TITLE PAGE FOR RESUBMISSION OF MANUSCRIPT

A risk-based fuzzy decision support for product development projects supported on R-VIKOR

Seyedeh Anahita Mousavi, Hamidreza Seiti, Ashkan Hafezalkotob, Sobhan Asian, Rouhollah Mobarra

Seyedeh Anahita Mousavi
College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran
E-mail address: anahita_mousavi67@yahoo.com
Tel: +98 930 319 4591,
Postal address: College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Entezari Aly, Oskoui St, Choobi Brg, Tehran, Iran; Postal-Code: 1151863411,

Hamidreza Seiti
Department of Industrial Engineering, Science and Research Branch, Islamic Azad University Tehran, Iran
E-mail address: h_seiti@yahoo.com
Tel: +98 912 488 7359,
Postal address: Department of Industrial Engineering, Science and Research Branch, shodada Hesarak blvd, Daneshgah Square,Sattari Highway,Tehran, Iran; 1477893855

Ashkan Hafezalkotob
College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran
E-mail address: a_hafez@azad.ac.ir, hafezalkotob@iust.ac.ir, ashkan.hafez@gmail.com
Tel: +98 912 778 5681,
Postal address: College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Entezari Aly, Oskoui St, Choobi Brg, Tehran, Iran; Postal-Code: 1151863411,

Sobhan Asian
La Trobe Business School, La Trobe University, Melbourne, Australia.
E-mail address: S.Asian@latrobe.edu.au; Sobhan.Asian@gmail.com
Tel: +61 416 452 016,
Postal address: Room 411, Level 4, Martin Building, Bundoora, Melbourne, VIC 3086, Australia,

Rouhollah Mobarra
Department of Metallurgy Engineering, Kerman University, Kerman, Iran, Tehran, Iran
E-mail address: Rouhollah.mobarra@gmail.com
Tel: +98 9027871747,

Abbot corresponding author:
Ashkan Hafezalkotob received the M.Sc. and Ph.D. degrees in industrial engineering from the Iran University of Science and Technology, Tehran, Iran, in 2007 and 2012, respectively. He is currently an Associate Professor and the Head of Department of Operational Research (Ph.D.) and the Head of Department of Logistics and Supply Chain (M.Sc.) with the College of Industrial Engineering, Islamic Azad University (South Tehran Branch), Tehran, Iran where he is also a member of Young Researchers and Elite Club. He has authored over 70 peer-reviewed papers, many in highly ranked international journals, including *IEEE transaction on Cybernetics*, *Information Fusion*, *Information Sciences*, *International Journal of Production Economics*, *Transportation*, *Research Part E: Logistics and Transportation Review*, *Journal of Cleaner Production*, *Expert Systems With Applications*, *Applied Soft Computing*, *Engineering Applications of Artificial Intelligence*, *Computers & Industrial Engineering*, *Applied Mathematical Modelling*, *Applied Mathematics and Computation*, *Materials & Design*, *Computers and Electronics in Agriculture*, and *Journal of Manufacturing*. His current research interests include environmental policy-making, game theory, supply chain management, multi-criteria decision-making with uncertainty, optimization, and mathematical modeling. Dr. Hafezalkotob was a recipient of the "Researcher of the Year: 2016 Award" from Islamic Azad University (South Tehran Branch), Tehran, Iran. Dr Hafezalkotob published 4 highly cited papers in *IEEE transaction on Cybernetics*, *Information science*, *Information Fusion* and *Computer & industrial Engineering* journals, and one most cited paper in the journal of Transportation research, part E.
https://scholar.google.com/citations?hl=en&user=i0YW2vMAAAAJ&view_op=list_works&sortby=pubdate

*Highlights

- ISM method is used for analyzing causal relationships of risk factors in NPD projects.
- The effects of possible influential factors on risk analysis data are extracted and modeled by R-numbers methodology.
- A new method based on fuzzy VIKOR and R-numbers is presented for dealing with risk-based risk analysis of NPD projects.

Application of risk-based fuzzy decision support systems in new product development: An R-VIKOR approach

Seyedeh Anahita Mousavi[1], Hamidreza Seiti[2], Ashkan Hafezalkotob[1]*, Sobhan Asian[3], Rouhollah Mobarra[4]

[1]*College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran*
[2]*Department of Industrial Engineering, Science and Research Branch, Islamic Azad University Tehran, Iran*
[3]*La Trobe Business School, La Trobe University, Melbourne, Australia.*
[4]*Department of Metallurgy Engineering, Kerman University, Kerman, Iran, Tehran, Iran*

Abstract. Innovative manufacturing firms strive to sustain and enhance their competitive advantages by running a range of new product development (NPD) projects in a consistent manner. The capital and time required to execute the NPD projects have substantially increased over the past years. This magnified the risk-aversion behavior of R&D managers and has increased their sensitivity towards the underlying risk of NPD projects. In particular, the R&D departments have recently started to proactively assess the accuracy of ambiguous information that is extensively used in preliminary market study and customer requirements analysis. Thanks to its high performance in dynamic environments, the R-numbers method can be employed to capture and analyze the risk of fuzzy numbers in a variety of decision making models. To tackle the complexity of such analysis, this paper proposes a novel risk-based fuzzy VIKOR (R-VIKOR) methodology. Using the interpretive structural modeling, the risk factors are first classified to identify and rank the existing critical risk factors of NPD projects. The ultimate goal of this study is to develop a practical yet simple decision support system tool that enables the R&D managers to effectively examine the riskiness of fuzzy information and assess the relevant risk factors. A real-world case study is presented to test and examine the accuracy and effectiveness of the proposed risk management method.

Keywords: New product development (NPD) projects, Fuzzy VIKOR, Interpretive structural modeling, R-numbers, R-VIKOR

Indices	Description
$W^{-}/\widetilde{W}$	Weight matrix/ Fuzzy weight matrix
$w_j/\widetilde{w}_j$	Wight of j-th attribute/ Fuzzy weight of j-th attribute
K	Number of decision-makers
m	Number of alternatives
n	Number of criteria
$\widetilde{D}^K$	Fuzzy decision matrix by k-th decision-maker
$\tilde{s}^k{}_{ij}$	The fuzzy evaluation in assessing i-th alternative related to j-th attribute.
$\widetilde{D}^T$	The normalized aggregated matrix.
s_j^*/s_j^-	The maximum value of all criteria/the minimum value of all criteria.
$\widetilde{S}_i/\widetilde{F}_i$	The utility measure for the alternative i/ the regret measure for the alternative i.
Q_i	The fuzzy VIKOR measure of each alternative.
ϑ	The weight of the strategy of ''the majority of criteria''.
$1\text{-}\vartheta$	The weight of individual regret.
$\widetilde{A}/\widetilde{B}$	Triangular fuzzy numbers.
$G(\widetilde{A})$	The graded mean of $\tilde{A}$.
$R_b(\widetilde{B})/R_c(\widetilde{B})$	R-numbers related to $\tilde{B}$ in the beneficial mode/ R-numbers related to $\tilde{B}$ in The non-beneficial mode.
$l_{\widetilde{B}}/u_{\widetilde{B}}$	The lower bound of $\tilde{B}$/The upper bound of $\tilde{B}$.
$\widetilde{AR}^-/\widetilde{AR}^+/\widetilde{RP}^-/\widetilde{RP}^+$	Fuzzy negative acceptable risk/Fuzzy positive acceptable risk/Fuzzy risk perception associated with the negative risk/Fuzzy risk perception associated with the positive risk.
$\tilde{r}^-/\tilde{r}^+$	Fuzzy negative risk matrix/ Fuzzy positive risk matrix.
α	A value close to one.
R^{+k}/R^{-k}	The positive R-numbers matrix by k-th expert/ The negative R-numbers matrix by the k-th expert.
R^T	The aggregated R-numbers matrix.
R^{TN}	The normalized R-numbers matrix.
RS_j^*/RS_j^-	The maximum value s_j^* and the minimum value s_j^- of all normalized. R-numbers in each criterion.
$R(\widetilde{RS}_I)/R(\widetilde{RF}_I)$	The utility and the regret measures of i-th alternative, which are themselves, are R-numbers.
$R(\widetilde{Q}_i)$	The R-VIKOR measure
$RS^*/RS^-/RF^*/RF^-$	The minimum value $R(\widetilde{RS}_I)$/The maximum value $R(\widetilde{RS}_I)$/ The maximum value $R(\widetilde{RF}_I)$/ The minimum value $R(\widetilde{RF}_I)$.
$GG(R(\widetilde{A}))$	The defuzzified values of $R(\widetilde{Q}_i)$.

Abbreviations	Description
AHP	Analytic hierarchy process
ANP	Analytical network Process
AS	Antecedent set
BN	Complex proportional assessment of alternative with grey relations
COPRAS-G	Complex proportional assessment of alternative with grey relations
DEMATEL	Decision-making trial and evaluation
EXIT	Express Cross-Impact Technique
GRA	Grey relational analysis
GDM	Grey relational analysis
IS	Intersection sets
ISM	Interpretive structural modeling
MARCOS	Measurement of alternatives and ranking according to compromise solution
MCDM	Multi-criteria decision making
MICMAC	Cross-impact matrix multiplication applied to classification
NPD	New product development
RS	Reachability sets
SAW	Simple additive weighting method
SWOT	Strengths, weaknesses, opportunities, and threats
SSIM	Structural self-interaction matrix
TODIM	Interactive and multi-criteria decision making

TOPSIS	Technique for order preference by similarity to the ideal solution
VIKOR	VIekriterijumska Optimizacija I Kompromiso Resenje

1. Introduction

Given the rapid growth of technology and the rapid pace of change in customer needs, the definition and implementation of new product development (NPD) projects is one of the best ways for companies to survive in a business and competitive environment. [1]. Initiating and executing NPD projects is commonly run by the research and development (R&D) departments and plays a significant role in translating the growth strategies of firms and sustaining their competitiveness. With the ever increasing technological advancements, the manufacturing companies are forced to consistently innovate by either developing new products or improving the existing items. These projects lead to innovative solutions and assist firms to swiftly adopt to the evolving market needs and respond to changes in customers' requirements [2].

Risk and ambiguity are inevitable features of any innovative idea, which significantly affect the costs and time of NPD projects. Hence, risk cognizance, risk control, and risk management are considered as essential tools required for the successful implementation of NPD projects [3]. Generally, effective risk management improves the performance of NPD projects and includes organizational risk management, technological risk management, commercialization risk management, and marketing risk management [4]. If the above risks are not managed appropriately, the NPD project may become economically unjustifiable [5]. However, analyzing all risk factors requires substantial time and investment. This often makes the R&D managers to only focus on identifying and calculating the most influential risk factors. Therefore, it is important to analyze the causal relationships among risk factors of NPD projects at an early design stage. To this aim, researchers have developed various techniques, such as cognitive maps [6], interpretive structural modeling (ISM) [7], express cross-impact technique (EXIT) [8], and AXIOM [9].

In most NPD risk management problems, the necessary data for forecasting and evaluation is provided by domain experts and usually involves a high degree of ambiguity and uncertainties [10]. Another concern in NPD risk management is the high degree of risk related to the fuzzy data. An example of such risks is the complexity of the technology and its accurate estimation, which is a function of time, future technology developments, and access to credible scientific resources [11]. Therefore, if competitors make a similar or more advanced product in a shorter time, customer needs and purchasing patterns will change. Consequently, the related strategic goals of the company – as well as the industry as a whole – will change, which may alter the direction of a project or even lead to a major failure. This means that there are various predictable and unpredictable risk factors that might affect our overall predictions.

Fuzzy sets is one of the practical approaches to capture the above mentioned ambiguities. An important issue to consider, however, is that the fuzzy sets cannot capture its own uncertainty [12]. Uncertainty of fuzzy numbers can be expressed in two ways [12]: (i) assigning some percentage of confidence to fuzzy sets(methods such as Z-numbers [13], fuzzy D-numbers [14], probabilistic linguistic term sets [15]); (ii) determining a range for fuzzy numbers (e.g., intuitionistic fuzzy sets [16], fuzzy rough numbers [17]). One of the practical fuzzy sets extension models to capture the impact of risk factors on fuzzy data is the R-numbers methodology [12, 18]. Different from the other models, such as fuzzy rough numbers and fuzzy D-numbers, the R-numbers method can model various risk scenarios by considering a range as fuzzy data variation. Moreover, multiple parameters, such as fuzzy negative and positive risks, fuzzy negative and positive acceptable risks, and risk perception, can be included within the R-numbers methodology in order to enhance the accuracy of final results [12].

R-numbers can be integrated into multi-criteria decision-making (MCDM) methods to improve the NPD risk management and capture the risk associated with fuzzy data. One of the applicable MCDM methods in risk management problems is VIekriterijumska Optimizacija I Kompromiso Resenje (VIKOR) approach. VIKOR method provides interesting characteristics, especially in group decision problems, including[19, 20]: (i) compromising is acceptable for conflict resolution, (ii) the decision-maker (DM) is willing to approve solution that is the closest to the ideal, (iii) there exist a linear relationship between each criterion function and a decision maker's utility, (iv) the criteria are conflicting and non-commensurable (different units), (v) the alternatives are evaluated according to all established criteria (performance matrix), (vi) the DM's preference is expressed by weights, given or simulated.

Several studies have been conducted on fuzzy NPD risk management using the VIKOR technique [21, 22]. To best of our knowledge, none of the previous studies identifies the critical risk factors by causal risk factors relation analysis to capture the risk of fuzzy data in NPD risk management.

To address the research gap and overcome the associated methodological challenge, the present study combines the R-numbers and VIKOR methods and develops a new risk-based decision framework (hereafter called, R-VIKOR). Our research objectives are threefold: (i) using the ISM technique to identify the causal relationships between the risk factors of NPD projects (estimating the penetration power and dependence of each risk factor), (ii) assessing and ranking the first layer risks of NPD projects (risk factors with the highest penetration power and the lowest dependence), (iii) reducing uncertainty and increase the accuracy of risk assessment of NPD projects by considering assessment errors.

The remainder of this article is organized as follows: Section 2 provides a brief literature review on the risk evaluation of NPD projects, and reviews the latest ISM and VIKOR developments.

Section 3 presents the preliminaries of ISM, fuzzy VIKOR, and R-numbers. The proposed R-VIKOR methodology is presented in Section 4. To investigate the proposed model, a case study analysis is carried out in Section 5. Finally, conclusion and future works are provided in Section 6.

2. Literature review

This section discusses the existing literature on NPD projects risk evaluation, and reviews the prior developments of ISM and VIKOR and their applications. Research gaps are also highlighted.

2.1. NPD projects' risk evaluation

In general, the risk management process consists of risk identification, risk evaluation and quantification, risk mitigation for impact minimization, and risk monitoring [23]. Since NPD projects are usually derived by innovation, they prone a high degree of risk in practical applications. Regardless of the sector or industry, the NPD projects pose a certain number of risk factors that are mostly inevitable [24]. There are three key risk factors that affect the performance of NPD projects, namely technology, marketing, and organization [25]. Salavati et al. [4] studied the relationship between NPD performance and risk management. They suggested that technology, marketing, and organization factors significantly affect the NPD performance. Marmier & Laarz [5] proposed a risk-oriented model to descry strategic decisions in NPD projects and highlighted three important factors: (1) achieving governance by reducing supplier contention; (2) different rules of transactional and relational governance in achieving limited supplier contention and organizing high levels of collaboration; and (3) transactional and relational governance are organizationally obsolete. Marmier, Deniaud & Gourc [25] proposed a model for making strategic decisions in NPD projects based on risk factors. They suggested a process that contains design, project management, and risk management, and proposed and tested a generic decision support system considering a satellite design project.

2.2. ISM method developments and applications

Interpretive structural modeling was developed by Warfield [26] in 1974 to provide insights into the interrelationships between factors with ranking and direction [27]. This method can be differentiated from other MCDM techniques, such as ANP, which cannot show dependencies between elements and where interrelations are not ideal and exact [28]. Tan et al. [29] studied barriers to the implementation of building information modeling in China's prefabricated construction industry. They applied the ISM method to detect the interrelationships among these barriers. Lin et al. [30] extended the ISM methodology by employing grey relational analysis (GRA) for hierarchical analysis of influential factors. In this study, GRA was used to calculate the correlation coefficient between significant factors. Additionally, ISM was applied to stratify and establish the multi-hierarchical structure of influential factors. Ultimately, they analyzed data regarding infant formula and sterilized milk food safety in China. Li et al. [31] proposed an integrated DEMATEL, ISM, and BN to study the effects of accident-causing factors on the urban subterranean gas pipeline network. They employed the DEMATEL method to specify a hierarchical network model by a cause-effect diagram. Then, the hierarchical network model was mapped onto a Bayesian network and expert judgments to quantify the strength of the coupling relationships among the accident-causing systems and to determine the main paths leading to system failure.

2.3. VIKOR method developments and applications

The VIKOR method has soon become one of the popular methods in MCDM since its introduction in 1998. Various studies have been conducted to analyze different MCDM problems using the VIKOR methodology. For instance, Bairagi et al. [32] used fuzzy-VIKOR, fuzzy-TOPSIS, and COPRAS-G methods to rank robots. In this study, the criteria weights were determined by fuzzy-AHP. In a similar study, Parameshwaran, Kumar, and Saravanakumar [33] studied a robot selection problem and ranked different alternatives using an integrated model of fuzzy-VIKOR and fuzzy-TOPSIS. They first selected the decision making criteria by fuzzy Delphi, and then calculated their weights by fuzzy-AHP. Using fuzzy VIKOR, Mehbodniya et al. [34]proposed a novel multi-attribute vertical handoff algorithm for heterogeneous wireless networks ranking. Zeng, Chen, and Kuo [35] presented a new multi-attribute decision-making method, based on the new score function of intuitionistic fuzzy values and modified VIKOR, to calculate the farthest worst score value. Chuan Yue [36] developed the VIKOR method in group decision-making. author used picture fuzzy numbers to illustrate and characterize the decision making information. They established and applied a new Grey relational analysis (GDM) model for software reliability assessment. Liang, Zhang, Xue & Jamaldeen [37] extended the VIKOR method to the Pythagorean fuzzy environment. They investigated how the criteria weights can be set by defining Pythagorean fuzzy entropy and cross-entropy measures. They designed two novel decision-making approaches by combining interactive and multi-criteria decision making (TODIM) and fuzzy VIKOR.

2.4. Research gaps

By reviewing the literature, the following research gaps are identified:

- Although project risk assessment has been extensively studied in prior works, majority of the existing models focus on non-NPD projects, such as oil and gas, construction, and infrastructure developments. A majority of studies in the field of NPD investigate the effects of risk management on NPD projects and categorize the general risk factors (e.g., re-evaluation and technical issues). Despite the important role they play in the success of NPD projects, identification of the particular NPD risk factors and defining the causal relationship between the mare rather underexplored in the literature.

- ISM technique and cross-impact matrix multiplication applied to classification (MICMAC) diagram have been widely used in prior works to analyze and classify various factors. Again, a few papers apply these methods to accurately assess the risks of NPD projects considering the penetration power within the identified risk factors and associated effects.
- There has been no study to simultaneously recognize critical risks (through causal risk factors relation analysis) and consider the risk of fuzzy data in NPD risk management using risk-based approaches, including R-numbers. Despite their high performance in fuzzy environments, R-numbers method is rarely applied to the existing decision making frameworks (e.g., R-TOPSIS [18] and R-SAW [11]).

The theoretical contributions of the current paper for bridging the identified research gaps can be summarized as follows: 1) the ISM method is used for analyzing the causal relationships of NPD project risk factors; 2) the effects of possible influential factors on risk analysis data are extracted and modeled by the R-numbers method; 3) a new R-VIKOR method based on fuzzy VIKOR and R-numbers is developed to deal with complexities of risk-based analysis in the NPD projects. Finally, focusing on the automotive industry, the present study is applied to a case study and practical implication in relation to partitioning, evaluation and ranking of NPD project risks are discussed.

3. Preliminaries

In this section, the preliminaries of this study, including the ISM, fuzzy VIKOR, and R-numbers methods, are briefly presented in Sections 3.1, 3.2, and 3.3, respectively.

3.1. ISM approach

The ISM method is available to analyze the interrelationships among factors in a complex system. In this paper, the ISM method is used to identify the most critical risk factors capture the direct and indirect interrelationships between various risk factors. Different steps of this method are presented in Algorithm 1 [38].

Algorithm 1: ISM algorithm

Input: Identified elements and their consequences (risk factors).
Output: A multilevel interpretive structural model in which the relations among risks are clarified.

Step 1. Organizing an ISM implementation group.
Form a group of experts from different areas throughout the firm to share their relevant knowledge, skills, and background.

Step 2. Structural Self-Interaction Matrix (SSIM)
Determine which factors lead to others. The SSIM is built up based on these "contextual relationships".

Step 3. Reachability Matrix
The SSIM is converted into a binary matrix by substituting the filled-in values with 1, if YES, and 0, if NO.

Step 4. Classification of Elements
Classify factors, according to their "depends" (how many factors they are influenced by) and "driving powers" (how many factors they influence). The output of this step is the dependence-driving power graph.

Step 5. ISM Level Partitioning
Associate two sets with each element: the Reachability Sets, that is, a set of all elements that can be reached from the elements, and the Antecedent Set, which is a set of all elements that the element can be reached by. The top element of the hierarchy will not reach any other element, so it is identified and separated.

3.2. The fuzzy VIKOR method

The fuzzy VIKOR method a standard MCDM method. Wecombine the fuzzy VIKOR with R-numbers in Section 4 for ranking the critical factors obtained by ISM. The steps of simple fuzzy VIKOR are presented in Algorithm 2 [36].

Algorithm2: Fuzzy VIKOR algorithm

Input: Fuzzy decision matrix
Output: Ranked alternatives

Step 1. Determining the weight vector of the criteria (W)

Step 2. Normalizing the fuzzy decision matrix by $\tilde{S}^{TN}{}_{ij} = \frac{\tilde{s}^{T}{}_{ij}}{\sqrt{\sum_{i=1}^{m} \tilde{s}^{T}{}_{ij}{}^{2}}}$

Step 3. Determining the best s_j^* and s_j^-
where $s_j^* = \underset{i}{Max}\, \tilde{s}^{TN}{}_{ij}$ and $s_j^- = \underset{i}{Min}\, \tilde{s}^{TN}{}_{ij}$

Step 4. Calculation of utility measure (S) and regret measure (F):

$$\tilde{S}_i = \sum_{j=1}^{n} \frac{\tilde{w}_j\left(s^*{}_j - \tilde{s}^{TN}{}_{ij}\right)}{\left(s_j^* - s_j^-\right)}, \tilde{F}_i = \underset{j}{max}\left[\frac{\tilde{w}_j\left(s_j^* - \tilde{s}^{TN}{}_{ij}\right)}{\left(s_j^* - s_j^-\right)}\right]$$

Step 5. Computing of VIKOR index (Q_i) by

$$\tilde{Q}_i = \vartheta \frac{\left(\tilde{S}_i - S^-\right)}{\left(S^* - S^-\right)} + (1-\vartheta)\frac{\left(\tilde{F}_i - F^*\right)}{\left(F^* - F^-\right)}$$

where $0 < \vartheta < 1$.

Step 6. Sorting of all alternatives based on the results of Step 5.

3.3. The R-numbers methodology

R-numbers methodology has been extended to justify the risks of future events associated with fuzzy data. This method is used in this paper to model the risk of fuzzy data in NPD risk management. The R-numbers for arbitrary fuzzy number $\tilde{B}$ for beneficial and non-beneficial attributes can be described as follows [18]:

$$R_b(\tilde{B}) = \left(R_{1b}(\tilde{B}), R_{2b}(\tilde{B}), R_{3b}(\tilde{B})\right), \quad (1)$$

where

$$\begin{cases} R_{1b}(\tilde{B}) = max\left(\tilde{B} \otimes \left(1 \ominus min\left(\frac{\tilde{r}^-}{1 \ominus \widetilde{RP}^-}, \alpha\right) \otimes (1 \ominus \widetilde{AR^-})\right), l_{\tilde{B}}\right) \\ R_{2b}(\tilde{B}) = \tilde{B} \\ R_{3b}(\tilde{B}) = min\left(\tilde{B} \otimes \left(1 \oplus \frac{\tilde{r}^+}{1 \ominus \widetilde{RP}^+} \otimes (1 \ominus \widetilde{AR^+}\right), u_{\tilde{B}}\right) \\ 0 < \tilde{r}^- < 1, \qquad \tilde{r}^+ > 0 \end{cases} \tag{2}$$

and

$$R_c(\tilde{B}) = \left(R_{1c}(\tilde{B}), R_{2c}(\tilde{B}), R_{3c}(\tilde{B})\right), \tag{3}$$

where

$$\begin{cases} R_{1c}(\tilde{B}) = max\left(\tilde{B} \otimes \left(1 \ominus min\left(\frac{\tilde{r}^+}{1 \ominus \widetilde{RP}^+}, \alpha\right) \otimes (1 \ominus \widetilde{AR^+})\right), l_{\tilde{B}}\right) \\ R_{2c}(\tilde{B}) = \tilde{B} \\ R_{3c}(\tilde{B}) = min\left(\tilde{B} \otimes \left(1 \oplus \frac{\tilde{r}^-}{1 \ominus \widetilde{RP}^-} \otimes (1 \ominus \widetilde{AR^-})\right), u_{\tilde{B}}\right) \\ \tilde{r}^- > 1, \qquad 1 < \tilde{r}^+ < 0 \end{cases} \tag{4}$$

The possible range for $\widetilde{RP}^-$ and $\widetilde{RP}^+$are [10]:

$$\begin{cases} Optimist\ Experts & 0 < \widetilde{RP}^-, \widetilde{RP} < 1 \\ Neutral\ Experts & 0 \\ Pessimist\ Experts & -\infty < \widetilde{RP}^-, \widetilde{RP} < 0 \end{cases} \tag{5}$$

Considering two R-numbers $R(\tilde{A}) = \begin{pmatrix} (a_{11}, a_{12}, a_{13}), \\ (a_{21}, a_{22}, a_{23}), \\ (a_{31}, a_{32}, a_{33}) \end{pmatrix}$ and $R(\tilde{B}) = \begin{pmatrix} (b_{11}, b_{12}, b_{13}), \\ (b_{21}, b_{22}, b_{23}), \\ (b_{31}, b_{32}, b_{33}) \end{pmatrix}$, we have [39]:

$$\tilde{\tilde{A}} \oplus \tilde{\tilde{B}} = \begin{pmatrix} (a_{11} + b_{11}, a_{12} + b_{12}, a_{13} + b_{13}), \\ (a_{21} + b_{21}, a_{22} + b_{22}, a_{23} + b_{23}), \\ (a_{31} + b_{31}, a_{32} + b_{32}, a_{33} + b_{33}) \end{pmatrix}, \tag{6}$$

$$\tilde{\tilde{A}} \ominus \tilde{\tilde{B}} = \begin{pmatrix} (a_{11} - b_{33}, a_{12} - b_{32}, a_{13} - b_{31}), \\ (a_{21} - b_{23}, a_{22} - b_{22}, a_{23} - b_{21}), \\ (a_{31} - b_{13}, a_{32} - b_{12}, a_{33} - b_{11}) \end{pmatrix}, \tag{7}$$

$$\tilde{\tilde{A}} \otimes \tilde{\tilde{B}} = \begin{pmatrix} (a_{11}b_{11}, a_{12}b_{12}, a_{13}b_{13}), \\ (a_{21}b_{21}, a_{22}b_{22}, a_{23}.b_{23}), \\ (a_{31}b_{31}, a_{32}b_{32}, a_{33}b_{33}) \end{pmatrix}, \tag{8}$$

$$\tilde{\tilde{A}} \oslash \tilde{\tilde{B}} = \begin{pmatrix} \left(\frac{a_{11}}{b_{33}}, \frac{a_{12}}{b_{32}}, \frac{a_{13}}{b_{31}}\right), \\ \left(\frac{a_{21}}{b_{23}}, \frac{a_{22}}{b_{22}}, \frac{a_{23}}{b_{21}}\right), \\ \left(\frac{a_{31}}{b_{13}}, \frac{a_{32}}{b_{12}}, \frac{a_{33}}{b_{11}}\right) \end{pmatrix}. \tag{9}$$

Example 1. Let us suppose $\tilde{B} = (0.25, 0.5, 0.75)$ is an expert's fuzzy evaluation and also $\tilde{r}^+ = (0.1,0.3,0.5)$, $\tilde{r}^- = (0.1, 0.3, 0.5), \widetilde{AR}^- = (0, 0, 0.3)$, $\widetilde{AR}^+ = (0.1, 0.3,0.5)$, $\widetilde{RP}^+ = (0, 0, 0.3)$and $\widetilde{RP}^- = (-0.3, 0, 0)$. According to Eqs. (1) and (2), the R-numbers in beneficial mode can beobtained as:

$$R_{1b}(\tilde{B}) = max\left(\tilde{B} \otimes \left(1 \ominus min\left(\frac{\tilde{r}^-}{1 \ominus \widetilde{RP}^-}, \alpha\right) \otimes (1 \ominus \widetilde{AR}^-)\right), l_{\tilde{B}}\right) =$$

$$R_{1b}(\tilde{B}) = max\left((0.25, 0.5, 0.75) \otimes \left(1 \ominus min\left(\frac{(0.1,0.3,0.5)}{1 \ominus (-0.3,0,0)}, 0.99\right) \otimes (1 \ominus (0, 0, 0.3))\right), 0.25\right) =$$

$$max\left((0.25, 0.5, 0.75) \otimes \left(1 \ominus min\left(\frac{(0.1,0.3,0.5)}{(1,1,1.3)}, 0.99\right) \otimes (0.7, 1, 1)\right), 0.25\right) =$$

$$max\left((0.25, 0.5, 0.75) \otimes \left(1 \ominus min((0.07, 0.3, 0.5), 0.99\right) \otimes (0.7, 1, 1)\right), 0.25\right) =$$

$$max((0.25, 0.5, 0.75) \otimes (0.5, 0.7, 0.923) \otimes (0.7, 1, 1), 0.25) = max((0.25, 0.5, 0.75) \otimes (0.35, 0.7, 0.923), 0.25) =$$

$$max((0.088, 0.35, 0.692), 0.25) = (0.088, 0.35, 0.692)$$

$$R_{2b}(\tilde{B}) = \tilde{B} = (0.25, 0.5, 0.75)$$

$$R_{3b}(\tilde{B}) = min\left(\tilde{B} \otimes \left(1 \oplus \frac{\tilde{r}^+}{1 \ominus \widetilde{RP}^+} \otimes (1 \ominus \widetilde{AR}^+\right), u_{\tilde{B}}\right) =$$

$$min\left((0.25, 0.5, 0.75) \otimes \left(1 \oplus \frac{(0.1,0.3,0.5)}{1 \ominus (0,0,0.3)} \otimes (1 \ominus (0.1, 0.3, 0.5)\right), 0.75\right) =$$

$$min((0.25, 0.5, 0.75) \otimes (1 \oplus (0.1, 0.3, 0.71) \otimes (0.5, 0.7, 0.9), 0.75) =$$

$$min((0.25, 0.5, 0.75) \otimes (1 \oplus (0.05, 0.21, 0.63), 0.75) = min((0.26, 0.6, 1), 0.75) = (0.26, 0.6, 1)$$

$$\rightarrow R_b(\tilde{B}) = ((0.088, 0.35, 0.692), (0.25, 0.5, 0.75), (0.26, 0.6, 1)).$$

4. The proposed R-VIKOR for the NPD risk analysis

As discussed in the Introduction, the available data in NPD risk management sometimes contains some levels of risk. Since, in this current paper, the available data from experts are fuzzy, in this section, the aim is to develop the R-VIKOR methodology to model various risk scenarios based on expert judgments, such as fuzzy negative risk, fuzzy positive risk, fuzzy acceptable risk and fuzzy expert's risk perception by R-numbers, and then rank failure modes by VIKOR. Suppose that the critical risk factors have been classified based on the ISM method. Now the objective is to evaluate m risk factors with respect to n criteria with the help of the R-VIKOR approach. The following are the proposed R-VIKOR steps.

Step 1. Determining the critical risk factors

In the first step, the risk factors are predicted and determined based on the opinions of experts and managers based on market knowledge and customer needs; analysis of technological growth trends in advanced vehicles; analysis of future strategic behavior of competitors; SWOT matrix of the company's strategic plan; and national and international economic and social trends. In addition, the risk factors identified are classified according to the ISM method.

Step 2. Forming the decision and weight matrices

In the first step, the fuzzy matrix of of $m$risk-factors assessment according to n criteria for K decision-makers, and the fuzzy weights of the criteria are determined.

$$\widetilde{D}^K = \left[\tilde{s}^k{}_{ij}\right]_{m\times n} k = 1,2,\dots,k, i = 1,\dots,m, j = 1,\dots,n \tag{10}$$

$$\widetilde{W} = \left[\widetilde{w}_j\right]_{1\times n,} j = 1,\dots,n \tag{11}$$

Step 3. Forming the fuzzy positive and negative risk matrices, and the positive and negative AR matrices

Now, if there are possible risks related to the evaluations, the fuzzy positive and negative risk matrices of $m$risk factors with respect to n criteria are specified by each expert. Additionally, the fuzzy positive and negative AR matrices are defined based on organization goals, which are given by:

$$R^{+^k} = \left[\tilde{r}_{ij}^{+^k}\right]_{m\times n}, \tag{12}$$

$$R^{-^k} = \left[\tilde{r}_{ij}^{-^k}\right]_{m\times n}, \tag{13}$$

$$AR^{+} = \left[AR_j^{+}\right]_{1\times n}, \tag{14}$$

$$AR^{-} = \left[AR_j^{-}\right]_{1\times n}. \tag{15}$$

where R^{+^k}, R^{-^k}, AR^{+}, and AR^{-}show the fuzzy positive risk, the fuzzy negative risk, the fuzzy positive AR, and the fuzzy negative AR matrices, respectively.

Step 4. Determining the R-numbers for the fuzzy evaluations by employing the fuzzy positive and negative risk matrices, and the fuzzy positive and negative AR matrices.

Now, let us consider that the fuzzy evaluations are triangular fuzzy numbers, and R^{+^k}, R^{-^k}, AR^{+}, and AR^{-} are obtained from each expert. The R-numbers for the fuzzy evaluations concerning the beneficial or non-beneficial types of the attributes are then obtained, which are denoted by $R_{ij}(S_{ij})$ as follows,

$$\begin{cases} R^k\left(\tilde{s}^k{}_{ij}\right) = R_b\left(\tilde{s}^k{}_{ij}\right) & if\ j \in Beneficial\ set \\ R^k\left(\tilde{s}^k{}_{ij}\right) = R_c\left(\tilde{s}^k{}_{ij}\right) & if\ j \in Non-beneficial\ set \end{cases} \tag{16}$$

$$R^k = \left[R^k(\tilde{s}_{ij})\right]_{m\times n} \tag{17}$$

Step 5. Aggregating the obtained decision matrices

In the fourth step, the aggregated matrix of all R-numbers is calculated using Eqs. (18) and (19).

$$R^T = \left[R^T(\tilde{s}_{ij})\right]_{m\times n,} \quad (18)$$

where

$$R^T = \frac{1}{K} +_{k=1}^{K} R^k\ . \quad (19)$$

Step 6. The normalization of the R-numbers matrix

In this step, the R-numbers matrix is normalized as follows using Eqs. (20) and (21):

$$R^{TN} = \left[R^{TN}(\tilde{s}_{ij})\right]_{m\times n,} \text{where} \quad (20)$$

$$R^{TN}(\tilde{s}_{ij}) = \frac{R^T(\tilde{s}_{ij})}{\sqrt{\sum_{i=1}^{m} R^T(\tilde{s}_{ij})^2}} \quad (21)$$

Step 7. Calculating the maximum value RS_j^* and the minimum value RS_j^-

Calculating the maximum value s_j^* and the minimum value s_j^- of all normalized R-numbers in each criterion,

$$RS_j^* = \underset{i}{Max}\, R^{TN}(\tilde{s}_{ij})\ , \quad (22)$$

$$RS_j^- = \underset{i}{Min}\, R^{TN}(\tilde{s}_{ij}). \quad (23)$$

Step 8. Calculating the utility and the regret measures

The utility and the regret measures of i-th alternative, which are themselves are R-numbers and shown by $R(\widetilde{RS}_I)$, and $R(\widetilde{RF}_\iota)$, are defined using Eq. (24).

$$R(\widetilde{RS}_I) = \sum_{j=1}^{n} \tilde{w}_j\left(RS_j^* - R^{TN}(\tilde{s}_{ij})\right) \Big/ \left(RS_j^* - RS_j^-\right),\ R(\widetilde{RF}_\iota) = \underset{j}{max}\left[\tilde{w}_j\left(RS_j^* - R^{TN}(\tilde{s}_{ij})\right) \Big/ \left(RS_j^* - RS_j^-\right)\right] \quad (24)$$

Step 9. Calculating the R-VIKOR measure

The R-VIKOR measure, which is a type of R-numbers, can be determined as follows:

$$R(\widetilde{Q_\iota}) = \vartheta\left(R(\widetilde{RS}_I), -RS^-\right) \Big/ (RS^* - RS^-) + (1-\vartheta)\left(R(\widetilde{RF}_\iota) - RF^*\right) \Big/ (RF^* - RF^-) \quad (25)$$

where $0 < \vartheta < 1$, and thus we have:

$$\begin{cases} RS^* = \underset{i}{min} R(\widetilde{RS}_I) \\ RS^- = \underset{i}{max} R(\widetilde{RS}_I), \\ RF^* = \underset{i}{min} R(\widetilde{RF}_\iota), \\ RF^- = \underset{i}{max} R(\widetilde{RF}_\iota). \end{cases} \quad (26)$$

Step 10: Ranking the alternatives

In the final step for ranking the alternatives, the values of $R(\widetilde{Q_i})$ are defuzzified. Let $R(\widetilde{A}) = ((a_{11}, a_{12}, a_{13}), (a_{21}, a_{22}, a_{23}), (a_{31}, a_{32}, a_{33}))$, and by twice defuzzification of $R(\widetilde{A})$, using graded mean integration [40], we have:

$$GG(R(\widetilde{A})) = \frac{1}{36}(a_{11} + 4a_{12} + a_{13} + 4a_{21} + 16a_{22} + 4a_{23} + a_{31} + 4a_{32} + a_{33}) \quad (27)$$

Now the defuzzification values of $R(\widetilde{Q_i})$, $R(\widetilde{S_i})$ and $R(\widetilde{F_i})$ are obtained according to Eq. (27) and the alternatives are ranked on this basis. The flowchart of the proposed R-VIKOR for NPD risk analysis is depicted in Fig. 1.

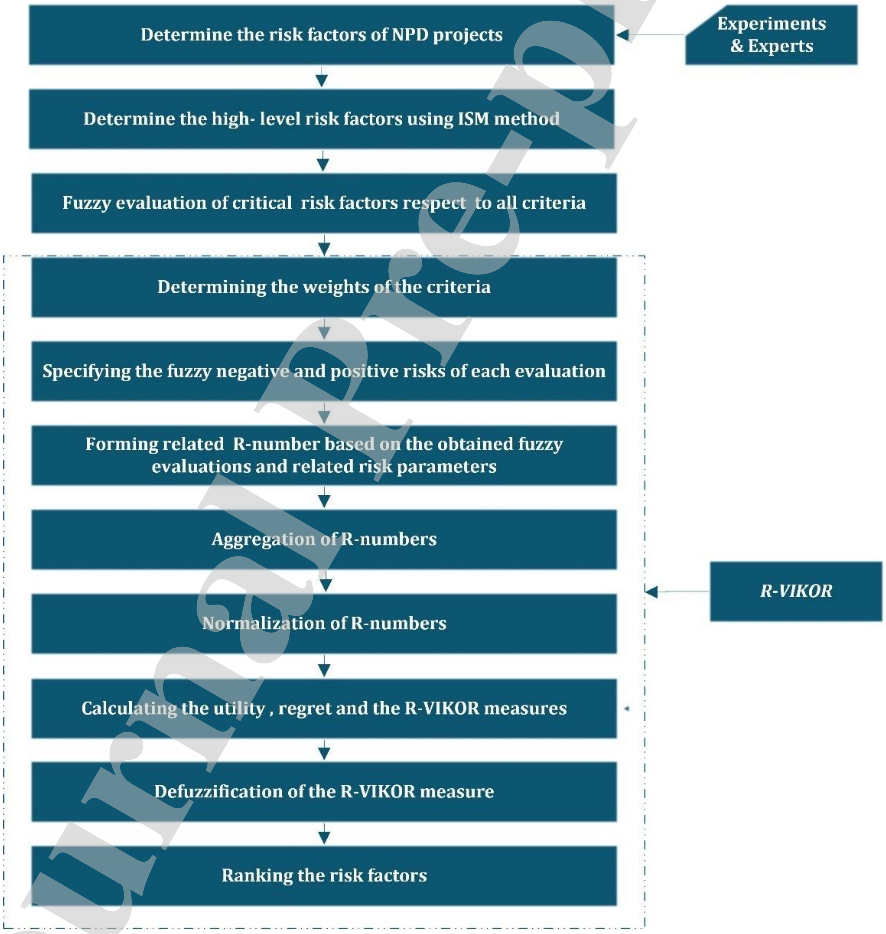

Fig. 1. The proposed model for NPD risk analysis

5. The case study

The case study proposed in this paper was carried out at the IranKhodro automotive organization. IranKhodro Company was founded and registered in August 1962. The company is currently largest Iranian automobile manufacturing company, assembling all kinds of light and heavy vehicles both in collaboration with foreign partners and independently. The company's production capacity is about 577,000 vehicles a year. The company first started producing LP buses, the chassis of which were imported from Germany and assembled in IranKhodro. The company's R&D department plays an important role in realizing the strategic goals of the organization and runs a range of NPD projects based on marketing and competitive environment orientation. To better understand the market trend and the customers' requirements, the company constantly analyzes the market information and conducts risk management as fundamental steps before initiating any NPD project. However, the company has had an issue with uncertainty of ambiguous information gathered by the R&D team and coping with high costs and time of implementing risk management processes. Therefore, the company decided to develop a simple yet practical method, enabling them to identify and prioritize the most important risk factors. Resulted by a collaborative research project, this section presents the outcome of application of the developed R-VIKOR model in the company's NPD risk management, including identification and analysis of one of their NPD projects' key risk factors. As Fig. 1 depicts, the employed model consists of two major parts. In the first part, the risk factors of NPD projects are predicted and determined by industry experts and company managers (Table 1), and partitioned by the ISM method according to what is stated in Section 3.1 (see Section 5.1.) In the second part, the risks of the first layer (with higher penetration power and less dependence) are evaluated and ranked using the R-VIKOR method (see Section 5.2).

5.1. Identifying and modeling the causal relationship of risk factors

Following the Algorithm 1 (Section 3.1), we first define and analyze the relationship between the risk factors and then partition and prioritize them using the Reachability and Antecedent Sets. According to Step 1 of the algorithm, the risk factors of NPD projects are identified by experts according to Table 1. As mentioned, managing all the risk factors of NPD projects requires a lot of time and money, so only level 1 risk factors were analyzed.

Table 1. Identified risks in NPD projects

The identified risks	Explanations	Risk Codes
Poor project feasibility	Due to the uncertainties of R&D projects, initial studies on the feasibility of the project may not be accurate and will fail despite the strong initial idea of the project.	R_1
Reject a good idea	Sometimes a good idea may be rejected due to a weakness in the proposal, or under the influence of the poor provider resume, lack of a business plan.	R_2
Accept a weak idea	Sometimes the reason for the failure of a project is the initial idea that it may be misunderstood for reasons of insufficient scrutiny. The risk is different from Risk 2, and should not be assumed to be the same.	R_3
Lack of team working	To successfully implement a research and development project, it is necessary to have	R_4

	a team consisting of specialized experts and experienced managers. A group composed of people who have the required specialized knowledge and skills in the field of project innovation. The absence of such a team will lead to the failure of the project.	
Lack of laboratory equipment	One of the basic requirements for the implementation of R&D projects is to have well equipped, and modern laboratory equipment can have adverse effects on the project goals.	R_5
Weakness in product design	Careful product design and technical drawings, along with details, play a vital role in the success of a project, in which any weakness or error will lead to rework and repetition of project phases.	R_6
Misleading market analysis	One of the goals of an R&D project definition and implementation is profitability and survival in today's competitive environment, so if an R&D project is not defined based on market analysis and customer needs, it can not lead to profitability and competitive advantage of the company.	R_7
Incorrect estimation of project time	Project planning and accurate estimation of project time and its activities is a prerequisite for the success of an R&D project, which, if not correct, will have many adverse consequences, such as increased costs, market loss, and customer dissatisfaction.	R_8
Lack of organizational support for the project	Due to uncertainty and complexity, R&D projects may be delayed and costly, which can lead to many problems if there is no organizational support.	R_9
Non-cooperation of suppliers	The cooperation of suppliers in these projects reduces time and increases profitability, and their lack of cooperation can lead to delays and failure of the project.	R_{10}
The complexity of technology	The technology of R&D projects is often new and complex, and learning and using them correctly has a significant impact on the success of the project and requires sufficient knowledge and skills.	R_{11}
Restrictions on access to raw materials	Because project phases may be repeated many times due to the complexity of the innovation, access to adequate and quality raw materials is another critical factor in the success of the project.	R_{12}
Lack of variable capital	R&D projects need sufficient variable capital due to their high cost and uncertainty.	R_{13}
Uncertain economic situation	Another risk factor in R&D projects is an ambiguous economic situation. Economic uncertainties such as changes in the national capital, changes in export and import rates, etc., if not managed, can have adverse effects on the implementation of an R&D project.	R_{14}
Incorrect estimation of project budget	Similar risk 8, an accurate estimation of the project budget, is a prerequisite for the success of an R&D project, which, if not correct, will have many adverse consequences.	R_{15}
Restrictions on access to technology	R&D projects require modern laboratory equipment and facilities because they are based on innovation, which will often be difficult and costly to access due to their novelty and complexity.	R_{16}

Table 2. The first level of risk partitioning

	Antecedent Sets (AS)	Reachability Sets (RS)	Intersection Sets (IS)	Rank
R_1	6-7-8-10-11-12-13-14-16	15-10-9-8-7-6-5-4-3-2-	10-8-7-6	-
R_2	1-5-6-7-8-9-10-11-12-13-14-15-16	15-9-5-4-3	15-5	-
R_3	16-15-14-13-12-11-10-9-8-7-6-5-4-2-1	9-4	9-4	1

R_4	16-15-14-13-12-11-10-9-8-7-6-5-3-2-1	9-3	9-3	1
R_5	16-15-14-13-12-11-10-8-7-6-2-1	15-9-4-3-2	15-2	-
R_6	16-14-13-12-11-10-8-7-1	15-10-9-8-7-5-4-3-2-1	10-8-7-1	-
R_7	16-14-13-12-11-10-7-6-1	15-10-9-7-6-5-4-3-2-1	10-8-6-1	-
R_8	16-14-13-12	15-10-9-7-6-5-4-3-2-1	10-7-6-1	-
R_9	16-15-14-13-12-11-10-9-8-7-6-5-2-1	4-3	4-3	1
R_{10}	16-14-13-12-8-7-6-1	15-10-9-7-6-5-4-3-2-1	8-7-6-1	-
R_{11}	16-14-13-12	10-9-8-7-6-5-4-3-2-1	16-14-13-12	-
R_{12}	16-14-13-11	16-15-14-13-9-8-7-6-5-4-3-2-1	16-14-13-11	-
R_{13}	16-14-12-11	16-15-14-12-11-10-9-8-7-6-5-4-3-2-1	16-14-12-11	-
R_{14}	16-13-12-11	16-15-13-12-11-10-9-8-7-6-5-4-3-2-1	16-13-12-11	-
R_{15}	16-14-13-12-11-10-8-7-6-5-2-1	9-5-4-3-2	5-2	-
R_{16}	14-13-12-11	15-14-13-12-11-10-9-8-7-6-5-4-3-2-1	14-13-12-11	-

According to Step 5 of Algorithm 1, if *Intersection Set* is the same as the Reachability Set of a risk factor, that risk factor is classified at the first level and removed from the calculations of the next step. In Table 2, these conditions are for R_3, R_4, and R_9. Therefore, these risk factors are classified at the first level, and the ISM algorithm is repeated without them.

Table 3. The second level of risk partitioning

	AS	RS	IS	Rank
R_1	6-7-8-10-11-12-13-14-16	15-10-8-7-6-2	10-8-7-6	-
R_2	1-5-6-7-8-10-11-12-13-14-15-16	15-5	15-5	2
R_5	1-2-6-7-8-10-11-12-13-14-15-16	15-2	15-2	2
R_6	16-14-13-12-11-10-8-7-1	15-10-8-7-5-2-1	10-8-7-1	-
R_7	16-14-13-12-11-10-7-6-1	15-10-7-6-5-2-1	10-8-6-1	-
R_8	16-14-13-12	15-10-7-6-5-2-1	10-7-6-1	-
R_{10}	16-14-13-12-11-8-7-6-1	15-10-7-6-5-2-1	8-7-6-1	-
R_{11}	16-14-13-12	16-15-14-13-12-10-8-7-6-5-2-1	16-14-13-12	-
R_{12}	16-14-13-11	16-15-14-13-11-10-8-7-6-5-2-1	16-14-13-11	-
R_{13}	16-14-12-11	16-15-14-12-11-10-8-7-6-5-2-1	16-14-12-11	-
R_{14}	16-13-12-11	16-15-13-12-11-10-8-7-6-5-2-1	16-13-12-11	-
R_{15}	16-14-13-12-11-10-8-7-6-5-2-1	5-2	5-2	2
R_{16}	14-13-12-11	15-14-13-12-11-10-8-7-6-5-2-1	14-13-12-11	-

In Table 3, Intersection Set and Reachability Set related to R_2, R_5, and R_{15} are the same, so they are classified in the second level, and the ISM algorithm is repeated without them.

Table 4. The third level of risk partitioning

	AS	RS	IS	Rank
R_1	6-7-8-10-11-12-13-14-16	10-8-7-6	10-8-7-6	3
R_6	16-14-13-12-11-10-8-7-1	10-8-7-1	10-8-7-1	3
R_7	16-14-13-12-11-10-7-6-1	10-8-6-1	10-8-6-1	3
R_8	16-14-13-12	10-7-6-1	10-7-6-1	3
R_{10}	1-6-7-8-11-12-13-14-16	8-7-6-1	8-7-6-1	3
R_{11}	16-14-13-12	16-14-13-12-10-8-7-6-1	16-14-13-12	-
R_{12}	16-14-13-11	16-14-13-11-10-8-7-6-1	16-14-13-11	-
R_{13}	16-14-12-11	16-14-12-11-10-8-7-6-1	13-14-12-11	-
R_{14}	16-13-12-11	16-13-12-11-10-8-7-6-1	16-13-12-11	-
R_{16}	14-13-12-11	14-13-12-11-10-8-7-6-1	14-13-12-11	-

In Table 4, Intersection Set and Reachability Set related to R_1, R_6, R_7, R_8, and R_{10} are the same, so they are classified in the third level, and the ISM algorithm is repeated without them.

Table 5. Forth level of risk partitioning

	AS	RS	IS	Rank
R_{11}	16-14-12-11	16-14-13-12	16-14-13-12	4
R_{12}	16-14-13-11	16-14-13-11	16-14-13-11	4
R_{13}	16-14-12-11	16-14-12-11	16-14-13-11	4
R_{14}	16-13-12-11	16-13-12-11	16-13-12-11	4
R_{16}	14-13-12-11	14-13-12-11	14-13-12-11	4

In Table 5, Intersection Set and Reachability Set related to R_{11}, R_{12}, R_{13}, R_{14}, and R_{16} are the same, so they are classified in the fourth level, and the ISM algorithm stops because all the risk factors are classified.

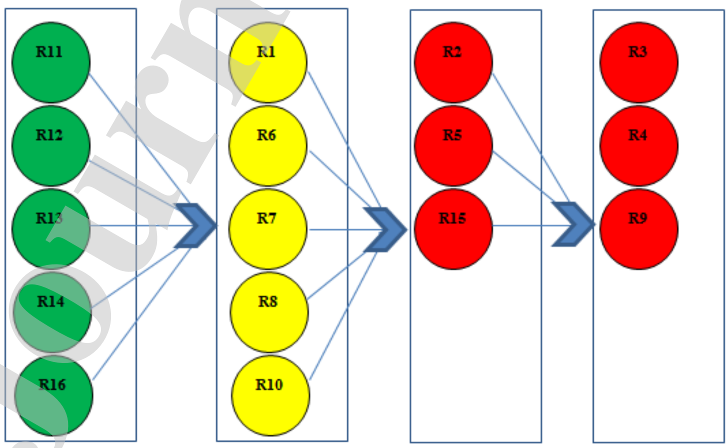

Fig. 2. Levels of the risk factors

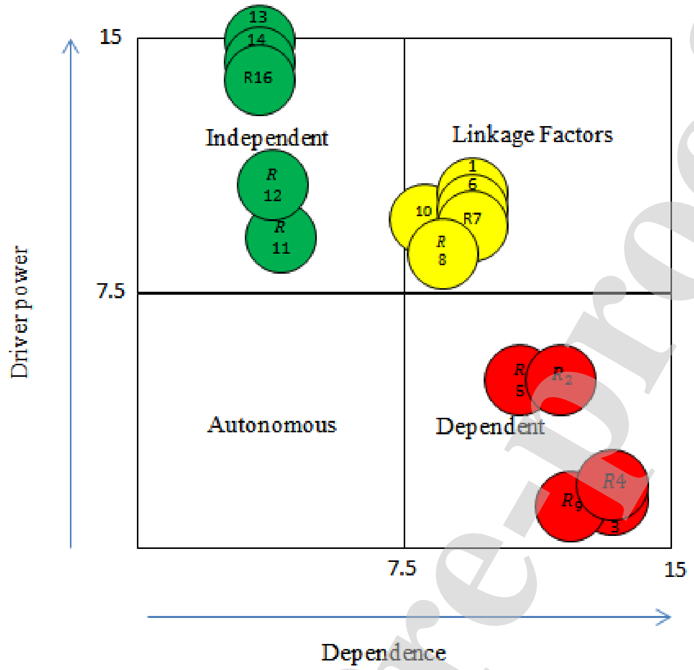

Fig. 3. Risk factor classification

In this section, risk factors were classified into four levels using the ISM method. As can be seen in Fig. 2, the risk factors categorized at the second level are the result of the occurrence of the risk factors categorized at the first level. The same pattern occurs up to the fourth level; the risk factors of each level are the result of the occurrence of the risk factors categorized at the previous level. Therefore, the risk factors classified in the first level are more influential than those in other levels. Thus, if they are well estimated and managed, the probability of occurrence of other risk factors will be low. An important consequence is that the risk level associated with each risk factor was consistent with the actual dependency on other factors as well.

As Fig. 3 shows, the ISM classification suggests four main groups of risk factors according to the respective dependence and driving-power values: independent factors (high driving power-low dependence); autonomous factors (low driving power-low dependence); linkage factors (high driving power-high dependence) and dependent factors (low driving power-high dependence). Independent factors are determined by high driving power and low dependence. This means that they have a wide-ranging influence on other risk factors (they lead to other potential risks), and a snowball effect is likely if and when they happen. Therefore, managing these factors is very important for project success. Autonomous factors are determined both by low driving and low dependence. They are faint drivers and faint dependents and are more isolated. Dependent factors have the highest degree of dependence and the lowest driving power, so they are found in the cluster of dependent factors. Linkage factors are determined by high driving power and high dependence. These factors are usually critical since any actions on them will have a spread effect on several dependent factors.

5.2. Risk analysis via R-VIKOR

In this section, the obtained critical risk factors of Section 5.1 are ranked using the steps of the proposed R-VIKOR as follows:

Step 1. Determining the critical risk factors

The critical risk factors were obtained from the ISM method are: R11: the complexity of technology; R12: restrictions on access to raw materials; R13: lack of variable capital; R14: uncertain economic situation; and R16: restrictions on access to technology, which are used as alternatives of the R-VIKOR method.

Step 2. Forming the decision and weight matrices

In this step, C_1 =quality , C_2 =cost , and C_3 =customer demand are selected as the beneficial criteria by the experts, with the weights of 0.5, 0.3, and 0.2, respectively. For ranking the risk factors, linguistic variables, according to Table 6, are used. The fuzzy decision matrix of evaluating the risk factors acceding to these criteria is tabulated in Table 8.

Step 3. Forming the fuzzy positive and negative risk matrices, and the positive and negative AR matrices

Here, the risks and errors of fuzzy evaluations of risk factors, including fuzzy negative risk and fuzzy positive risk, are obtained (Table 8) according to the linguistic variables of Table 6. Additionally, experts determine the positive and negative acceptable risks according to the strategic plan of the company. The values of AR^- and AR^+ are shown in Table 8. It should be pointed out that the expert risk perceptions are considered to be zero.

Table 6. Linguistic variables for the assessment of risk factors [11].

Linguistic variables	Triangular fuzzy numbers
Very high (VH)	(0.75,1,1)
High (H)	(0.5,0.75,1)
Medium (M)	(0.25,0.5,0.75)
Low (L)	(0,0.25,0.5)
Very low (VL)	(0,0,0.25)

Table 7. Linguistic variables for the assessment of positive risk and negative risk [11].

Linguistic variables	Triangular fuzzy numbers
Very low (VL)	(0,0,0.3)
Low (L)	(0.1,0.3,5)

Medium (M)	(0.3,0.5,0.7)
High (H)	(0.5,0.7,0.9)
Very high (VH)	(0.7,0.99,0.99)

Table 8. The AR^{+} and AR^{-}values of each attribute.

	C_1	C_2	C_3
AR^{+}	0.1	0.2	0.1
AR^{-}	0	0.4	0

Table 9. The fuzzy evaluations and the fuzzy negative and positive risks.

		C_1	C_2	C_3			C_1	C_2	C_3
Expert 1	R_{11}	L	H	L	**Expert 2**	R_{11}	H	H	L
	$\tilde{r}^{+}$	L	L	VL		$\tilde{r}^{+}$	VL	L	L
	$\tilde{r}^{-}$	L	VL	L		$\tilde{r}^{-}$	L	L	L
	R_{12}	VH	L	L		R_{12}	H	VL	H
	$\tilde{r}^{+}$	VL	M	M		$\tilde{r}^{+}$	L	M	H
	$\tilde{r}^{-}$	VK	L	L		$\tilde{r}^{-}$	L	VL	VL
	R_{13}	H	VH	L		R_{13}	L	VL	L
	$\tilde{r}^{+}$	L	L	VL		$\tilde{r}^{+}$	L	VL	L
	$\tilde{r}^{-}$	VL	L	M		$\tilde{r}^{-}$	VL	L	L
	R_{14}	H	VH	H		R_{14}	L	VH	VH
	$\tilde{r}^{+}$	L	H	L		$\tilde{r}^{+}$	L	H	VL
	$\tilde{r}^{-}$	VL	VL	M		$\tilde{r}^{-}$	L	VL	M
	R_{16}	VH	H	VH		R_{16}	VH	H	H
	$\tilde{r}^{+}$	VL	L	M		$\tilde{r}^{+}$	L	L	M
	$\tilde{r}^{-}$	VL	L	VL		$\tilde{r}^{-}$	L	VL	VL
Expert 3	R_{11}	L	H	L	**Expert 4**	R_{11}	L	H	L
	$\tilde{r}^{+}$	L	VL	VL		$\tilde{r}^{+}$	VL	VL	VL
	$\tilde{r}^{-}$	L	L	VL		$\tilde{r}^{-}$	L	L	VL
	R_{12}	H	H	L		R_{12}	VH	L	VL
	$\tilde{r}^{+}$	VL	L	L		$\tilde{r}^{+}$	VL	M	L
	$\tilde{r}^{-}$	VL	L	VL		$\tilde{r}^{-}$	VL	VL	VL
	R_{13}	H	H	L		R_{13}	L	H	L
	$\tilde{r}^{+}$	L	L	VL		$\tilde{r}^{+}$	L	L	L
	$\tilde{r}^{-}$	VL	VL	L		$\tilde{r}^{-}$	L	VL	L
	R_{14}	VH	VH	VH		R_{14}	H	VH	H
	$\tilde{r}^{+}$	L	L	VL		$\tilde{r}^{+}$	VL	M	VL
	$\tilde{r}^{-}$	L	L	L		$\tilde{r}^{-}$	L	VL	L
	R_{16}	H	H	H		R_{16}	VH	VH	VH
	$\tilde{r}^{+}$	VL	L	M		$\tilde{r}^{+}$	L	L	M
	$\tilde{r}^{-}$	VL	VL	L		$\tilde{r}^{-}$	L	L	VL

Step 4. Determining the R-numbers for the fuzzy evaluations by employing the fuzzy positive and negative risk matrices, and the fuzzy positive and negative AR matrices.

In this step, first, the R-numbers of all expert's evaluations are formed using Eq. (1) due to the beneficial nature of the attributes. The obtained R-numbers of Expert 1's decision matrix are tabulated in Table 10.

Table 10. The obtained R-numbers of Expert 1

	$R_b{}^1(C_1)$	$R_c{}^1(C_2)$	$R_b{}^1(C_3)$
R11	((0.125, 0.351, 0.675), (0.25, 0.5, 0.75), (0.247, 0.585, 1))	((0.251, 0.451,1), (0.5, 0.75, 1), (0.44, 0.781, 1))	((0.125, 0.35,0.675), (0.25, 0.5,0.75), (0.225, 0.451,0.877))
R12	((0.525, 1 , 1), (0.75, 1, 1), (0.675, 0.925, 1))	((0.075, 0.211, 0.405), (0.25, 0.5, 0.75), (0.261, 0.611, 1))	((0.125, 0.35,0.675), (0.25, 0.5,0.75), (0.292, 0.675,1))
R13	((0.351, 0.75,1), (0. 5, 0.75, 1), (0.451, 0.675, 1))	((0.075, 0.211, 0.315), (0.75, 1, 1), (0.911, 1, 1))	((0.075, 0.25 , 0.525), (0.25, 0.5 , 0.75), (0.225, 0.451 , 0.878))
R14	((0.351, 0.75, 1), (0.5, 0.75, 1), (0.451, 0.675, 1))	((0.151, 0.315 , 0.421), (0. 5, 0.75, 1), (0.44, 0.78,0.15))	((0.152, 0.375,0.675), (0. 5, 0. 75, 1), (0.495, 0.878, 1))
R16	((0.525, 1,1), (0. 75, 1, 1), (0.675, 0.91,1))	((0.25, 0.5, 0. 75), (0.5625, 0.8125, 1), (0.6075, 1, 1))	((0.525, 1, 1), (0.75, 1, 1), (0.878, 1, 1))

Step 5. Aggregating the obtained decision matrices

In this step, the aggregated matrix of all the expert opinions is obtained by using Eq. (18) which can be seen Table 11.

Table 11. The $R_b{}^T(C_1), R_c{}^T(C_2)$, and $R_b{}^T(C_3)$.

	$R_b{}^T(C_1)$	$R_c{}^T(C_2)$	$R_b{}^T(C_3)$
R11	((0.1562, 0.3937, 0.7312), (0.3125, 0.5625, 0).8125), (0.3237, 0.63, 1)	((0.365, 0.6487,0.955), (0.5, 0.75, 1), (0.52, 0.84, 1))	((0.125, 0.35,0.675), (0.25, 0.5,0.75), (0.2556, 0.5337,0.9862))
R12	((0.4125, 0.8187 , 0.975), (0.625, 0.875, 1), (0.6362, 0.9256, 1))	(0.1825, 0.4437, 0.7237), (0.25, 0.5, 0.75), (0.29, 0.67, 1)	((0.15, 0.4437,0.725), (0.25, 0.5,0.75), (0.3287, 0.725,1))
R13	((0.25, 0.5875,0.8562), (0.375, 0.625, 0.875), (0.4087, 0.7937, 1))	((0.2487, 0.5287, 0.7937), (0.3125, 0.5625, 0.8125), (0.3375, 0.6825, 1))	((0.1625, 0.4625 , 0.7312), (0.25, 0.5 , 0.75), (0.2612, 0.5675 , 1))
R14	((0.275, 0.5812, 0.8687), (0.5, 0.75, 0.9375), (0.5337, 0.9018, 1)	((0.5925, 0.955,0.985), (0.75, 1, 1), (0.96, 1,1))	((0.3375, 0.6687,0.925), (0.625, 0.875, 1), (0.6362, 0.9256, 1))
R16	((0.4062, 0.7875,0.95), (0.6875, 0.9375, 1), (0.7212, 1,1))	((0.4237, 0.7337, 0.97), (0.5625, 0.8125, 1), (0.6075, 1, 1))	((0.375, 0.7437, 0.95), (0.625, 0.875, 1), (0.7937, 1, 1))

Step 6. The normalization of the R-numbers matrix

Now, the aggregated matrix of Table 11 is normalized using Eq. (20). The normalized matrix is depicted in Table 12.

Table 12. The normalized matrix

	$R_b{}^{TN}(C_1)$	$R_c{}^{TN}(C_2)$	$R_b{}^{TN}(C_3)$
R_{11}	((0.069, 0.204, 0.601), (0.151, 0.329, 0.678), (0.164, 0.432, 1))	((0.163, 0.337,0.785), (0.241, 0.439, 0.811), (0.264, 0.576, 1))	((0.055, 0.182,0.555), (0.151, 0.329,0.579), (0.229, 0.366,1))
R_{12}	((0.184, 0.425 , 0.801), (0.301, 0.513, 0.922), (0.323, 0.635, 1))	((0.082, 0.231, 0.595), (0.121, 0.292, 0.624), (0.147, 0.459, 1))	((0.067, 0.231,0.595), (0.301, 0.512,0.713), (0.342, 0.678,1))
R_{13}	((0.112, 0.306,0.704), (0. 181, 0.366, 0.862), (0.208, 0.544, 1))	((0.111, 0.275, 0.652), (0.151, 0.329, 0.723), (0.171, 0.468, 1))	((0.073, 0.241 , 0.601), (0.181, 0.366 , 0.624), (0.211, 0.389 , 1))
R_{14}	((0.123, 0.302, 0.714), (0.241, 0.441, 0.745), (0.271, 0.618, 1))	((0.264, 0.496 , 0.809), (0. 361, 0.585, 0.812), (0.487, 0.685,1))	((0.151, 0.348,0.760), (0. 241, 0. 439, 0.798), (0.323, 0.635, 1))
R_{16}	((0.182, 0.402,0.781), (0. 331, 0.549, 0.793), (0.366, 0.686,1))	((0.189, 0.381, 0. 797), (0.271, 0.475, 0.823), (0.308, 0.685, 1))	((0.168, 0.387, 781), (0.301, 0.549, 0.844), (0.403, 0.686, 1))

Step 7. Calculating the maximum value RS_j^* and the minimum value RS_j^-

Next the minimum and maximum values of all normalized R-numbers in each criterion are obtained, which are displayed in Table 13.

Table 13. The minimum and maximum values

	RS_j^*	RS_j^-
C_1	((0.182, 0.402,0.781), (0. 331, 0.549, 0.793), (0.366, 0.686,1))	((0.069, 0.204, 0.601), (0.151, 0.329, 0.678), (0.164, 0.432, 1))
C_2	((0.264, 0.496 , 0.809), (0. 361, 0.585, 0.812), (0.487, 0.685,1))	((0.082, 0.231, 0.595), (0.121, 0.292, 0.624), (0.147, 0.459, 1))
C_3	((0.168, 0.387, 781), (0.301, 0.549, 0.844), (0.403, 0.686, 1))	((0.055, 0.182,0.555), (0.151, 0.329,0.579), (0.229, 0.366,1))

Step 8. Calculating the utility and the regret measures and the R-VIKOR measures and ranking

As mentioned in Section 4, $GG(R(\widetilde{Q_i}))$, $GG(R(\widetilde{S_i}))$, and $GG(R(\widetilde{F_i}))$ for each risk factor are calculated considering $\vartheta = 0.5$. The results are presented in Table 14 and Fig. 4.

5.3. Results validation

In this section, the validation of the obtained results is performed. For verification of the proposed R-VIKOR outcomes, the criticality of the risk factors is calculated again by employing existing methods, including R-TOPSIS [18] and R-SAW [11] and extensions of MARCOS [43] and COPRAS [44] integrated with R-numbers, which are indicated by R-MARCOS and R-COPRAS. The compared results are given in Table 14 and Fig. 4.

Table 14. Final results of the R-VIKOR and other methods.

Risk factor	R-VIKOR				R-TOPSIS		R-SAW		R-COPRAS		R-MARCOS	
	$GG(R(\widetilde{Q_i}))$	$GG(R(\widetilde{F_i}))$	$GG(R(\widetilde{S_i}))$	Rank	Rank		Rank		Rank		Rank	
R_{11}	1	0.3162	0.6154	5	0.3346	5	0.59	5	76.016	4	0.084	5
R_{12}	0.3728	0.2132	0.5603	3	0.3462	3	0.67	3	83.678	3	0.172	3
R_{13}	0.8827	0.2871	0.6261	4	0.335	4	0.597	4	74.101	5	0.095	4
R_{14}	0.3474	0.2513	0.4678	2	0.372	2	0,778	2	96.327	2	0.821	2
R_{16}	0	0.2135	0.4388	1	0.378	1	0,815	1	100	1	1.033	1

Now, the parameters of the proposed model were changed, such as fuzzy positive risks and negative risks. Changing the parameters changed the corresponding results. The three scenarios that are considered are:

Scenario 1: It is supposed that only optimistic values are investigated for the risk factor values.

Scenario 2: It is supposed that for the risk factor values, only the pessimistic state is investigated.

Scenario 3**:** It is supposed that there is no risk in the proposed model.

The results of the three scenarios are obtained and compared with the final results from the default scenario, as shown in Table 15 and Fig. 4.

Table 15. The results of the scenarios

Risk factor	Scenario 1				Scenario2				Scenario 3			
	$GG(R(\widetilde{Q}_i))$	$GG(R(\widetilde{F}_i))$	$GG(R(\widetilde{S}_i))$	Rank	$GG(R(\widetilde{Q}_i))$	$GG(R(\widetilde{F}_i))$	$GG(R(\widetilde{S}_i))$	Rank	$GG(R(\widetilde{Q}_i))$	$GG(R(\widetilde{F}_i))$	$GG(R(\widetilde{S}_i))$	Rank
R_{11}	1	0.27	0.604	5	1	0.32	0.63	4	1	0.30	0.61	4
R_{12}	0.82	0.24	0.64	3	0.39	0.22	0.58	3	0.961	0.31	0.56	5
R_{13}	0.97	0.25	0.67	4	0.88	0.29	0.65	5	0.963	0.28	0.63	3
R_{14}	0.11	0.23	0.41	2	0.34	0.26	0.48	2	0.41	0.25	0.47	2
R_{16}	0	0.21	0.49	1	0	0.22	0.41	1	0	0.21	0.39	1

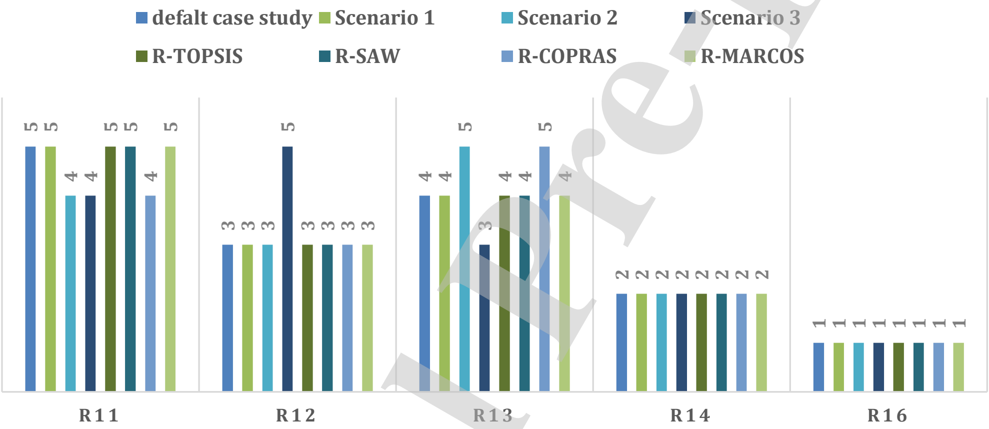

Fig. 4. Ranking results of different cases

6. Conclusion

Since NPD projects are based on innovation and new marketing, have high-risk levels, due to their uncertain and dynamic natures. Therefore, an appropriate risk management model is necessary for guaranteeing project success. In this study, at first, the ISM method was employed for modeling the causal relationship between risk factors and then a novel risk-based fuzzy model was developed based on the integration of R-numbers and fuzzy VIKOR to assess NPD projects' risk factors, taking into account the effects of possible influential factors on data risk. To investigate the efficiency of the proposed model in real-world applications, a case study was presented involving the research and development unit of an automaker in Iran. In the case study, the critical risk factors obtained by implementing the ISM method were: The complexity of technology, restrictions on access to raw materials and technology, lack of variable capital and uncertain economic situation. Moreover, the R-VIKOR methodology shows the importance of the complexity of technology, lack of variable capital and restrictions on access to raw materials compared to other risk factors of NPD projects in Iranian Automaker Company. Other findings and outline the possible implications of this study are as following:

- The presented model in this paper deals with information ambiguity problem and associated uncertainties by identifying, separating, and ranking the risk factors of NPD projects and analyzing the risk of data inaccuracy. Using the ISM method, the identified risk factors were first classified based on the opinions gathered from an expert panel who provide their inputs after a careful review of the previously registered information. In other words, the ISM method analyzes the input in formation of experts and provides an output in the form of risk factors classification. The risk factors in our case study were identified by the ISM method and include: complexity of technology; restrictions on access to raw materials; lack of variable capital; uncertain economic situation; and access restrictions to technology.
- Analysis of causal relationships between the risk factors of NPD projects and their partitioning leads to the identification of risk factors with higher penetration power and lesser dependence. In other words, evaluation of the selected risk factors instead of all risk factors leads to substantial time savings and shortening the risk evaluation process of NPD projects. Evaluating and ranking all project risk factors in real-world setting can be time-consuming and complex. Thus, ranking the risk factors in a systematic way enables the R&D managers to identify the most influential risk factors and simultaneously reduce the costs of risk management and avoid NPD failure.
- To validate the main theoretical results, the proposed model was tested under three other scenarios: 1) only optimistic values are considered, 2) only pessimistic values considered, and; 3) the research model was tested without risk. The results of the three scenarios are summarized in Table 15. For example, the risk factor R_{11} is ranked fifth in the first scenario and ranked fourth first in the second scenario. Changes in ranking in scenario 2 and 3 can be due to a variety of reasons (e.g., experts' judgmental biases). The result of scenario 1 was the same as the proposed R-VIKOR, which shows that a majority of expert opinions were Non-conservative. Considering pure optimistic or pessimistic values in risk assessment is not realistic and could also cause several issues. For example, an unnecessary focus on managing a risk factor can increase the risk management costs and reduce the success of risk management plan, so failing the firms in achieve their strategic goals. To avoid these, the proposed R-VIKOR model offers higher flexibility to future changes, due to its consideration of various risk configurations.

- After validating the R-VIKOR model under different scenarios, the problem was solved using four other methods, including R-SAW, R-TOPSIS, R-MARCOS, and R-COPRAS. By comparing the ranking of risk factors, we find that the R-VIKOR, R-TOPSIS and R-MARCOS methods lead to the same R-SAW rank of all risk factors.
- Comparing the ranking results with the lessons learned in previous NPD projects shows that the proposed R-VIKOR provides more robust results, while maintaining the accuracy of final outputs. In addition, the proposed R-VIKOR takes advantage of simple fuzzy VIKOR, including the maximum "group utility of the majority" and the minimum "individual regret of the opponent". In addition, it captures various data risk scenarios, such as pessimistic, optimistic and acceptable risks
- Uncertainty is a crucial feature of NPDs. Thus, to improve time and costs of risk management, the NPD project managers are encouraged to employ flexible risk-based models, such as R-VIKOR, for analyzing the risk factors of NPD projects. Another important point is that using positive and negative AR can be seen as managerial control tools in capturing the various amount of data risk.

There were some limitations in this study which can be further explored in future. First, to reduce the complexity of solution, the risk of ISM data was not considered in this paper. Incorporating this risk and solving the presented problem could serve as a future research direction. The data risk refers to the uncertainties caused by the unreliable sources of data and/or any data changes associated with the future events. In this paper, the risk of R-numbers data was obtained qualitatively from the experts. This may lead to new risk factors in the assessment and, hence, needs further research. Besides, analyzing the risk factors of NPD projects by other MCDM and risk analysis methods using the R-numbers – such as Bayesian networks [41], fault trees [42], and other uncertainty theories– can provide novel risk response solutions for NPD projects and can be considered as another future research avenue. Finally, identifying and evaluating the risk factors of NPD projects in other industries with high-paced technological advancements, such as pharmaceutical, communication, aerospace, can be recommended as other future research direction.

References

[1] Abbasi, D., Ashrafi, M., and Ghodsypour, S.H. (2020), "A multi objective-BSC model for new product development project portfolio selection", Expert Systems with Applications, 162. 113757.

[2] Wang, J. and Yung, L. (2009), "An overlapping process model to assess schedule risk for new product development", Computers & Industrial Engineering, Vol.57 No. 2, PP.460-474.

[3] Virgil and Dorina (2008). Project management on new product development and lunch in the automotive industry.2nd International Conference on Manufacturing Engineering, Quality and production Systems, 217-223.

[4] Salavati, M., Tuyserkani, M., Mousavi, S. A., Falahi, N., & Abdi, F. (2016). Improving new product development performance by risk management.*Journal of Business & Industrial Marketing*, *31*(3), 418-425.

[5] Marmier, F., Gourc, D., &Laarz, F. (2013). A risk oriented model to assess strategic decisions in new product development projects. *Decision Support Systems*, *56*, 74-82.

[6] Fekri, R., Aliahmadi, A., & Fathian, M. (2009). Predicting a model for agile NPD process with fuzzy cognitive map: the case of Iranian manufacturing enterprises. *The International Journal of Advanced Manufacturing Technology*, *41*(11-12), 1240-1260.

[7] Guan, L., Abbasi, A., & Ryan, M. J. (2020). Analyzing green building project risk interdependencies using Interpretive Structural Modeling. *Journal of Cleaner Production*, *256*, 120372.

[8] Panula-Ontto, J., & Piirainen, K. A. (2018). EXIT: An alternative approach for structural cross-impact modeling and analysis. *Technological Forecasting and Social Change*, *137*, 89-100.

[9] Panula-Ontto, J. (2019). The AXIOM approach for probabilistic and causal modeling with expert elicited inputs. *Technological Forecasting and Social Change*, *138*, 292-308.

[10] Mohagheghi, V., Mousavi, S. M., Vahdani, B., & Shahriari, M. R. (2017). R&D project evaluation and project portfolio selection by a new interval type-2 fuzzy optimization approach. *Neural Computing and Applications*, *28*(12), 3869-3888.

[11] Um, K. and Oh, J. (2021). The mediating effects of cognitive conflict and affective conflict on the relationship between new product development task uncertainty and performance. International journal of project management, 39 (1), 85-95.

[12] Seiti, H., Hafezalkotob, A., &Martínez, L. (2019). R-numbers, a new risk modeling associated with fuzzy numbers and its application to decision making. *Information Sciences*, *483*, 206-231.

[13] Zadeh, L. A. (2011). A note on Z-numbers. *Information Sciences*, *181*(14), 2923-2932.

[14] Seiti, H., Hafezalkotob, A., Najafi, S. E., &Khalaj, M. (2019). Developing a novel risk-based MCDM approach based on D numbers and fuzzy information axiom and its applications in preventive maintenance planning. *Applied Soft Computing*, 105559.

[15] Pang, Q., Wang, H., & Xu, Z. (2016). Probabilistic linguistic term sets in multi-attribute group decision making. *Information Sciences*, *369*, 128-143.

[16] Atanassov, K. (2016). Intuitionistic fuzzy sets. *International Journal Bioautomation*, *20*, 1.

[17] Zhu, G. N., Hu, J., & Ren, H. (2020). A fuzzy rough number-based AHP-TOPSIS for design concept evaluation under uncertain environments. *Applied Soft Computing*, *91*, 106228.

[18] Seiti, H., &Hafezalkotob, A. (2019). Developing the R-TOPSIS methodology for risk-based preventive maintenance planning: A case study in rolling mill company. *Computers & Industrial Engineering*, *128*, 622-636.

[19] Opricovic, S., Tzeng, G-H., 2004. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research 156 (2004) 445–455.

[20] Opricovic, S., Tzeng, G-H., 2007. Extended VIKOR method in comparison with outranking methods. European Journal of Operational Research 178 (2007) 514–529.

[21] Pourjavad, E., & Peng, W. (2017). An integrated fuzzy MCDM approach for risk evaluation of new product in a pipe industry. *International Journal of Product Development*, *22*(3), 165-188.

[22] Yeh, T. M., Pai, F. Y., & Liao, C. W. (2014). Using a hybrid MCDM methodology to identify critical factors in new product development. *Neural Computing and Applications*, *24*(3-4), 957-971.

[23] Tixier, J., Dusserre, G., Salvi, O., & Gaston, D. (2002). Review of 62 risk analysis methodologies of industrial plants. *Journal of Loss Prevention in the process industries*, *15*(4), 291-303.

[24] Kwak, Y. H., &LaPlace, K. S. (2005). Examining risk tolerance in project-driven organization.*Technovation*, *25*(6), 691-695.

[25] Marmier, F., Deniaud, I. F., &Gourc, D. (2014). Strategic decision-making in NPD projects according to risk: Application to satellites design projects. *Computers in Industry*, *65*(8), 1107-1114.

[26] Warfield, J. N. (1974). Toward interpretation of complex structural models.*IEEE Transactions on Systems, Man, and Cybernetics*, (5), 405-417.

[27] Attri, R., Dev, N., & Sharma, V. (2013). Interpretive structural modeling (ISM) approach: an overview. Research.*Journal of Management Sciences*, 2319, 1171

[28] Wu, W. W. (2008). Choosing knowledge management strategies by using a combined ANP and DEMATEL approach.*Expert Systems with Applications*, *35*(3), 828-835.

[29] Tan, T., Chen, K., Xue, F., & Lu, W. (2019). Barriers to Building Information Modeling (BIM) implementation in China's prefabricated construction: An interpretive structural modeling (ISM) approach. *Journal of Cleaner Production*, *219*, 949-959.

[30] Lin, X., Cui, S., Han, Y., Geng, Z., &Zhong, Y. (2019). An improved ISM method based on GRA for hierarchical analyzing the influencing factors of food safety.*Food control*, *99*, 48-56.

[31] Li, F., Wang, W., Dubljevic, S., Khan, F., Xu, J., & Yi, J. (2019). Analysis on accident-causing factors of urban buried gas pipeline network by combining DEMATEL, ISM and BN methods. *Journal of Loss Prevention in the Process Industries*.

[32] Bairagi, B., Dey, B., Sarkar, B., & Sanyal, S. (2014). Selection of robot for automated foundry operations using fuzzy multi-criteria decision making approaches. *International Journal of Management Science and Engineering Management*, *9*(3), 221-232.

[33] Parameshwaran, R. , Praveen Kumar, S. , &Saravanakumar, K. (2015). An integrated fuzzy MCDM based approach for robot selection considering objective and sub- jective criteria. Applied Soft Computing, 26 , 31–41 .

[34] Mehbodniya, A., Kaleem, F., Yen, K. and Adachi, F., (2013), " A fuzzy extension of VIKOR for target network selection in heterogeneous wireless environments", Physical Communication, Vol 7, pp. 145–155.

[35] Zeng, Sh., Chen, Sh. and Kuo, L.W., (2019), "Multiattribute decision making based on novel score function of intuitionistic fuzzy values and modifiedVIKOR method", Information Sciences.

[36] Yue, C. (2020). Picture fuzzy normalized projection and extended VIKOR approach to software reliability assessment. *Applied Soft Computing*, 106056.

[37] Liang, D., Zhang, Y., Xu, Z., & Jamaldeen, A. (2019). Pythagorean fuzzy VIKOR approaches based on TODIM for evaluating internet banking website quality of Ghanaian banking industry. *Applied Soft Computing*, *78*, 583-594.

[38] Colin, J., Estampe, D., Pfohl, H. C., Gallus, P., & Thomas, D. (2011). Interpretive structural modeling of supply chain risks. *International Journal of physical distribution & logistics management*.

[39] Seiti, H., Hafezalkotob, A., & Martinez, L. (2019). R-sets, Comprehensive Fuzzy Sets Risk Modeling for Risk-based Information Fusion and Decision-making. *IEEE Transactions on Fuzzy Systems*.

[40] Deng, Y., Chen, Y., Zhang, Y., & Mahadevan, S. (2012). Fuzzy Dijkstra algorithm for shortest path problem under uncertain environment. *Applied Soft Computing*, *12*(3), 1231-1237.

[41] Ojha, R., Ghadge, A., Tiwari, M. K., & Bititci, U. S. (2018). Bayesian network modelling for supply chain risk propagation. *International Journal of Production Research*, *56*(17), 5795-5819.

[42] de Gusmão, A. P. H., Silva, M. M., Poleto, T., e Silva, L. C., & Costa, A. P. C. S. (2018). Cybersecurity risk analysis model using fault tree analysis and fuzzy decision theory. *International Journal of Information Management*, *43*, 248-260.

[43] Chattopadhyay, R., Chakraborty, S., Chakraborty, S.,2020. An integrated D-MARCOS method for supplier selection in an iron and steel industry. Decision Making: Applications in Management and Engineering 3,2,49-69.

[44] Turanoglu Bekar, E., Cakmakci, M., & Kahraman, C. (2016). Fuzzy COPRAS method for performance measurement in total productive maintenance: a comparative analysis. *Journal of Business Economics and Management*, *17*(5), 663-684.

*Declaration of Interest Statement

Declaration of Interest Statement

- All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

- This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

- The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript

Seyedeh Anahita Mousavi Conceptualization, Methodology, Data curation, Visualization, Validation, Writing- Original draft, preparation, Writing- Reviewing, and Editing.

Hamidreza Seiti: Methodology, Writing- Original draft, preparation, Writing- Reviewing, and Editing.

Ashkan Hafezalkotob: Methodology, Supervision, Reviewing, Editing

Sobhan Asian: Supervision, Reviewing, Editing

Rouhollah Mobarra: Case study analysis-Data gathering