—Good, E—Excellent

4.3 Phase III: Score assessment for alternatives

Phase III utilises the fuzzy TOPSIS approach.

4.3.1 Calculating initial criteria scores for alternatives by fuzzy TOPSIS

The decision-makers grade all three alternatives regarding the performance of all the eight criteria and get $\widetilde{\mathbf{CP}}$ (see Table 19). On top of this, the weighted normalised fuzzy score matrix $\widetilde{\mathbf{Z}}$[8] can be computed by compositing the consolidated weight of criteria $\mathbf{W}$. The values in $\widetilde{\mathbf{Z}}$ are provided in the round brackets in Table 18, which are considered as the initial assessment scores of criteria.

4.3.2 Tuning initial criteria scores by risk discounted weight

The initial criteria scores, i.e., the weighted normalised fuzzy score matrix $\widetilde{\mathbf{Z}}$ should be tuned by the risk discounted weight $\mathbf{RW}$ to produce the risk-tuned fuzzy score matrix $\widetilde{\mathbf{RZ}}$. The values of $\widetilde{\mathbf{RZ}}$ can be calculated from Table 18.

4.3.3 Determining final scores of alternatives by fuzzy TOPSIS

The final score, i.e., the closeness coefficient of each alternative CC_h can be calculated based on the distance between the risk-tuned fuzzy scores $\widetilde{\mathbf{RZ}}$ and FPIS or FNIS. We can get the result of $CC_1 = 0.6159$ for alternative A, $CC_2 = 0.6191$ for alternative B, and $CC_3 = 0.6195$ for alternative C. It is indicated that hydrogen storage method C is ranked highest in the assessment as the best option to be recommended for use in lightweight vehicles, while method B is the second, and method A is the last in this ranking.

4.4 Discussions

A sensitivity analysis is performed to assess the robustness of time-based satisfaction factor, and a comparison with a classic fuzzy MCDM method is conducted. For sensitivity analysis,

[8] Among all the eight criteria, C1-1 (gravimetric capacity), C1-2 (volumetric capacity), and C3-2 (pressure) are benefit criteria, while the remaining are cost criteria.

Table 20 Sensitivity analysis and method comparison

Our method		Short-term-only		Medium-term-only		Long-term-only		Classic MCDM	
Ranking of the consolidated weights of criteria **W**									
C4-2	0.4008	C4-2	0.3839	C4-2	0.4018	C4-2	0.4260	C4-2	0.3449
C1-1	0.1695	C1-1	0.1714	C1-1	0.1854	C1-2	0.1613	C1-1	0.1752
C1-2	0.1648	C1-2	0.1712	C1-2	0.1673	C1-1	0.1583	C1-2	0.1752
C4-1	0.1310	C4-1	0.1221	C4-1	0.1321	C4-1	0.1318	C4-1	0.1480
C3-1	0.0683	C3-1	0.0775	C3-1	0.0582	C3-2	0.0615	C3-1	0.0780
C3-2	0.0651	C3-2	0.0733	C3-2	0.0547	C3-1	0.0606	C3-2	0.0780
C2-1	0.0005	C2-1	0.0005	C2-1	0.0005	C2-1	0.0005	C2-1	0.0005
C3-3	0.0001	C3-3	0.0001	C3-3	0.0001	C3-3	0.0001	C3-3	0.0001
Ranking of the alternatives and closeness coefficient scores CC									
Alt C	0.6195	Alt B	0.6217	Alt C	0.6210	Alt C	0.6169	Alt C	0.6232
Alt B	0.6191	Alt C	0.6217	Alt B	0.6210	Alt B	0.6163	Alt B	0.6226
Alt A	0.6159	Alt A	0.6176	Alt A	0.6173	Alt A	0.6136	Alt A	0.6202

our proposed method is compared with ones that consider only short-, medium-, and long-term effects when decision-makers respond to the SKQ for all criteria. The results are presented in the first four columns of Table 20. Discrepancies are observed in the consolidated weight of criteria **W** with a rank reversal for criteria C3-1 and C3-2 between our method and the long-term-only method. The findings reveal a notable shift from the preferred hydrogen storage alternative C ($CC_3 = 0.6195$) in our method to alternative B ($CC_2 = 0.6217$) in the short-term-only method. It is evident that our method offers a more comprehensive perspective. The divergence in short-term-only and long-term-only results underscores the significance of our method in considering the time effects.

The results of method comparison with a classic fuzzy MCDM (fuzzy AHP and fuzzy TOPSIS) are illustrated in the first and last columns of Table 20. While the rankings of criteria weights and alternatives share the same one as our method, specific differences in the weights and closeness coefficient scores are observed. Our method integrates time-based satisfaction and risk factors, effectively preventing substantial biases or deviations that might surface as the project progresses. Consequently, our method ensures a more accurate and inclusive assessment, thereby enhancing the reliability and applicability of overall findings in planning high-investment and long-life cycle projects.

Our method is applied to the sustainable transport industry, especially for automotive companies seeking the best hydrogen storage method for lightweight vehicles. The results of the example case have demonstrated its efficacy in tackling the complex decision-making process involved in evaluating and selecting options that require high investment and a long-life cycle. When considering the four primary criteria identified, health & safety dominated the importance weight followed by capacity. The consolidated weight of criteria indicates permeation & leakage is the most important criterion, followed by gravimetric capacity and volumetric capacity with similar weights. The fill time is the least important criterion which accounts for only 0.0001.

Risk assessment of all alternatives shows that hydrogen storage alternative A exposes the least to all risks. The highest risk discount hits criterion temperature for hydrogen storage alternative B: elevated temperature over 5% of standard temperature due to poor quality control will cause a serious leak and tank cracking. This risk can be controlled by cooling system temperature monitoring and stopping charging as soon as possible. After assessing the performance of alternatives on each criterion and tuning the score by risks, the closeness coefficient of each alternative can be determined by fuzzy TOPSIS. In this implication, the most favorable method is hydrogen storage alternative C which uses a cryo-compressed hydrogen tank with 250–350 bar at cryogenic temperature.

5 Web application and policy implications

A free, user-friendly, and interactive web application with GUI is translated from the proposed 3-phase MCDM method. It is built in the HyChain platform to evaluate any stakeholders in the hydrogen supply chains (see the homepage in Fig. 3, accessible via https://hychain.co.uk/). Decision-makers can create a decision hierarchy structure, evaluate alternatives, and select the best option for stakeholders. This section briefly illustrates the user interface of the application by using it to solve the example case in Sect. 4.

As the first step, the primary form needs to be filled out to define the dimensions of the decision structure (as shown in Fig. 4, which is based on Sect. 4's data). Under 'Criteria', users can click the '+' or '-' button on the right to add or delete a main criterion. The names of all the main and sub-criteria are required, as well as the number of failure modes under each sub-criterion. Users need also to specify the number of decision-makers, their importance, and the names of alternatives at this stage. Once the initial inputs are done, users should click the 'Build Secondary Form' button, which proceeds to generate the remaining forms based on the dimensions stipulated. Users then need to fill out the secondary forms, which contain the sections of 'Criteria Type' (Fig. 5), 'Kano Questionnaire' (Fig. 6), 'Pairwise Comparisons for Relative Importance' (Fig. 7), 'Failure Mode and Effects Analysis (FMEA)' (Fig. 8), and 'Criteria Performance Scoring for Alternatives' (Fig. 9)[9]. Some forms, e.g., the 'Kano Questionnaire' (Fig. 6) requires users to switch sub-forms by picking specific 'Decision Maker', 'Main Criteria', and 'Sub Criteria' from the drop-down lists. After all the secondary forms are completed, users should click the 'Calculate Results' button. The back-end 3-phase MCDM method programmed in MATLAB computes and returns the final results, given in the 'Final Ranking of Alternatives' form (Fig. 10). The results match what are obtained from Sect. 4.3.3. The web application allows users to import input data and export output data via Microsoft Excel spreadsheet as well.

This tool can be customised to suit the specific circumstances of various industries or companies' contexts. However, practitioners need to be mindful of several critical aspects: It is essential that all members of the decision-making team receive comprehensive training and ensure each step of the tool is clearly defined, discussed within the team and properly executed. Additionally, there exists the possibility of decision-makers not fully grasping the risk landscape, which can lead to the potential overlooking of critical risks. Finally, it is vital to communicate the significance and benefits of the method to all stakeholders, particularly to the high-level managers, who may need to be convinced of the value of engaging.

This tool can be strategically employed by companies and policymakers to guide the allocation of resources, particularly for projects that require long-term investment. Our research supports the creation of comprehensive regulatory frameworks that reinforce reliable and viable business decisions, where the mandatory risk evaluation emphasises the importance

[9] Figures 5, 6, 7, 8 and 9 illustrate the generated blank secondary forms. They need to be further filled out by using the example case data in Sect. 4.

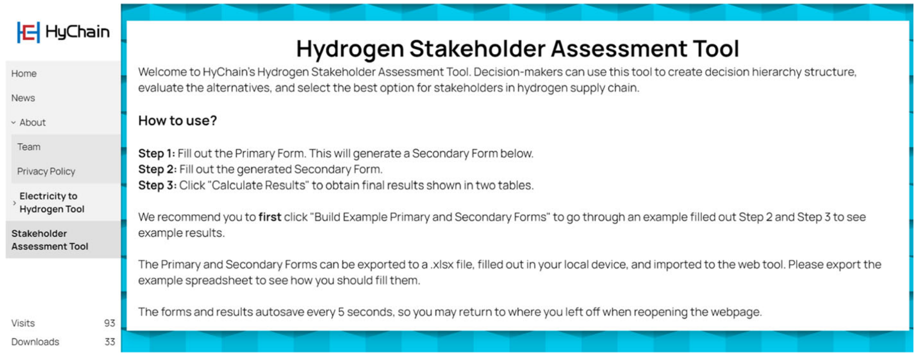

Fig. 3 Homepage of the web application for hydrogen supply chain stakeholder assessment

of foreseeing and mitigating potential risks. The application of the method enhances the understanding of the returns and risks across the lifespan of projects, leading to projects that not only meet immediate needs but also contribute to long-term sustainability goals. The integration of AI-powered decision support tools into educational programs for future managers and policymakers will ensure the new generation of leaders who are well-versed in sophisticated project reliable assessment methodologies. On an international scale, such assessment tools can inform the development of global standards for evaluating and benchmarking long-life cycle projects, thereby encouraging international collaboration and investment.

6 Conclusions

Selecting and evaluating sustainable alternatives, such as suppliers, sites, and technologies for investment is a critical and complex decision for business managers, particularly due to the inflexible nature of such choices once they are made. The classical fuzzy MCDM approaches like fuzzy AHP and fuzzy TOPSIS can identify the core of investors' requirements and rank the alternatives based on their closeness to the ideal solutions. However, our results indicate that these classical approaches fail to address the key aspects of the selection and evaluation process, particularly the decision-makers' satisfaction and potential risks, leading to questionable reliability.

This study addresses these limitations by introducing an innovative 3-phase fuzzy MCDM method that uniquely integrates time-based satisfaction and risk factors as dual pillars of reliability assessment in high-investment, long-life cycle projects. This method enhances the conventional MCDM framework by:

1. Pioneering SKQ in the time-based satisfaction weight, which applies a dynamic mechanism in Kano model. This adaptation considers uncertainties in long-life cycle projects, quantifying the vagueness of human thinking by including a 0–5 scaled degree of agreement on SKQ.
2. Tuning the initial criteria scores using a risk-discounted weight from FMEA method. This adjustment diminishes the result deviation between expected and actual outcomes caused by risks, acknowledging that FMEA documents are live and can evolve with new information and collective team experience to refine decision-making accuracy.

The application of this advanced MCDM method is demonstrated through a case study on a hydrogen storage method selection for lightweight vehicles, a decision that requires

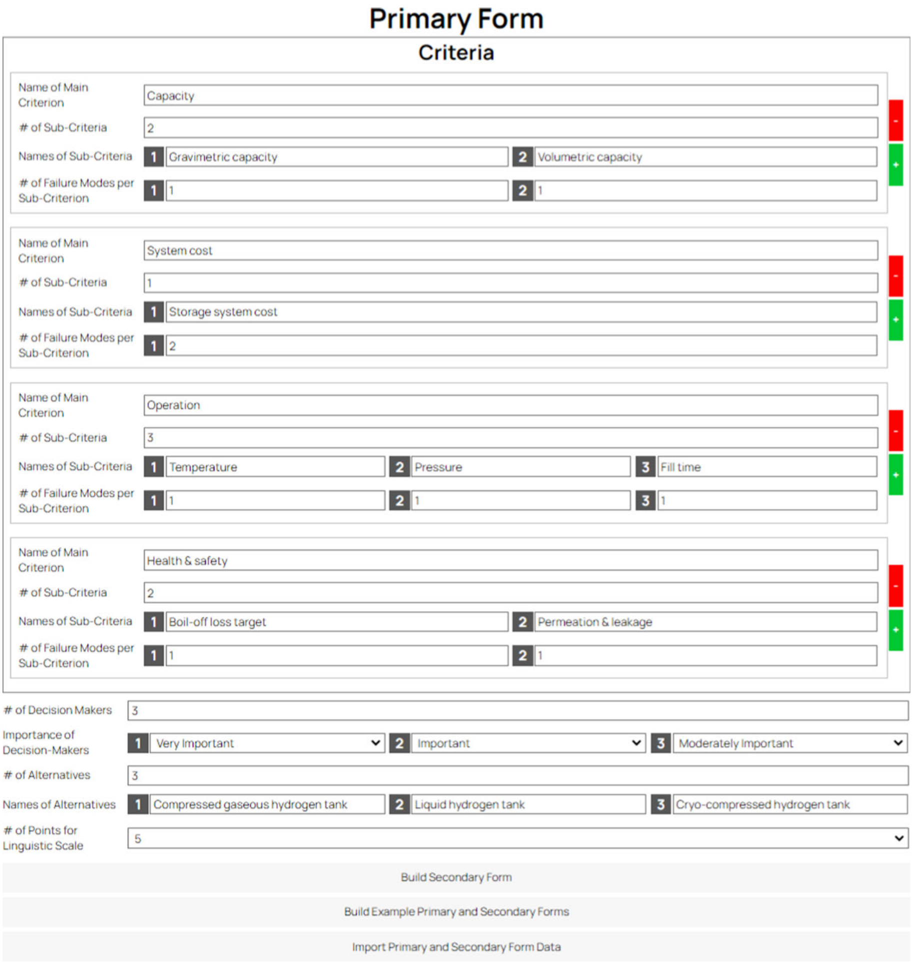

Fig. 4 The primary form interface of the web application (filled out based on Sect. 4)

sustainability and is typically set for the vehicle's lifespan of up to 20 years. The results indicate that 'health & safety' with a weight of 0.5318, emerges as the most important main criterion, in which 'permeation & leakage' with a weight of 0.4008, is the most important sub-criterion among all. The results identify 'hydrogen storage method C (cryo-compressed hydrogen tank)' as the optimal choice among the alternatives, followed by method B (liquid hydrogen tank) and method A (compressed gaseous hydrogen tank).

Debates over the final decision are inevitable. This novel 3-phase fuzzy MCDM method for reliable assessment not only ranks alternatives overall but also directs decision-makers to the consolidated weight of criteria and risk discounted weight as shown in Tables 13 and 18 to check for the most important and risk-related criteria. Therefore, this insight offers a transparent advantages and disadvantages analysis for each alternative to investors.

Furthermore, we have developed the proposed MCDM method into a user-friendly web application to ensure accessibility and continuous improvement. The tool is freely available, empowering end-users across various industries to engage in a reliable assessment of sus-

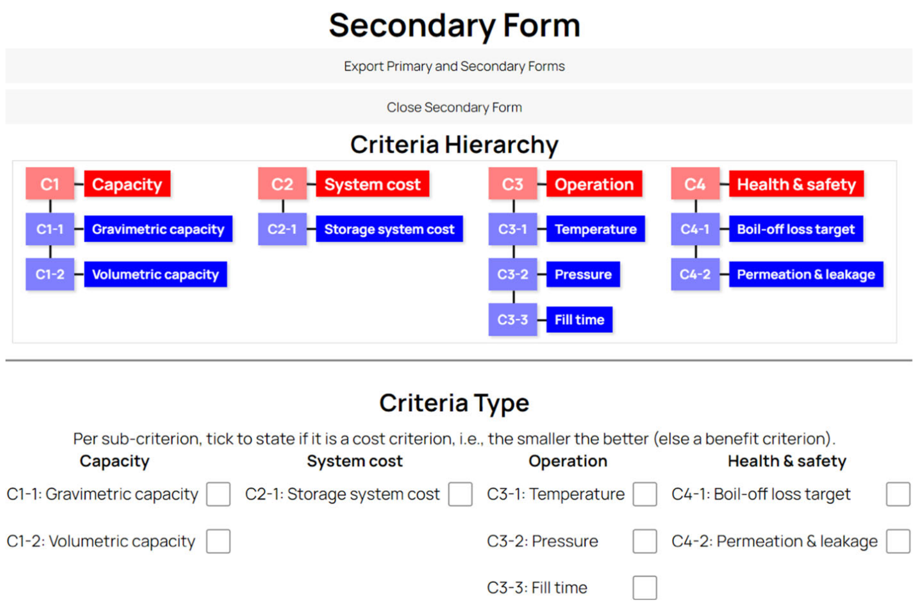

Fig. 5 ‘Criteria Hierarchy’ and ‘Criteria Type’ interface in the secondary form (based on Sect. 4)

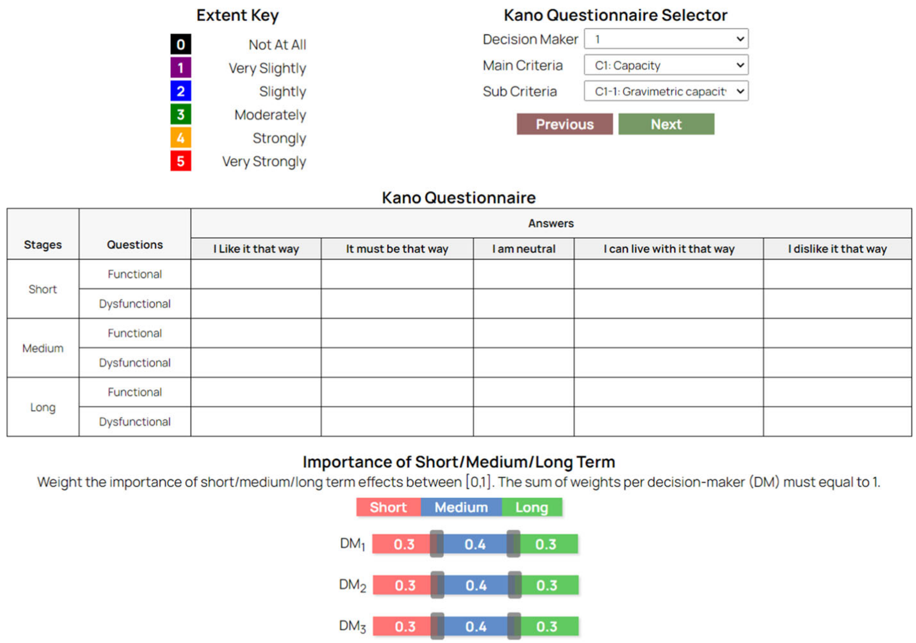

Fig. 6 ‘Kano Questionnaire’ interface in the secondary form (based on Sect. 4)

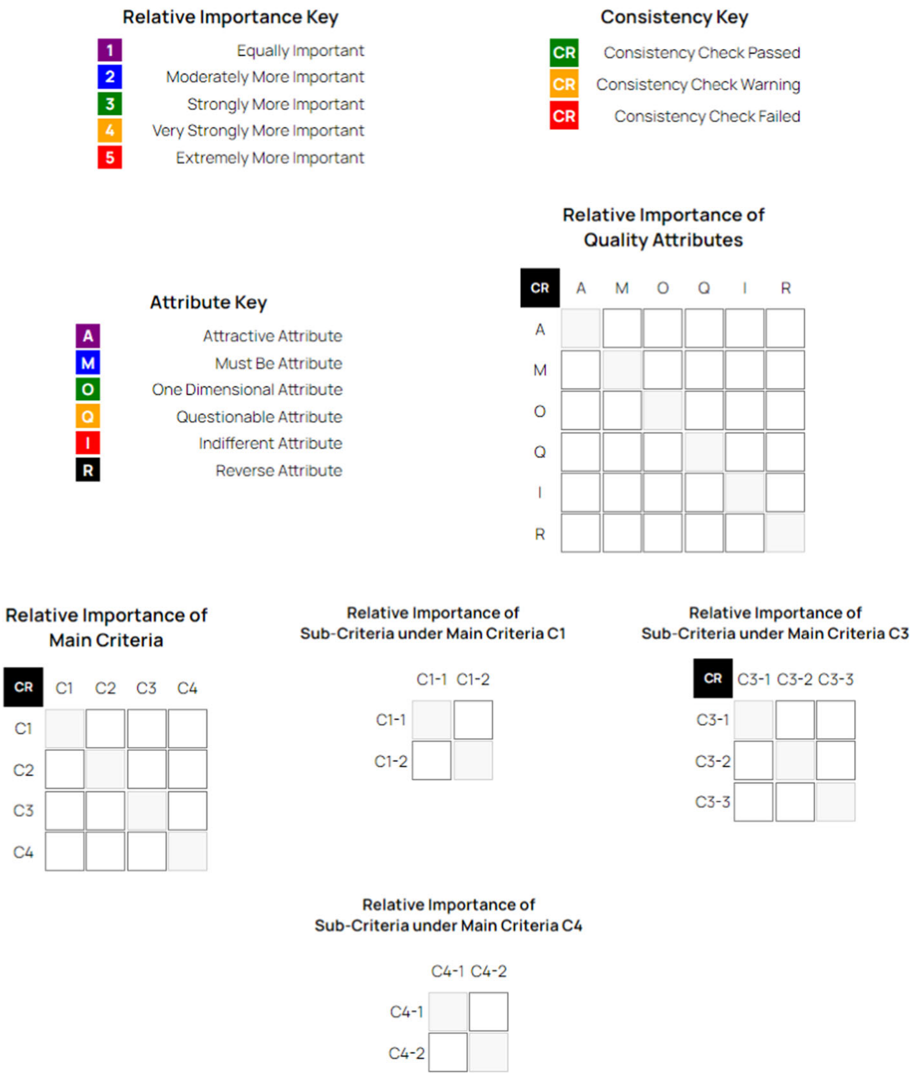

Fig. 7 ‘Pairwise Comparisons for Relative Importance’ interface in the secondary form (based on Sect. 4)

tainable hydrogen supply chain management, or more broadly, any other high-investment and long-life cycle projects.

In conclusion, this paper bridges the gaps between the theoretical and practical development of reliable assessment, offering a reliable, dynamic, and comprehensive decision-making tool for large-scale and long-term sustainable investments. This tool can be strategically utilised by businesses and policymakers to guide resource allocations and to promote the establishment of comprehensive regulatory frameworks that underpin reliable and sustainable business decisions.

Finally, the future direction of research is broad and promising. A primary area involves the integration of additional reliability-oriented factors that can be considered and incorporated

FMEA Evaluation Scheme for Risk Severity (S)

No. Rank Groups 5

Criteria	Rank of S				
	1	2-4	5-6	7-8	9-10
Capacity: Gravimetric capacity					
Capacity: Volumetric capacity					
System cost: Storage system cost					
Operation: Temperature					
Operation: Pressure					
Operation: Fill time					
Health & safety: Boil-off loss target					
Health & safety: Permeation & leakage					

FMEA Evaluation Scheme for Risk Likelihood (L)

No. Rank Groups 5

Criteria	Rank of L				
	1	2-4	5-6	7-8	9-10
Capacity: Gravimetric capacity					
Capacity: Volumetric capacity					
System cost: Storage system cost					
Operation: Temperature					
Operation: Pressure					
Operation: Fill time					
Health & safety: Boil-off loss target					
Health & safety: Permeation & leakage					

FMEA Evaluation Scheme for Risk Control (C)

No. Rank Groups 5

Criteria	Rank of C				
	1	2-4	5-6	7-8	9-10
Capacity: Gravimetric capacity					
Capacity: Volumetric capacity					
System cost: Storage system cost					
Operation: Temperature					
Operation: Pressure					
Operation: Fill time					
Health & safety: Boil-off loss target					
Health & safety: Permeation & leakage					

(a) 'FMEA Evaluation Scheme' interface in the secondary form (based on Section 4).

FMEA Document

Alternative Compressed gaseous hydrogen tank

Criteria	Failure Modes	Effects	S	Causes	L	Control	C
Capacity: Gravimetric capacity							
Capacity: Volumetric capacity							
System cost: Storage system cost							
Operation: Temperature							
Operation: Pressure							
Operation: Fill time							
Health & safety: Boil-off loss target							
Health & safety: Permeation & leakage							

(b) 'FMEA Document' interface in the secondary form (based on Section 4).

Fig. 8 'Failure Mode and Effects Analysis (FMEA)' interface in the secondary form (based on Sect. 4)

Criteria Performance Scoring for Alternatives

Each decision-maker needs to grade all the alternatives regarding the performance of all the criteria, using the scale below. Use the dropdown option below to switch between criteria performance scoring per decision maker.

Performance Key

1 Bad 2 Fair 3 Average 4 Good 5 Excellent

Decision Maker 1

Criteria Performance Scoring

Criteria	Alternatives		
	Compressed gaseous hydrogen tank	Liquid hydrogen tank	Cryo-compressed hydrogen tank
Capacity: Gravimetric capacity			
Capacity: Volumetric capacity			
System cost: Storage system cost			
Operation: Temperature			
Operation: Pressure			
Operation: Fill time			
Health & safety: Boil-off loss target			
Health & safety: Permeation & leakage			

Fig. 9 ‘Criteria Performance Scoring for Alternatives’ interface in the secondary form (based on Sect. 4)

Final Ranking of Alternatives

Alternative	Closeness Coefficient	Rank
Compressed gaseous hydrogen tank	0.6159	3
Liquid hydrogen tank	0.6191	2
Cryo-compressed hydrogen tank	0.6195	1

Fig. 10 ‘Final Ranking of Alternatives’ as the final results (based on Sect. 4)

in more harmonised and effective ways, as suggested by (Kannan et al., 2023). In addition, other suitable (fuzzy) MCDM can be adapted to combine with the Kano model and FMEA for creating a new MCDM for reliable assessment (Amor et al., 2023). Moreover, alternative methods except the Kano model can be stimulated to refine the performance of the time-based satisfaction factor and the risk factor (Choudhary et al., 2023).

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Declarations

Competing Interests The authors whose names are listed above certify that they have no affiliations with or involvement in any organisation or entity with any financial interest (such as honoraria; educational grants; participation in speakers’ bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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