A novel intuitionistic fuzzy FMEA framework with Dombi aggregation for service quality in industry 4.0: application in higher education

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Abstract:

Introduction/purpose: Higher educational service quality (HSQ) is one of the prominent areas redefined in I4, imposing many challenges on higher educational institutions (HEIs). In this context, the present work aims to fulfill two objectives: a) to develop a novel risk assessment framework for failure mode and effect analysis (FMEA) using the intuitionistic fuzzy set (IFS) and b) to assess potential risk factors or failures faced by HEIs in delivering superior HSQ in Industry 4.0 (I4).

Methods: The present work uses a multi-criteria decision-making (MCDM) model, such as comparisons between ranked criteria (COBRAC), with IFS-based Dombi aggregation for group decision making to develop a novel extension of the FMEA framework. The present work proposes an innovative approach by incorporating an additional dimension in the classical FMEA model such as intractability. The failure modes (FMs) are identified from the viewpoint of the HSQ attributes. Subsequently, the present work examines the validity of the outcome by comparing several MCDM models and sensitivity analysis.

Results: Based on the opinions of 23 experts, the current work reveals the dominance of risk factors such as ethical concerns (FM-9), infrastructural constraints (FM-2), and shortage of funds (FM-6).

Conclusion: The paper highlights the need to build a holistic ecosystem with available resources. The ongoing study provides several novelties, such as an extension of FMEA with an additional dimension and IFS-Dombi *aggregation, using the COBRAC model for FMEA, and an innovative approach to risk assessment for HSQ, which are helpful for decision makers and researchers.*

Key words: service quality, higher educational institutions, FMEA, intuitionistic fuzzy set, COBRAC, Dombi aggregation.

Introduction

The higher education system (HES) is pivotal in ensuring economic growth, fostering sustainable development, developing and nurturing talents for future potential, and building an innovative ecosystem while integrating society, business, and government. A well-developed and executed HES promotes innovation and technical progress, sustaining economic prosperity. It advances social fairness, enabling more seamless transfers within the job market. Higher education investments favourably correlate with economic growth, particularly in human capital development (Chaabouni & Mbarek, 2023). After the beginning of Industry 4.0 in 2011, the HES and higher educational institutions (HEIs) have witnessed phenomenal technological growth in Industry 4.0 (I4). The recent pandemic has pronounced the power of digital technologies in higher education. Digital technologies like smart classrooms, augmented and virtual reality, the Internet of Things (IoT), cloud-based interactivity and computing, cutting-edge computing tools and techniques, digital twins, chatbots, and blockchains have redefined HSQ offered by the HES in I4. The changes are reflected in the curriculum transformation (emphasizing technical, cognitive, and problem-solving skills, entrepreneurial mindset and adaptive thinking for career development, and ethical concerns), innovative teaching-learning environment (using flipped classrooms, AR/VR-based interactions, use of avatars and simulations, emphasis on experiential learning, personalized and blended learning and content delivery), student engagement, stakeholder connect, administrative process, and collaborative research and partnerships (Jamaludin et al, 2020; Moraes et al, 2023; Dempere et al, 2023; Alenezi, 2023; Biswas et al, 2023; Wang et al, 2023).

While technological progress has offered several opportunities for HEIs, the HES has also been exposed to many unprecedented challenges or potential risk factors. The risks stem from the factors such as digital inclusion, accessibility and implementation of technological advancements, competency building for faculty members and students, and re-alignment of the existing HES and teaching-learning processes in the realm of technological progress while maintaining diversity and ethics to satisfy the needs of stakeholders (Majid et al, 2022). The digital revolution of higher education encounters obstacles in equipping educators with essential digital competencies for effective teaching. Assessing digital competencies is essential for successful digital learning programs, and inadequate training may impede these advantages (Akhmetshin et al, 2020; Chaabouni & Mbarek, 2023). Given the opportunities and challenges posited by technological advancements for HEIs, the present age invokes adaptability to the evolving demands of students and other stakeholders, including corporate bodies, efficient technology utilization, and prioritization of quality and accessibility (Liu & Shi, 2023; Abulibdeh et al, 2024). Digital transformation in higher education emphasizes tailored learning environments, improving engagement and motivation, and aligning with the connectivism theory to ensure sustainability and academic achievement and address different student requirements (Shenkoya & Kim, 2023; Leow et al, 2023). HEIs must bring about a cultural shift within and around the HES to overcome the challenges and risk factors for developing a conducive and adaptable innovative ecosystem to ride on technological growth (Alenezi & Akour, 2023). The myriad of contributions toward unlocking the potential and challenges for HEIs in I4 necessitates the development of a comprehensive risk assessment framework for evaluating possible failure modes or risk factors. The existing literature does not reveal plentiful contributions using a multidimensional risk assessment framework for unearthing criticalities of the risk factors. The aforesaid gap in the literature motivates us to be committed to this work.

The current work utilizes a widely used risk assessment framework such as failure mode and effects analysis (FMEA). The classical FMEA framework embodies priority scores of the risk factors based on three dimensions such as severity (S) (signifying the extent to which the concerned risk factor is affecting the system), occurrence (O) (indicating the likelihood of occurrence of the corresponding risk factor), and detectability (D) (reflects the extent to which the system can identify the corresponding risk factor). The overall priority of the risk factor is determined by a risk priority number (RPN) ($RPN = S \times O \times D$) (Bowles & Peláez, 1995).

FMEA has been widely applied by scholars in various risk assessment problems, *see,* e.g., (Peddi et al, 2023; Sun et al, 2023; Resende et al, 2024). The existing literature shows several applications of FMEA in higher education, *see,* e.g., (Lin & Lo, 2024; Nasrallah et al, 2023). Nevertheless, FMEA has enormous potential for applications in higher education to evaluate risk priority in various processes, including HSQ (Zulfiqar et al, 2024). Some contributions used FMEA vis-à-vis HSQ (Anastasiadou & Zirinoglou, 2020). However, the applications of FMEA for figuring out service quality risks for higher education in I4 are limited, almost rare. This has motivated us to utilize FMEA to evaluate the priorities of the failure modes (FM) of HSQ. Further, we learn some limitations of the classical FMEA model from scholars (Salah et al, 2023; Liu et al, 2024; Sumrit & Keeratibhubordee, 2025). The classical FMEA model suffers from limitations such as the following ones: a) Conventional FMEA model cannot capture the impreciseness of information and subjective bias; b) In the conventional FMEA model, there is no prioritization of individual dimensions. Further, there is no room for assigning relative importance to the risk factors from the perspective of the context of the problem. As a result, on many occasions, there may be multiple FMs having the same RPN value; c) There are no options to assign weights to decision makers (based on their expertise or experience, etc.) in traditional FMEA; and d) The calculation of the RPN is relatively simple, which often dilutes the outcome.

Given these limitations, numerous contributions have modified classical FMEA using uncertainty-based modelling (Yu et al, 2023; Sun et al, 2023). This paper uses IFS-based analysis to capture uncertainty and subjective bias for carrying out FMEA. Some studies incorporated additional dimensions in the conventional FMEA model. For instance, Salah et al. (2023) used an additional criterion, such as the dependency of the risk factors on each other. Besides dependency, the aforesaid work also applied the Pareto principle to classify the risk factors. The work of Sumrit & Keeratibhubordee (2025) proposes three additional dimensions: cost of FM, complexity of resolution, and impact on business. However, none of the previous extensions of FMEA have precisely considered a crucial aspect called the manageability of risk. It is important to determine the mitigation plan for managing the risks effectively. Given volatility, uncertainty, complexity, and ambiguity (VUCA) prevailing over the external environment, the identified risks' manageability helps decision makers prepare contingency and preventive action plans. The proposed FMEA approach of this study is thus an action plan driven approach with wide practical applications. In this work, we fill the stated gap in the literature by providing an innovative approach of carrying out FMEA. Hence, the current study sets the following research objectives:

- *RO 1*. To develop a multi-perspective framework for evaluating the priorities of the risk factors or failure modes of higher education service quality in Industry 4.0.

- *RO2.* To modify the conventional FMEA framework and extend it using subjective information under uncertainty.

To widen the applicability of classical fuzzy sets (CFSs) (Zadeh, 1965), the concept of IFSs was proposed to capture the vagueness through two types of membership functions such as the membership (μ) and the non-membership (ϑ), subject to their interrelationship determined by the inequality $\mu + \vartheta \leq 1$ (Atanassov, 1986). Table 1 provides a summary of some of the advancements of CFSs. Table 1 shows that the IFS provides more pragmatic analysis under uncertainty than the CFS, yet it is simple to apply and conceptualize.

Table 1 – Evolution of fuzzy sets and its advancements

Type of Fuzzy Sets	Concept	Remarks	Reference
CFSs	Consider only $\mu \in [0,1]$	Limited but straightforward to consider the imprecision	Zadeh (1965)
Type 2 Fuzzy Sets	Fuzziness of the membership degree	Can handle a higher level of uncertainty, but complex in calculation, and consider a single membership	Zadeh (1975a)
Interval-Valued Fuzzy Sets	Membership degree is expressed in terms of the interval	A better representation than CFSs but limited to a single membership interval	Zadeh (1975b)
IFSs	Consider both $\mu, \vartheta \in [0,1]$ such that $\mu + \vartheta \leq 1$	Simple to understand and a better representation of imprecision. However, they are constrained by the cases where $\mu + \vartheta > 1$	Atanassov (1986)
Hesitant Fuzzy Sets	Existence of multiple membership degrees	Able to deal with indeterminacy but computationally complex for large datasets	Torra (2010)
Spherical Fuzzy Sets	Consider the neutral membership degree such that $\mu^2 + \eta^2 + \vartheta^2 \leq 1$.	A generalization of PyFS with the degree of neutrality. They are limited to spherical constraint and complex	Gündoğdu & Kahraman (2019)
p, q-Quasirung Orthopair Fuzzy Sets	Consider both $\mu, \vartheta \in [0,1]$ such that $\mu^p + \vartheta^q \leq 1; p, q \geq 1$	Further generalization of qROFSs but suffer from complexity in parameter selection	Seikh & Mandal (2022)

The remainder of this manuscript is organized in the following manner. The subsequent section (Section 2) revisits recent studies published in related fields. Section 3 exhibits the preliminary concepts of the IFS. Section 4 outlines the steps of the research methodology. Section 5 records significant findings. Section 6 discusses the findings and outlines research implications. In the end, Section 7 provides the concluding remarks and highlights future scopes.

Underpinning of related work

This section revisits the existing literature to provide a theoretical foundation for the current study.

Theoretical underpinning: Service quality models

The SERVQUAL model defines service quality (SQ) as a measure to close the gap between expected and experienced service levels. The classical SERVQUAL framework has five underlying dimensions: reliability, tangibles, responsiveness, assurance, and empathy. HEIs have adopted the SERVQUAL model to define HSQ. According to the SERVQUAL model used in the HES, HSQ is measured by the effectiveness in teaching and learning, faculty and student quality, and facilitating conditions to support students. Many HEIs have used the SERVQUAL model to define measurable performance attributes while upholding the reliability and trust of service delivery, ultimately leading to stakeholder satisfaction and organizational excellence (Oliso et al, 2024; Fuchs & Fangpong, 2021; Abbas, 2020). For the enduring performance and competitiveness of HEIs to achieve sustainable growth, the nexus between service quality, satisfaction, and loyalty is essential (Nguyen et al, 2024).

Nevertheless, several scholars highlighted the pressing need to revise the conventional SERVQUAL model while being adopted in the HES. Researchers devised an alternative framework, such as the HEdPERF (Higher Education PERFormance) model (Abdullah, 2005). This model evaluates service quality in higher education through five dimensions: academic and non-academic components, reputation, access, and program-related difficulties. It assesses instructional quality, extracurricular attributes, prestige, accessibility, and course pertinence to ensure an exceptional educational experience (Feifei et al, 2022).

The SQM-HEI approach, created by Indian academics, emphasizes the assessment of service quality in higher education, incorporating instructional methods, environmental modifications, and disciplinary measures to improve educational quality in the nation (Khan et al, 2022; Subandi & Hamid, 2021). Research indicates a favorable correlation between transformative service quality and satisfaction in higher education. The technical dimension of service quality, incredibly transformational service quality, profoundly influences student satisfaction. Students' mental goodness shapes their emotional response toward their university, and they anticipate equitable treatment. Functional service quality significantly influences the perceived value more than the technical component (Teeroovengadum et al, 2019).

The theoretical contributions reveal that HSQ depends on several attributes. Some of the crucial attributes are outlined below.

- The evolving and contemporary curriculum is a pivotal attribute in enhancing HSQ. It is the cornerstone for skill development, enhancing students' employability, promoting analytical reasoning, innovative concepts, efficient decision making, and adaptability to evolving educational requirements.
- Knowledge discovery and dissemination play crucial roles in HSQ. They indicate the development of requisite competencies and skills, fostering research, innovation, curriculum development, and stakeholder engagement.
- Innovative teaching-learning environment: This is required to foster experiential learning, linking theoretical knowledge to practical application, and equipping students for employment.
- Physical and technological infrastructure: This attribute entails the resources supporting interdisciplinary programs, experiential learning, and entrepreneurial programs, innovative teaching and learning through flipped classrooms, online platforms, innovative delivery, and simulations to provide students with a comprehensive, personalized and immersive learning experience while enhancing student satisfaction and upholding institutional prestige.
- Support services: Refer to the availability of responsive, empathetic, and accessible administrative and academic support to cater to the needs of diverse student categories while offering necessary guidance and counseling.
- Organizational culture is about shared values and ethics and promoting community impact. An open culture, led by good governance, promotes student development, equity, and adaptability.

Challenges of HEIs in the digital age

This section summarizes some related past studies discussing challenges or potential risk factors for HEIs to deliver superior HSQ in I4. The challenges are discussed in various contexts, and scholars have adopted different methodologies, as recorded in Table 2.

Table 2 – Summary of some research contributions discussing challenges for HEIs

Author(s)	Context	The ory	Key challenges	Methodology
Benavides et al, 2020	Digital technology applications in higher education	NA	Curriculum upgradation and flexibility, lack of innovation, knowledge and competencies, organizational change	Qualitative: a review of the literature
Bonfield et al, 2020	Application of I4 technologies in HEIs across different countries	NA	Shortage of skills, creation of a memorable student experience, security and privacy, innovative teaching methods	Qualitative – scenario analysis and case studies
Mahyoob, 2020	Challenges faced by learners attending e-learning programs in the context of COVID-19	Activity theory	Inefficiency in technology use, language issues	Descriptive analysis of the responses received from 148 students
Fahim et al, 2021	Enrolment in MBA programs offered by HEIs	NA	Poor employability, lack of entrepreneurial programs, cost, long payback period, poor ROI	Subjective information-based grey incidence analysis
Žalėnienė & Pereira, 2021	Sustainability in higher education	NA	Sustainability-focused curriculum development and organizational culture, community connect	Qualitative-discussions and perspectives
Wang et al, 2023	HEIs in I4	NA	Upgradation and development of contemporary curriculum, integration of digital technologies, adoption of advanced computing such as cloud computing	Subjective and objective information-based application of the q Rung Orthopair fuzzy MEREC-SWARA-CoCoSo framework

Author(s)	Context	Theory	Key challenges	Methodology
Rasul et al, 2023	Use of generative AI (ChatGPT) in higher education	Constructivist theory of learning	Maintenance of ethics and equity, academic integrity, information distortion, lack of skills, evaluation of learning outcome	Qualitative: a review of the literature and conceptual framework
Chan & Hu, 2023	Students' perception of the use of generative AI in higher education	NA	Ethics and privacy issues, lack of competencies, diluted human values, improper policy	Mixed method: empirical analysis of 339 responses from Hong Kong using descriptive and thematic analysis
Abulibdeh et al, 2024	Digital technologies for sustainable development	NA	Shortage of IT and analytical skills, curriculum update, shortage of infrastructure, and industry connect	Qualitative: a review of the literature
Li, 2024	Role of higher education in developing workforce for manufacturing	NA	Skill development	Qualitative: a review of the literature and conceptual framework
This paper	HSQ of Indian HEIs in I4	Mixed theory	Ethical concerns, infrastructural constraints, shortage of funds	Modified FMEA framework with the IFS-Dombi aggregation-based COBRAC method

Failure Modes and Effect Analysis framework for risk assessment

The FMEA framework is a widely used model for evaluating risk factors. Its applications are found in various domains such as engineering, technology, basic science, social science, and management. Scholars have modified and extended the FMEA model using uncertainty measures, MCDM models, and machine learning methods. Table 3 provides a summary of some of the recent contributions.

Table 3 – Summary of research contributions applying FMEA

Author(s)	Application area	Dimen sions	Information type	Approach
Sun et al, 2023	Lead-acid battery manufacturing process	S, O, D	Subjective	FMEA using regret theory and ORESTE
Ervural & Ayaz, 2023	Manufacturing	S, O, D	Objective	FMEA using modified CRITIC and Alternative by Alternative Comparison (ABAC)
Park et al, 2023	Cybersecurity	S, O, D	Subjective	FMEA using a rule-based Bayesian network (RBN)
Ceylan et al, 2023	Maritime logistics	S, O, D	Objective and subjective	Classical FMEA
Liu et al, 2023a	Aircraft power system	S, O, D	Subjective	FMEA using the unbalanced hesitant fuzzy linguistic term sets and experts' weighting
Peddi et al, 2023	Food waste management in the supply chain	S, O, D	Subjective	Dynamic prediction of RPN values using deep neural network (machine learning) based FMEA
Liu et al, 2023b	Social network analysis	S, O, D	Subjective	Probabilistic double hierarchy linguistic term sets and WASPAS method and weight determination
Yu et al, 2023	Maritime logistics (submarine pipeline failures)	S, O, D	Subjective	Interval-valued intuitionistic fuzzy rough number and modified TODIM and PROMETHEE-II methods
Xue et al, 2024	Identification of barriers to electric vehicles	S, O, D	Subjective	FMEA using interval-valued intuitionistic fuzzy sets, grey relational analysis, and expert weighting

Author(s)	Application area	Dimensions	Information type	Approach
Sumrit & Keeratibhuborde e, 2025	Sustainable supply chain management	S, O, D + cost, complexity, and impact on business	Objective and subjective	FMEA with MCDM models such as LOPCOW, AHP, and ARAS
Nasrallah et al, 2023	Safety risk measures in laboratories	S, O, D	Objective	Classical FMEA
This paper	Higher education service quality in I4	S, O, D + **Intractability (new dimension)**	Subjective	FMEA with intuitionistic fuzzy sets and the Dombi aggregation-based COBRAC method and experts' weighting

MCDM methods for criteria weighting

The field of MCDM methods for determining criteria weights using subjective opinions has been rapidly expanded over the last few decades. The Analytic Hierarchy Process (AHP) method is one of the widely used approaches. However, AHP suffers from more pairwise comparisons and demonstrates inconsistencies in decision making while considering more criteria and respondents. Scholars (Keršuliene et al, 2010) gradually developed a SWARA method that requires only (n-1) pairwise comparisons. However, this method requires sorting the criteria at the beginning and considerably depends on the values assigned to the criteria. Rezaei (2015) introduced BWM to solve the issue of cognitive burden. BWM sets the references at the beginning by identifying the best and worst criteria. BWM requires much fewer pairwise comparisons (2n-3) than AHP, can deal with an extensive criteria set, and provides a consistency checking. Pamucar et al. (2019) developed the FUCOM method to reduce pairwise comparisons while checking for consistency. FUCOM requires only (n-1) number of global pairwise comparisons.

Related work on the applications of Dombi aggregation

Several researchers have applied Dombi aggregation to MCDM-related problems using imprecise information. Seikh and Chatterjee (2024) developed a confidence level based IFS Dombi aggregation for e-learning website selection. Zhang & Ye (2024) introduced single-valued neutrosophic fuzzy trigonometric Dombi aggregation operators for vaccine selection. Ali & Yang (2024) defined circular qROFS based Dombi aggregation operators for MCDM applications. Liu et al. (2024) devised complex Pythagorean fuzzy Dombi aggregation for green supply chain management applications. Recently, Khan et al. (2025) applied intuitionistic fuzzy rough set and Dombi aggregation to solar cell selection problem.

Research gaps and motivations of the present study

The following research gaps, revealed from Table 1, can be noticed. First, studies using theoretical lenses are not plentiful. Second, except for a few studies, most past contributions used conceptual and review papers to address the application and challenges of digital technologies in higher education. Third, there is a lack of focus on HSQ in I4.

It can be noticed (Table 2) that most contributions are made in manufacturing, logistics, supply chain management, and engineering problems. However, FMEA has also been used in several problems concerning the HES. It is evident that FMEA has not been applied extensively concerning HSQ in I4. Several studies have used subjective information-based analysis, many of which have used MCDM models. A few studies have put forth extended FMEA models, but none have considered manageability.

Some studies incorporated additional dimensions in the conventional FMEA model. For instance, Salah et al. (2023) used an additional criterion such as the dependency of risk factors on each other. Besides dependency, the aforesaid work also applied the Pareto principle to classify risk factors. The work of Sumrit and Keeratibhubordee (2025) proposes three additional dimensions: cost of FM, complexity of resolution, and impact on business. However, none of these extensions have precisely considered a crucial aspect called the manageability of risk, which is very important to know for mitigation.

Scholars have felt the importance of Dombi aggregation in solving complex real-life problems with MCDM applications. However, we could not trace any application of Dombi aggregation with FMEA to discover the key risk factors of HSQ. The application of Dombi aggregation in higher education is scant. Because of its usefulness, Dombi aggregation effectively decides the key risk factors. Furthermore, the use of IFSs reduces the computational complexity.

Contributions of the present study

In summary, the present work offers several contributions to the growing strand of literature, as outlined below.

1) The present work is the first contribution that provides a novel modification of the existing FMEA framework with an additional dimension known as Intractability (I).
2) A novel IFS and Dombi aggregation-based modified FMEA is proposed that uses the robust algorithm of COBRAC to determine the relative importance of FMs from the perspective of higher education and compute the scores of the FMs under each dimension of FMEA. COBRAC has an inherent advantage in examining deviations from consistency. Further, the COBRAC method uses fewer local pairwise comparisons, reducing computational complexity. Thus, the COBRAC method provides a more reliable approach to determining the risk appraisal score (RAS). Further, IFS and Dombi aggregation helps capture the respondents' impreciseness and subjective bias simply and flexibly.
3) The use of Dombi aggregation provides several advantages (Dombi, 1982; Xu & Yager, 2006): a) it provides a flexible aggregation by tuning the parameter (β) to capture optimism, neutrality, and pessimism; b) it helps to aggregate the effect values when criteria are not additive in nature, rather following a nonlinear relationship; c) depending on the parameter values, Dombi aggregation stands as a generalization of the simple arithmetic, geometric or harmonic means; d) it provides a better discrimination of the alternatives or criteria when the performance or effect values are subtle, i.e., very close to each other; and e) it also enables the examination of the sensitivity of the outcome concerning the variations in the external conditions. In this problem, we decide the RAS depending on the aggregated result of four risk dimensions. The experts who rated the risk factors have different risk perceptions - aggressive, conservative, and neutral. Hence, a small imprecision in the subjective opinion-based prioritization of the risk factors may result in an amplified error in the RAS. Therefore, the IFS with Dombi aggregation provides a reliable risk assessment framework for complex real-life problems.
4) An innovative approach using the conceptual approach of a simple additive weighting (SAW) method to determine the RAS using the relative importance of FMs and their positions based on FMEA

dimensions such as S, O, D, and I. In effect, a scientific basis is provided to arrive at the RAS other than a simple multiplication of the dimensions of FMEA.

5) It is also evident that the application of FMEA in HSQ literature is minimal, almost negligible. Hence, the present paper demonstrates an efficient approach to determining the RAS of various risk factors of HSQ in I4.
6) Four-dimensional modified FMEA with IFS and Dombi aggregation is apparently the first application for assessing the RAS of the FMs to ensure HSQ in I4. The existing literature shows past contributions related to various barriers or challenges to the HEIs' adoption of digital technologies in I4. However, there is a scantiness of contributions weighing the risk factors based on their likelihood of happening, consequence, detectability, and manageability. This paper fulfills the gap in the literature on HSQ concerning the effect of advanced digital technologies.
7) It demonstrates the sensitivity analysis and reliability assessment of the FMEA framework with an additional dimension and IFS-based appraisal.

Preliminary concepts

The present module discusses some preliminary definitions and rules for operating with IFSs. Past studies (Atanassov, 1986; Hong & Choi,2000; Xu & Yager, 2006; Xu, 2007) have given the basic definitions and operations below.

Definition 1.

Let Ω be the universe of discourse containing the IFS, defined as

$$\Upsilon = \left\{ \left\langle y, \mu(y), \vartheta(y) \right\rangle \middle| y \in \Omega \right\}$$

where $\mu(y), \vartheta(y)$ are defining the degree of membership and non-membership of the elements y such that

$$0 \le \mu(y) + \vartheta(y) \le 1 \quad for\ all\ y \in \Omega \to [0,1]$$

The degree of indeterminacy is derived from the definition of the IFS as

$$\zeta(y) = 1 - \mu(y) - \vartheta(y) . \tag{1}$$

In line with the definition of the IFS, an intuitionistic fuzzy number (IFN) can be expressed as $\gamma = (\mu, \vartheta)$ such that $\mu \in [0,1]; \vartheta \in [0,1]; \mu + \vartheta \le 1$.

Definition 2.

Let $\gamma = (\mu, \vartheta), \gamma_1 = (\mu_1, \vartheta_1)$ and $\gamma_2 = (\mu_2, \vartheta_2)$ be three IFNs. Here are the following definitions for operations on IFNs.

$\gamma_1 \oplus \gamma_2 = (\mu_1 + \mu_2 - \mu_1\mu_2, \vartheta_1\vartheta_2)$

$\gamma_1 \otimes \gamma_2 = (\mu_1\mu_2, \vartheta_1 + \vartheta_2 - \vartheta_1\vartheta_2)$

$a\gamma = (1-(1-\mu)^a, \vartheta^a); a > 0$ is any scalar quantity

$\gamma^a = (\mu^a, 1-(1-\vartheta)^a); a > 0$

$\gamma^c = (\vartheta, \mu)$

Definition 3.

The following definition is used to determine the score value of an IFN.

$$\wp = Score(\gamma) = \mu - \vartheta; \wp \in [-1,1] \quad (2)$$

The accuracy value of an IFN is obtained as

$$\lambda = accuracy(\gamma) = (\mu + \vartheta); \lambda \in [0,1] \quad (3)$$

The following comparison rules are used to compare two IFNs.

If $\wp_1 > \wp_2$ then $\gamma_1 \succ \gamma_2$ otherwise

If $\wp_1 < \wp_2$ then $\gamma_1 < \gamma_2$ else

If $\wp_1 = \wp_2$ then if $\lambda_1 < \lambda_2$ then $\gamma_1 < \gamma_2$

Proceeding further, the scholars (Deb et al, 2022, 2023) came up with a new definition of the score function below.

$$\wp^* = \frac{1}{2}(1 + \mu - \vartheta) \quad (4)$$

Definition 4.

Dombi aggregation

The Dombi t-norm and t-conorm (Dombi, 1982) for any two real numbers R_1 and R_2 with the parameter value $\beta \ge 1;\ (R_1, R_2) \in [0,1] \times [0,1]$ can be expressed as

$$\mathrm{T}_{norm}(R_1, R_2) = \frac{1}{1 + \left\{\left(\frac{1-R_1}{R_1}\right)^\beta + \left(\frac{1-R_2}{R_2}\right)^\beta\right\}^{\frac{1}{\beta}}} \quad (5)$$

$$T_{co-norm}(R_1,R_2)=1-\frac{1}{1+\left\{\left(\frac{R_1}{1-R_1}\right)^{\beta}+\left(\frac{R_2}{1-R_2}\right)^{\beta}\right\}^{\frac{1}{\beta}}} \tag{6}$$

Given a series of IFNs $\gamma_i=(\mu_i,\vartheta_i);\ (i=1,2...n)$ having weights $w_i\ (w_i>0;\ \sum_{i=1}^{n}w_i=1)$, the intuitionistic fuzzy Dombi weighted geometric aggregation (IFDWGA) is defined by scholars (Seikh & Mandal, 2021) as

$$IFDWGA(\gamma_1,\gamma_2,\gamma_3,....\gamma_n)=\overset{n}{\underset{i=1}{\otimes}}(\gamma_i)^{w_i}$$

$$=\left(\begin{array}{c}\dfrac{1}{1+\left\{\sum_{i=1}^{n}w_i\left(\dfrac{1-\mu_i}{\mu_i}\right)^{\beta}\right\}^{\frac{1}{\beta}}},\\ 1-\dfrac{1}{1+\left\{\sum_{i=1}^{n}w_i\left(\dfrac{\vartheta_i}{1-\vartheta_i}\right)^{\beta}\right\}^{\frac{1}{\beta}}}\end{array}\right) \tag{7}$$

Materials and methods

In this section, the research methodology is briefly outlined.

Description of the failure modes

The present study identifies nine FMs, as described below in Table 4.

Table 4 – Failure modes or risk factors for delivering HSQ in I4

S/L	Failure mode	Description
FM-1	Lack of information about digital technologies	It describes the stakeholders' unfamiliarity and lack of knowledge (students, parents, and staff) about digital technologies and their usage.
FM -2	Infrastructural constraints	It indicates inadequate digital infrastructure, including tools, internet connectivity, and resources. It also includes good administrative support services.

S/L	Failure mode	Description
FM-3	Potential skill gap	It indicates a lack of expertise among instructors and students in using advanced digital technologies, a lack of training programs and development initiatives, and a lack of connection among industry, R&D, society, and HEIs. It also entails inadequate knowledge capital and intellectual outputs.
FM-4	Cultural inertia	It describes the cultural barriers and resistance to adopting new technologies and modes of operation, such as flipped classrooms, hybrid modes, self-paced personalized learning, immersive experiential learning, fear of becoming outdated, and a lack of room for innovation. It also showcases the absence of supportive leadership.
FM-5	Difficulty in matching diverse student needs	It entails difficulty offering personalized learning experiences to students with diverse socio-demographic backgrounds and ineffective academic advising, career counseling, and mental health services. This is a critical issue, especially for students from rural and less tech-savvy backgrounds. In effect, student engagement becomes a challenge.
FM-6	Shortage of funds	It indicates the inadequacy of fund support for adopting advanced technologies, building supportive infrastructure, providing experiential learning, connecting with the community, and instilling training and development programs to bridge the skill gaps.
FM-7	Interoperability risk	It is important to compare a new technology system with the existing one before adopting it. The advanced technologies of I4 and new systems like flipped classrooms, experiential learning, and gaming require seamless integration with the existing process.
FM-8	Inability to scale up	This indicates the limited access of all departments in HEIs or all regional units to advanced technologies and processes. Further, implementing a new system on a massive scale within a short period poses a significant operational challenge.
FM-9	Ethical concerns	This includes security and privacy issues, data mismanagement, gender disparity, lack of equity, and regulatory and compliance issues.

Data collection

Twenty-three experts participated in this study's survey. These experts have substantial experience in higher education management and recruitment. Their profiles are summarized in Table 5.

An online questionnaire (using the identified FMs) was prepared and circulated to the experts. Informal discussions were also held with them while finalizing the FMs. The rating scales in linguistic terms and their corresponding IFNs are given in Table 6. Weights were also assigned to the experts based on their experience. Table 7 gives the linguistic scale to rate the experts.

Table 5 – Profile of the experts

Role	Number	Qualification	Number
Faculty member	13	Ph.D./ post-doctorate	11
Academic administrator	7	Master degree	11
Industry Practitioners/Entrepreneurs	3	Graduation	1
Total	23	Total	23
Background	Number	Experience	Number
Management/ Social Science	8	More than 25 years	7
Basic Science/ Technology	7	20 to 25 years	8
Arts/Humanities	3	15 to 20 years	4
Commerce	5	10 to 15 years	4
Total	23	Total	23

Table 6 – Linguistic rating scale and the IFNs (to rate the FMs on the dimensions S, O, D, and I)

Linguistic scale	Code	μ	ϑ
Very High	5	0.9	0.1
High	4	0.7	0.3
Medium	3	0.5	0.5
Low	2	0.3	0.7
Very Low	1	0.1	0.9

Table 7 – Linguistic rating scale and the IFNs (to rate the experts)

		IFN	
Linguistic scale	Code	μ	ϑ
Very experienced	4	0.85	0.1
Experienced	3	0.6	0.35
Medium	2	0.35	0.6
Less experienced	1	0.1	0.85

Modified FMEA framework with the IFS and Dombi aggregation

The steps of the modified FMEA framework with the IFS and Dombi aggregation are below.

Step 1. Figure out the FMs

The FMs are identified based on a literature review and experts' opinions (Table 4). Suppose fm_j denotes the j^{th} FM.

Step 2. Selection of experts and finding out their weights

Suppose there are $i = 1, 2, ..., k$ experts. Then, the weight of the i^{th} expert is calculated by using Eq. 8 (Tooranloo & sadat Ayatollah, 2016)

$$\omega_k = \frac{\left(\mu_k + \zeta_k\left(\frac{\mu_k}{\mu_k + \vartheta_k}\right)\right)}{\sum_{i=1}^{k}\left(\mu_i + \zeta_i\left(\frac{\mu_i}{\mu_i + \vartheta_i}\right)\right)} \tag{8}$$

Step 3. Rating of each FM by the experts based on each of the dimensions of the modified FMEA model, such as S, O, D and I.

Let $\varphi_{ij(S)} = \left(\mu_{ij(S)}, \vartheta_{ij(S)}\right), \varphi_{ij(O)} = \left(\mu_{ij(O)}, \vartheta_{ij(O)}\right), \varphi_{ij(D)} = \left(\mu_{ij(D)}, \vartheta_{ij(D)}\right) \text{ and } \varphi_{ij(I)} = \left(\mu_{ij(I)}, \vartheta_{ij(I)}\right)$ be the ratings (expressed in terms of IFNs corresponding to the linguistic scale selected for rating) of j^{th} FM, given by the i^{th} expert based on the dimensions of the modified FMEA model, such as S, O, D, and I, respectively.

Step 4. For each of the dimensions of the modified FMEA (M-FMEA) model, aggregate expert responses by using Dombi aggregation (Eq. 7).

The aggregated ratings of the FMs for all dimensions of M-FMEA are given by $\varphi_{j(S)} = \left(\mu_{j(S)}, \vartheta_{j(S)}\right), \varphi_{j(O)} = \left(\mu_{j(O)}, \vartheta_{j(O)}\right), \varphi_{j(D)} = \left(\mu_{j(D)}, \vartheta_{j(D)}\right) \text{ and } \varphi_{j(I)} = \left(\mu_{j(I)}, \vartheta_{j(I)}\right)$ respectively. For instance,

$$\varphi_{j(S)} = \left(\mu_{j(S)}, \vartheta_{j(S)}\right) = IFDWGA(\varphi_{1j(S)}, \varphi_{2j(S)}, ..., \varphi_{kj(S)})$$

$$= \left(\begin{array}{l} \dfrac{1}{1+\left\{\sum_{i=1}^{k}\omega_i\left(\dfrac{1-\mu_{ij(S)}}{\mu_{ij(S)}}\right)^{\beta}\right\}^{\frac{1}{\beta}}}, \\ 1-\dfrac{1}{1+\left\{\sum_{i=1}^{k}\omega_i\left(\dfrac{\vartheta_{ij(S)}}{1-\vartheta_{ij(S)}}\right)^{\beta}\right\}^{\frac{1}{\beta}}} \end{array} \right) \tag{9}$$

where $\omega_i > 0; \sum_{i=1}^{k}\omega_i = 1$ is the weight assigned to the i^{th} expert (see Eq. 8) and β is the parameter of Dombi aggregation. In a similar way, all other aggregations are calculated.

For example, $\varphi_{j(O)} = \left(\mu_{j(O)}, \vartheta_{j(O)}\right), \varphi_{j(D)} = \left(\mu_{j(D)}, \vartheta_{j(D)}\right)$ *and* $\varphi_{j(I)} = \left(\mu_{j(I)}, \vartheta_{j(I)}\right)$

Step 5. Obtain the score values of the aggregated ratings.

The score values are obtained using Eq. 4 for all aggregated ratings. For example, the score value of $\varphi_{j(S)} = \left(\mu_{j(S)}, \vartheta_{j(S)}\right)$ is obtained as

$$\wp^*_{j(S)} = \frac{1}{2}(1 + \mu_{j(S)} - \vartheta_{j(S)}) \tag{10}$$

In a similar way, $\wp^*_{j(O)}, \wp^*_{j(D)}$ *and* $\wp^*_{j(I)}$ are derived.

Step 6. Use the computed score values for ranking, pairwise comparison, and calculation of FMs' risk scores for each dimension of M-FMEA separately. For this purpose, the procedural steps of the COBRAC method (see Section 4.4) are followed. Let $\phi_{j(S)}, \phi_{j(O)}, \phi_{j(D)}$ *and* $\phi_{j(I)}$ denote the risk scores of j^{th} FM on the dimensions of M-FMEA.

Step 7. Obtain the priority weights of the FNs based on their importance to HEIs.

The experts use the linguistic scales and the corresponding IFNs in Table 5 to rate the FNs. Let, w_j be the priority weight of j^{th} FM. The priority weight is obtained by executing the process described in steps 2 to 5.

Step 8. Find out the weighted risk scores of the FNs for each dimension of M-FMEA separately. This can be obtained by multiplying the risk score with the priority weight. For example, the weighted risk score of j^{th} FM for the dimension S is found as

$$\psi_{j(S)} = w_j \times \phi_{j(S)} \tag{11}$$

In a similar way, the weighted risk scores for all other dimensions of M-FMEA, i.e., $\psi_{j(O)}, \psi_{j(D)}$ *and* $\psi_{j(I)}$ are found.

Step 9. Obtain the final risk appraisal scores (RASs) of the FMs.

The simple additive weighting (SAW) method (MacCrimmon, 1968) is followed to calculate the RAS. Accordingly, the RAS of j^{th} FM is calculated using Eq. 12, as follows:

$$\alpha_j = \psi_{j(S)} + \psi_{j(O)} + \psi_{j(D)} + \psi_{j(I)} \tag{12}$$

The higher the RAS, the more significant the corresponding FM.

Conventional COBRAC method

The Comparisons Between Ranked Criteria (COBRAC) method is developed to derive criteria weights based on localized pairwise comparison and minimization of deviation from the consistency level. COBRAC offers several benefits to analysts, providing: a) a lesser number of local comparisons helping to reduce subjective bias and produce reliable decision making; b) a large scale for local comparisons to decision makers; c) a built-in mechanism to examine consistency in decision making; and d) a reliable and consistent calculation for varying the size of attributes or criteria sets. COBRAC has started garnering attention from researchers in various applications (Biswas et al, 2024; Demir & Moslem, 2024).

The procedural steps of the conventional COBRAC method are described below.

Step 1. Ranking of the criteria

Assuming that $C_j(j \in [1,n])$ is the most influential or important criterion as compared with other criteria from the set, the preferential order is obtained as $C_{j(1)} > C_{j(2)} > ...... > C_{j(t)}$ where $t \in [1,m]$ Indicates the corresponding rank. This selection can be based on experts' opinions on a pre-defined linguistic scale or their performance score values.

Step 2. Pairwise comparison of the criteria

COBRAC works on the philosophy of local pairwise comparisons. After a pairwise comparison of the criteria, each pair of criteria is assigned a value. $\xi_{j-1,j} \in [0,1]$. For instance, $\xi_{1,2}$ is the assigned value to the first and second-ranked criteria, and $\xi_{n-1,n}$ is the assigned value for the pairwise comparison between the next to the last and the last ranked criterion. The result of the local pairwise comparison is expressed as a percentage contribution of the corresponding criteria in the interval [0,1]. For example, if $C_{j-1} > C_j$ with an assigned value $\xi_{j-1,j} = 0.60$, then it implies that C_{j-1} holds 60% of the interval [0,1], while the contribution of C_j is 40%. In the next step, a transitive relationship is formulated to obtain the global significance of the criteria.

Step 3. Obtain the weights of the criteria

The COBRAC method performs a total of $(n-1)$ number of pairwise comparisons for the n criteria. The relationships can be expressed as

$$\begin{aligned} & w_1 : w_2 = \xi_{1,2} : (1-\xi_{1,2}); \\ & w_2 : w_3 = \xi_{2,3} : (1-\xi_{2,3}); \\ & \dots\dots \quad \dots\dots\dots\dots \\ & w_{n-1} : w_n = \xi_{n-1,n} : (1-\xi_{n-1,n}) \end{aligned} \qquad (13)$$

Consistency in decision making can be achieved by meeting the transitivity condition.

$$\frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})} = 0 \qquad (14)$$

In reality, the objective is set to minimize the deviations from the consistency, i.e., $\left| \frac{\omega_{m-1}}{\omega_m} - \frac{\xi_{m-1,m}}{(1-\xi_{m-1,m})} \right| \le 0; j = 1,2...m$

To achieve the aforementioned objective, the following model is formulated.

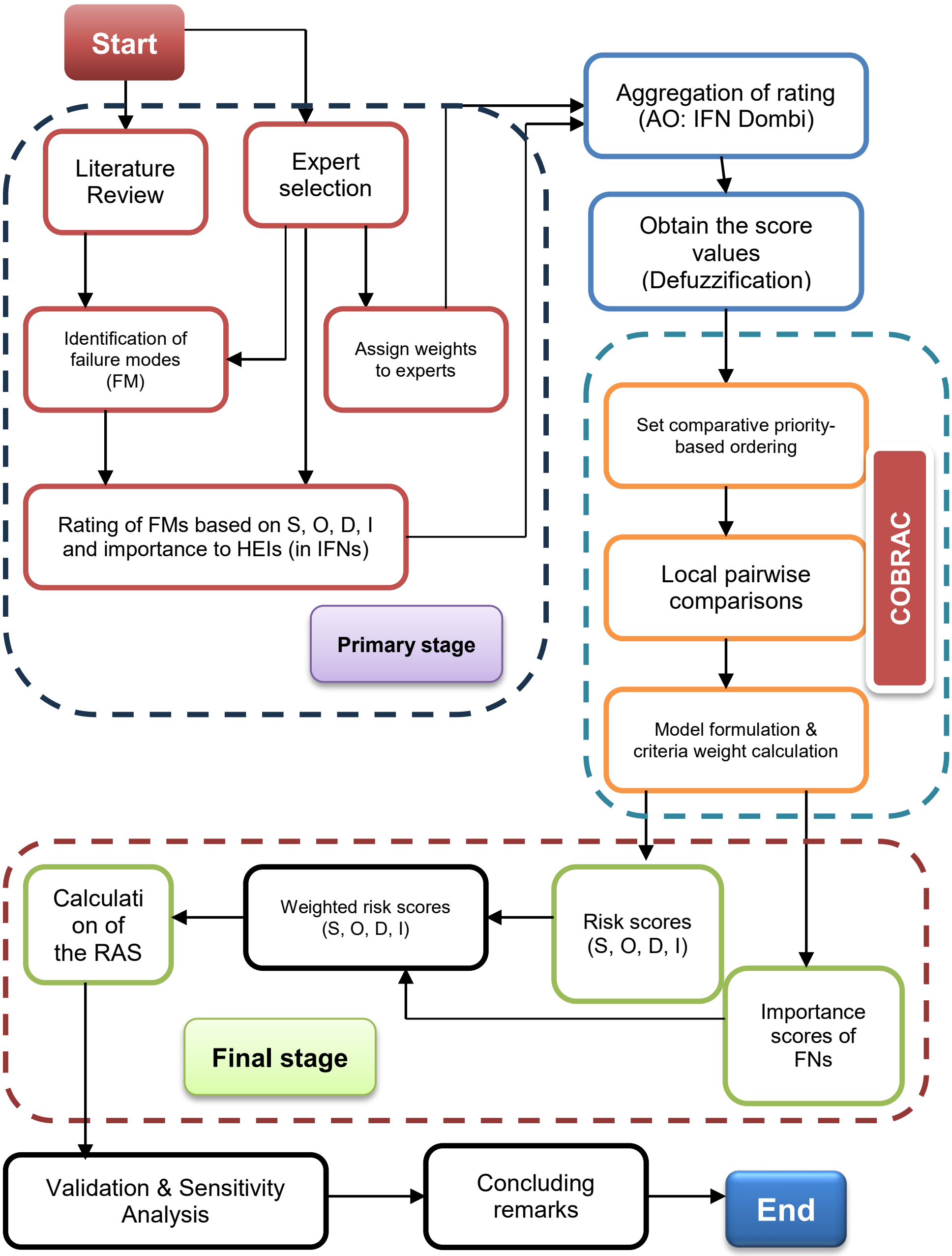

Figure 1 – Flowchart of the research methodology

$$\min \max_j \left\{ \left| \frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})} \right| \right\}$$
$$s.t.$$
$$\sum_{j=1}^{n} w_j = 1; w_j \geq 0 \ \forall j \tag{15}$$

The above model (Expression 15) is converted into a final model, from which the criteria weights are obtained.

$$Min\ \chi$$
$$s.t.$$
$$\left| \frac{w_{n-1}}{w_n} - \frac{\xi_{n-1,n}}{(1-\xi_{n-1,n})} \right| \leq \chi, \forall j$$
$$\sum_{j=1}^{n} w_j = 1; w_j \geq 0 \forall j \tag{16}$$

The steps of the research methodology are depicted in Figure 1.

Findings

This section demonstrates the step-by-step findings. Nine FMs (mentioned in Table 3) are involved in this work, and 23 experts participated in the study. Hence, there are j = 9 and k = 23. The experts are rated in linguistic terms (Table 7) according to their experience. Then, the experts' weights are found using Eq. 8. Table 5 outlines the experts' profiles, and Table 8 summarizes the calculation of their weights.

Table 8 – Calculation of the weights of the experts

Expert	Rating	μ	ϑ	ω	Expert	Rating	μ	ϑ	ω
R1	4	0.85	0.10	0.0677	R13	4	0.85	0.10	0.0677
R2	1	0.10	0.85	0.0080	R14	3	0.60	0.35	0.0478
R3	3	0.60	0.35	0.0478	R15	4	0.85	0.10	0.0677
R4	4	0.85	0.10	0.0677	R16	3	0.60	0.35	0.0478
R5	2	0.35	0.60	0.0279	R17	2	0.35	0.60	0.0279
R6	3	0.60	0.35	0.0478	R18	3	0.60	0.35	0.0478

Expert	Rating	μ	ϑ	ω	Expert	Rating	μ	ϑ	ω
R7	3	0.60	0.35	0.0478	R19	1	0.10	0.85	0.0080
R8	2	0.35	0.60	0.0279	R20	4	0.85	0.10	0.0677
R9	4	0.85	0.10	0.0677	R21	1	0.10	0.85	0.0080
R10	3	0.60	0.35	0.0478	R22	3	0.60	0.35	0.0478
R11	2	0.35	0.60	0.0279	R23	4	0.85	0.10	0.0677
R12	1	0.10	0.85	0.0080					

As a demonstration, the weight of the fifth expert is calculated as

$$\omega_5 = \frac{\left(\mu_5 + \zeta_5\left(\frac{\mu_5}{\mu_5+\vartheta_5}\right)\right)}{\sum_{i=1}^{23}\left(\mu_i + \zeta_i\left(\frac{\mu_i}{\mu_i+\vartheta_i}\right)\right)} = \frac{\left(\mu_5 + \zeta_5\left(\frac{\mu_5}{\mu_5+\vartheta_5}\right)\right)}{\left(\mu_1 + \zeta_1\left(\frac{\mu_1}{\mu_1+\vartheta_1}\right)\right) + \left(\mu_2 + \zeta_2\left(\frac{\mu_2}{\mu_2+\vartheta_2}\right)\right) + \ldots + \left(\mu_{23} + \zeta_{23}\left(\frac{\mu_{23}}{\mu_{23}+\vartheta_{23}}\right)\right)}$$

$$= \frac{\left(0.35 + 0.05\left(\frac{0.35}{0.35+0.6}\right)\right)}{\left(0.85 + 0.05\left(\frac{0.85}{0.85+0.1}\right)\right) + \left(0.1 + 0.05\left(\frac{0.1}{0.1+0.85}\right)\right) + \ldots + \left(0.85 + 0.05\left(\frac{0.85}{0.85+0.1}\right)\right)} = 0.0279$$

The experts rate various FMs based on their severity (S), occurrence (O), detectability (D), and intractability (I) using the linguistics scales provided in Table 6. For instance, experts' responses to rate various FMs based on severity are shown in Table 9. Table 6 is then used to find the corresponding IFNs for the linguistic ratings. The ratings of FMs for other dimensions (i.e., occurrence, detectability, and intractability) are shown in Tables A1 to A3 (Appendix A). Tables A5 to A8 exhibit the corresponding IFNs. Then proceed to step 4. The IFDWGA operator (Eq. 7) aggregates individual ratings of various FMs. For example, the aggregation of individual ratings for the fifth FN (indicating its severity) can be demonstrated by applying Eq. 9.

$$\varphi_{5(S)} = \left(\mu_{5(S)}, \vartheta_{5(S)}\right) = IFDWGA(\varphi_{(1)5(S)}, \varphi_{(2)5(S)}, ..., \varphi_{(23)5(S)})$$

$$= \left(\begin{array}{l} \dfrac{1}{1+\left\{\sum_{i=1}^{23}\omega_i\left(\dfrac{1-\mu_{i5(S)}}{\mu_{i5(S)}}\right)^{\beta}\right\}^{\frac{1}{\beta}}}, \\ 1-\dfrac{1}{1+\left\{\sum_{i=1}^{k}\omega_i\left(\dfrac{\vartheta_{i5(S)}}{1-\vartheta_{i5(S)}}\right)^{\beta}\right\}^{\frac{1}{\beta}}} \end{array} \right)$$

By setting $\beta = 1$ (initial case), one gets $\varphi_{5(S)} = \left(0.7046, \quad 0.2954\right)$

The aggregated values for all other FNs are similarly obtained according to their severity. It may be noted that all these aggregated results are IFNs. Next, Eq. 10 is applied to get the score values (i.e., defuzzified values) of these aggregated IFNs. For instance, the score value of $\varphi_{5(S)}$ is obtained as $\wp^{*}_{5(S)} = \frac{1}{2}(1+\mu_{5(S)} - \vartheta_{5(S)}) = \frac{1+0.7046-0.2954}{2} = 0.7046$

Table 9 – Rating of the FNs by the experts (Dimension: severity)

Respondent	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9
R1	4	4	4	4	4	4	4	4	4
R2	1	4	5	3	5	4	4	5	5
R3	3	3	3	3	5	3	4	3	4
R4	5	4	4	2	4	4	3	3	2
R5	4	5	4	4	4	3	4	4	4
R6	4	5	4	2	3	5	5	5	2
R7	3	4	4	4	3	4	3	2	4
R8	2	3	4	3	2	5	4	3	4
R9	3	4	4	4	4	3	3	4	4
R10	4	3	3	4	3	4	3	4	4
R11	4	5	5	4	5	4	5	5	4
R12	1	4	4	2	3	4	3	4	3
R13	2	2	3	3	4	5	5	5	5
R14	4	4	5	2	4	3	4	4	5

Respondent	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9
R15	2	3	3	3	3	3	3	3	3
R16	4	5	3	2	3	5	5	4	5
R17	5	5	5	5	5	5	5	5	5
R18	1	5	2	1	2	5	2	4	1
R19	3	4	4	3	4	3	3	4	4
R20	5	4	5	3	3	5	4	4	4
R21	2	3	3	3	3	5	4	4	3
R22	2	4	3	3	4	5	3	2	5
R23	2	5	4	4	3	4	4	2	4

Table 10 – Dombi aggregation (β = 1) and the calculated score values (Dimension: severity)

Failure mode	μ	ϑ	Score
FM1	0.7148	0.2852	0.7148
FM2	0.7961	0.2039	0.7961
FM3	0.7495	0.2505	0.7495
FM4	0.6045	0.3955	0.6045
FM5	0.7046	0.2954	0.7046
FM6	0.8208	0.1792	0.8208
FM7	0.7630	0.2370	0.7630
FM8	0.7459	0.2541	0.7459
FM9	0.7798	0.2202	0.7798

The aforementioned defuzzified score values are used as inputs to the procedural steps of the COBRAC method for determining the risk scores of the FNs based on their severity. The use of the COBRAC method is justified for two reasons: the consistency in decision making is thus examined and, in some instances, two FNs may obtain the same defuzzified score values making them inseparable. Following the steps mentioned in Section 4.4, one derives the risk scores of the FNs based on their severity (Table 11). The final model to derive the risk scores is given below.

$$
\begin{aligned}
& Min\ \chi \\
& s.t. \\
& \left|\frac{w_6}{w_2}-1.0310\right| \le \chi, \left|\frac{w_2}{w_9}-1.0208\right| \le \chi, \left|\frac{w_9}{w_7}-1.0221\right| \le \chi, \left|\frac{w_7}{w_3}-1.0181\right| \le \chi, \\
& \left|\frac{w_3}{w_8}-1.0047\right| \le \chi, \left|\frac{w_8}{w_1}-1.0436\right| \le \chi, \left|\frac{w_1}{w_5}-1.0144\right| \le \chi, \left|\frac{w_5}{w_4}-1.1657\right| \le \chi \\
& \sum_{j=1}^{9} w_j = 1; w_j \ge 0 \forall j
\end{aligned} \tag{17}
$$

Table 11 – Calculation of the risk scores using the COBRAC method (Dimension: severity)

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM6	0.8208	0.5076	0.4924	1.0310	0.1229
FM2	0.7961	0.5052	0.4948	1.0208	0.1192
FM9	0.7798	0.5055	0.4945	1.0221	0.1168
FM7	0.7630	0.5045	0.4955	1.0181	0.1142
FM3	0.7495	0.5012	0.4988	1.0047	0.1122
FM8	0.7459	0.5107	0.4893	1.0436	0.1117
FM1	0.7148	0.5036	0.4964	1.0144	0.1070
FM5	0.7046	0.5383	0.4617	1.1657	0.1055
FM4	0.6045				0.0905
	χ	0.00000		Sum	1.0000

Similarly, one calculates the risk scores of the FNs based on occurrence, detectability, and intractability (see Tables 12 to 14). Lingo (version 20) was used for solving Eq. 17. The sample code is given in Appendix A.

Table 12 – Calculation of the risk scores using the COBRAC method (Dimension: occurrence)

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM2	0.8101	0.5136	0.4864	1.0559	0.1252
FM6	0.7672	0.5035	0.4965	1.0139	0.1186
FM9	0.7566	0.5071	0.4929	1.0289	0.1170
FM1	0.7354	0.5059	0.4941	1.0238	0.1137

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM8	0.7183	0.5010	0.4990	1.0042	0.1111
FM7	0.7154	0.5102	0.4898	1.0416	0.1106
FM3	0.6868	0.5117	0.4883	1.0481	0.1062
FM4	0.6553	0.5125	0.4875	1.0511	0.1013
FM5	0.6234				0.0964
	χ	0.00000		Sum	1.0000

Table 13 – Calculation of the risk scores using the COBRAC method (Dimension: detectability)

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM9	0.7394	0.5370	0.4630	1.1600	0.1389
FM7	0.6374	0.5037	0.4963	1.0150	0.1198
FM4	0.6280	0.5130	0.4870	1.0533	0.1180
FM5	0.5962	0.5094	0.4906	1.0384	0.1120
FM6	0.5742	0.5119	0.4881	1.0486	0.1079
FM1	0.5476	0.5015	0.4985	1.0058	0.1029
FM3	0.5444	0.5055	0.4945	1.0224	0.1023
FM8	0.5325	0.5049	0.4951	1.0198	0.1001
FM2	0.5221				0.0981
	χ	0.00000		Sum	1.0000

Table 14 – Calculation of the risk scores using the COBRAC method (Dimension: Intractability)

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM6	0.7748	0.5089	0.4911	1.0363	0.1275
FM9	0.7477	0.5019	0.4981	1.0075	0.1231
FM2	0.7421	0.5062	0.4938	1.0252	0.1222
FM4	0.7238	0.5129	0.4871	1.0530	0.1192
FM7	0.6874	0.5217	0.4783	1.0909	0.1132
FM5	0.6301	0.5017	0.4983	1.0069	0.1037
FM8	0.6258	0.5110	0.4890	1.0451	0.1030
FM3	0.5988	0.5237	0.4763	1.0997	0.0986
FM1	0.5445				0.0896
	χ	0.00000		Sum	1.0000

Next, the priority weights of the FNs are calculated based on their importance to HEIs. The rating of the FNs in the linguistic scales and the corresponding IFNs are given in Tables A4 and A9 (Appendix A). The same process is followed as in finding out the risk scores. Table 15 shows the calculated priority weight values of the FNs. It may be noted that in all these calculations (of risk scores and priority weights), the deviations from consistency (χ) are almost negligible (≈ 0.0000). It reflects the robustness of the calculation.

Table 15 – Calculation of the priority weights of the FNs using the COBRAC method

Failure mode	Score	ξ	1-ξ	ξ/(1-ξ)	w
FM2	0.8426	0.5121	0.4879	1.0496	0.1282
FM6	0.8028	0.5012	0.4988	1.0048	0.1222
FM9	0.7990	0.5151	0.4849	1.0624	0.1216
FM1	0.7520	0.5074	0.4926	1.0302	0.1144
FM3	0.7299	0.5135	0.4865	1.0553	0.1111
FM7	0.6917	0.5035	0.4965	1.0142	0.1053
FM5	0.6820	0.5005	0.4995	1.0022	0.1038
FM8	0.6805	0.5355	0.4645	1.1530	0.1036
FM4	0.5902				0.0898
	χ	0.00000		Sum	1.0000

Eq. 11 is subsequently used to obtain the weighted risk scores of the FNs for each dimension of M-FMEA, i.e., severity, occurrence, detectability, and intractability. Then, Eq. 12 is used to compute the RASs of all FNs and to rank them (Table 16).

Table 16 – Calculation of the RASs of the FNs (M-FMEA)

		Weighted risk scores					
Failure Modes	Priority weights of failure modes	S	O	D	I	RAS	Rank
FM-1	0.1144	0.1070	0.1137	0.1029	0.0896	0.0473	5
FM-2	0.1282	0.1192	0.1252	0.0981	0.1222	0.0596	2
FM-3	0.1111	0.1122	0.1062	0.1023	0.0986	0.0466	6
FM-4	0.0898	0.0905	0.1013	0.1180	0.1192	0.0385	9
FM-5	0.1038	0.1055	0.0964	0.1120	0.1037	0.0433	8

Failure Modes	Priority weights of failure modes	S	O	D	I	RAS	Rank
FM-6	0.1222	0.1229	0.1186	0.1079	0.1275	0.0583	3
FM-7	0.1053	0.1142	0.1106	0.1198	0.1132	0.0482	4
FM-8	0.1036	0.1117	0.1111	0.1001	0.1030	0.0441	7
FM-9	0.1216	0.1168	0.1170	0.1389	0.1231	0.0603	1

Validation

A two-stage validation is performed in this paper.

First, the FMs are ranked based on their weighted risk scores related to the dimensions of M-FMEA. The FM with the highest weighted risk score is ranked first. Then, the rank index method (RIM) (Yang et al, 2019) is used to obtain the rank frequency numbers and the final rank index values. The alternative with the lowest rank index value is ranked first. Next, both ranking orders (the one obtained with M-FMEA and the other obtained with RIM) are compared, followed by the Spearman's rank correlation test. The value of the Spearman's rank correlation coefficient is obtained using Eq. 18.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{18}$$

d_i is the difference in the ranks between the constituent elements of the i^{th} pair and n is the number of elements.

The value of $\rho = 0.9167$ is obtained. This is significant at the 0.05 level (two-tailed), which confirms a significantly positive association or consistency between M-FMEA and RIM.

The existing literature shows the comparison of several MCDM models to ascertain the reliability of a specific method (Biswas & Pamucar, 2021; Pamucar et al, 2023). The FMs are ranked based on the RASs for each such case. Then, the study examines the correlation of the rankings (obtained using alternative methods) with the original results obtained using the COBRAC method. The Spearman's rank correlation test is performed to examine the correlation (Table 17).

Table 17 – Comparison of the MCDM models for the ranking of the FNs (M-FMEA)

Method		COBRAC	LBWA	PIPRECIA-S	FUCOM
LBWA	Spearman's rho	0.933 ***	—		
	p-value	< .001	—		
PIPRECIA-S	Spearman's rho	0.904 ***	0.979 ***	—	
	p-value	< .001	< .001	—	
FUCOM	Spearman's rho	0.983 ***	0.917 **	0.887 **	—
	p-value	< .001	0.001	0.001	—

* p < .05, ** p < .01, *** p < .001

The MCDM models maintain a very high and significant correlation with the COBRAC method, suggesting its reliability.

Sensitivity analysis

MCDM models are susceptible to various external conditions that influence the outcome of data analysis. The selection of methodological steps, model formulation, normalization schemes, the interplay between alternatives and criteria, the size of the alternatives and criteria sets, and aggregation approaches often make MCDM results sensitive to external variations. Therefore, the stability of the outcome is a crucial aspect of its reliability (Puška et al, 2023). Sensitivity analysis is performed to examine the stability of the outcome. The study varies the parameter values in Dombi aggregation (Görçün et al, 2023). Eight experimental cases are generated and the FNs are ranked under each such case (Table 18). The result of the sensitivity analysis is plotted in Figure 2. It is visible that the top five and bottom-most positions remain unaltered despite changes in the value. It indicates the stable ordering of the superior and inferior options. It can be noticed that for high values of β (focusing more on the membership aspect), the sub-optimum alternative FM-5 shows an improvement in its risk scores (a jump of two positions), while FM-3 and FM-8 exhibit one-step inferiority. Hence, it may be contended that this paper's model shows considerable stability.

Table 18 – Ranking of the FNs (M-FMEA) under various experimental cases

Failure Mode	Initial	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
	β = 1	β = 2	β = 3	β = 5	β = 7	β = 9	β = 20	β = 30	β = 50
FM1	5	5	5	5	5	5	5	5	5
FM2	2	2	2	2	2	2	2	2	2
FM3	6	6	6	6	6	6	7	7	7
FM4	9	9	9	9	9	9	9	9	9
FM5	8	8	8	8	8	8	6	6	6
FM6	3	3	3	3	3	3	3	3	3
FM7	4	4	4	4	4	4	4	4	4
FM8	7	7	7	7	7	7	8	8	8
FM9	1	1	1	1	1	1	1	1	1

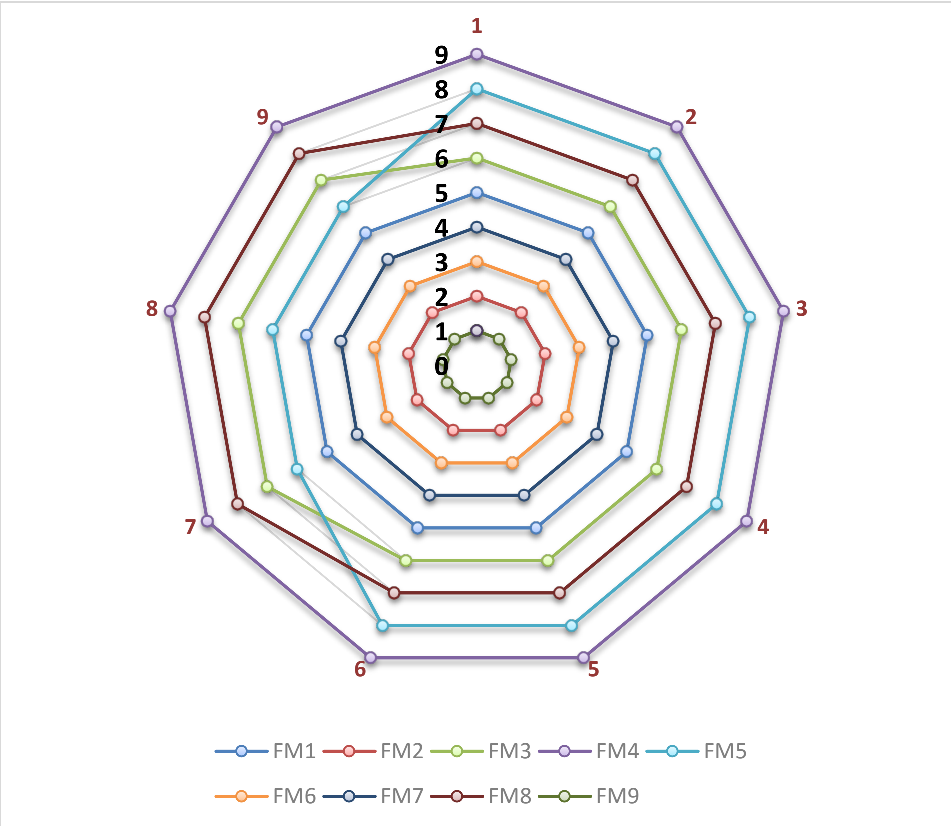

Figure 2 – Result of the sensitivity analysis

Discussion

The paper introduces a new methodology for assessing the risk factors associated with HSQ in I4. It proposes a new M-FMEA model that utilizes IFS and Dombi aggregation to fill the gaps in the literature on risk assessment frameworks and measurement of HSQ. The newly added feature (intractability) evinces the manageability of risks while providing practical insights for HEIs. From the result analysis, it is noticed that ethical concerns (FM-9), infrastructural constraints (FM-2), and shortage of funds (FM-6) are positioned as the top three FMs. More advanced technologies are invading all spheres of higher education, and ethical conduct breaches have risen. For instance, the recent development of generative AI has a double-edged effect on HSQ for good and evil intentions. Cybersecurity and privacy are of great concern today and are often affected implicitly. Moreover, scholars have been emphasizing the dark side of technology in terms of its effect on mental health and social misconduct. The breach of ethical conduct is, in fact, a silent enemy that can make or break HEIs.

Although there is a proliferation of data and rapid technological developments, many HEIs cannot leverage them because of inadequate infrastructure and resources. The availability of adequate infrastructure is a key cornerstone of the successful use of advanced technologies to deliver superior HSQ. In I4, internet connectivity and digital tools are essential to providing fast, timely, and personalized services. The traditional HES needs to undergo a massive transformation, which requires a lot of initial capital expenditure. Moreover, HEIs need to be prepared for offsetting technological obsolescence. In order to make use of digital technologies, HEIs need to create awareness and educate their stakeholders at all corners. A conducive ecosystem must connect all stakeholders, including alumni and corporates. For this, visionary and vigilant governance is of paramount importance. HEIs must prioritize the implementation of rigorous data governance frameworks and cultivate an egalitarian digital ecosystem to prevent these threats. However, the elevation of the level of HSQ requires a seamless transition, during which the compatibility of the new and existing systems stands out as a crucial success factor.

The proposed method shows high reliability, resulting in a) almost no deviation from consistency, b) a highly significant correlation with other MCDM models, and c) a high amount of internal stability. The modified FMEA approach has several advantages. First of all, this model considers the manageability aspect, which helps analysts understand the risks from the perspective of mitigation. Also, the proposed framework uses IFS-based analysis which enables to capture the subjectivity in a simple manner. Further, the use of Dombi aggregation allows decision makers to flexibly select the parameter values to examine the model sensitivity. In addition, the present model assigns weights to experts (based on their expertise/experience), which enables to consider their opinions comprehensively. Then, the developed model uses the COBRAC method to calculate the risk scores of FNs on each of the dimensions (S, O, D and I). In effect, an inherent consistency checking is built into the process for each such calculation. Hence, the calculation is examined for its robustness. The same is examined when one calculates the importance of FNs from the perspective of HEIs. Finally, in this model, the final RAS considers the dimensions like S, O, D, and I, and the priorities of FNs to HEIs. Therefore, the modified FMEA model provides a comprehensive prioritization of FNs.

The focal point of the developed FMEA framework is the use of the COBRAC method that requires only the $(n-1)$ number of local pairwise comparisons, contrast to its counterparts like BWM ($2n-3$) and AHP ($n(n-1)/2$). In this study, the number of risk factors is $n=9$. The COBRAC method (8) clearly has an advantage over BWM (15) and AHP (36). The contemporary methods like FUCOM, LBWA and SWARA also require the $(n-1)$ number of comparisons. However, FUCOM works with a globalized comparison. The LBWA method sometimes suffers from the issue of the criteria's level-wise inseparability, resulting in a high elasticity coefficient value. The SWARA method often suffers from judgmental errors.

However, the current model showcases foreseeable limitations, one of them being a slight limitation in selecting the membership and non-membership grades from a wider perspective because of linear inequality. Also, it does not consider the degree of indeterminacy. These limitations could be avoided by using other variants of fuzzy sets like p, q – Quasirung Orthopair fuzzy sets, picture fuzzy sets, and spherical fuzzy sets. Another drawback is that this framework considers a single aggregation operator and suffers from generalizability. It may be an interesting study to use multiple aggregation methods such as Dombi-Bonferroni (DOBI) that also considers the risk attitude of decision makers. Finally, the present model does not separately calculate the weights of the risk dimensions since we use priority to business as a multiplier for each of them. Nevertheless, in some cases, multiplier values and risk scores on the dimensions of the modified FMEA may be equal, resulting in possible inseparability of FNs.

The results of this study possess considerable social consequences, especially in improving equity and accessibility in higher education. By emphasizing infrastructural enhancements and tackling ethical issues like data privacy and digital ethics, HEIs may cultivate inclusive educational settings. The focus on customizing solutions for varied student requirements, particularly for individuals from minority or rural backgrounds, reduces systemic inequalities. Furthermore, the framework facilitates the identification of practical measures to establish a resilient and adaptive higher education ecosystem, crucial for cultivating socially responsible graduates prepared to succeed in a digitally driven environment.

From a managerial viewpoint, the present study demonstrates a systematic framework for resource allocation and risk management in higher education institutions. It integrates intractability to prioritize investments in feasible domains, maximizing resource allocation. The COBRAC-based ranking ensures a consistent risk assessment, facilitating strategic planning and operational efficacy. The framework incorporates modern digital technologies while adhering to ethical and legal requirements, enabling higher education institutions to be competitive in Industry 4.0. Ethical concerns, such as security, privacy, and compliance, are identified as the primary risk factor. Institutions must prioritize data governance rules and create an egalitarian digital ecosystem. Infrastructural limitations, such as inadequate digital resources and connectivity, highlight the need for scalable and sustainable infrastructure.

Conclusion

The present work demonstrates the use of a novel FMEA framework with uncertainty measures for risk appraisal. This paper considers HSQ as a problem statement. The attributes of HSQ in I4 are figured out through literature review and theoretical underpinning. Subsequently, potential risk factors or FMs have been identified. This work has formulated a focus group of 23 experts to confirm and prioritize the identified FMs according to their severity, occurrence, detectability, and a new dimension called intractability. The modified FMEA used IFSs to capture subjective bias involved in group decision making. Dombi aggregation is used to aggregate experts' responses, which provides notable flexibility to decision makers when examining the model sensitivity. The COBRAC method has been used to ascertain the least deviation from consistency, ensuring the robustness of the model. The results indicate that the essential risk factors, including ethical issues, infrastructural limitations, and financial deficiencies, profoundly affect the provision of quality education in the digital era.

Nevertheless, the current study offers several scopes for further research. First, the present work has not used any causal analysis to delve into the interrelationship among various risk factors and their effects on the performance of HEIs. Second, technological capability and intention to use have not been studied distinctly. In future work, the effect of technology adaptation as a mediator can be analysed. Third, the perspectives of various stakeholders have not been precisely considered regarding their expectations of the services rendered to them. Future studies may try to figure out the additional attributes of HSQ and incorporate these aspects into the FMEA framework to update FMs. Fourth, future studies may further augment the dimensions of M-FMEA by adding dimensions like complexity and opportunity cost. Fifth, the proposed M-FMEA framework may be applied to other various complex problems. Sixth, the IFS has a limitation in selecting membership and non-membership grades. Future studies may overcome these issues using q Rung Orthopair or p, q – Quasirung Orthopair fuzzy sets. Rough sets or intuitionistic fuzzy rough sets may also be explored for granular analysis. Seventh, the present work is also constrained by the limited sample size, which may be overcome by conducting analysis on a large scale.

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Un nuevo marco intuicionista de FMEA difuso con agregación Dombi para la calidad del servicio en la industria 4.0: aplicación en la educación superior

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CAMPO: matemáticas, ciencias de la decisión
TIPO DE ARTÍCULO: artículo científico original

Resumen:

Introducción/objetivo: La calidad de los servicios de educación superior (CSS) es una de las áreas destacadas que se han redefinido en la I4, lo que plantea numerosos desafíos a las instituciones de educación superior (IES). En este contexto, el presente trabajo busca cumplir dos objetivos: a) desarrollar un nuevo marco de evaluación de riesgos para el análisis modal de fallos y efectos (AMEF) mediante el conjunto difuso intuicionista (IFS) y b) evaluar los posibles factores de riesgo o fallos que enfrentan las IES al ofrecer una CSS superior en la Industria 4.0 (I4).

Métodos: El presente trabajo utiliza un modelo de toma de decisiones multicriterio (MCDM), como la comparación entre criterios jerarquizados (COBRAC), con agregación Dombi basada en IFS para la toma de decisiones grupales, con el fin de desarrollar una nueva extensión del marco AMFE. El presente trabajo propone un enfoque innovador al incorporar una dimensión adicional al modelo AMFE clásico, como la intratabilidad. Los modos de fallo (MF) se identifican desde la perspectiva de los atributos HSQ. Posteriormente, se examina la validez de los resultados mediante la comparación de varios modelos MCDM y un análisis de sensibilidad.

Resultados: Basado en las opiniones de 23 expertos, el trabajo actual revela el predominio de factores de riesgo como preocupaciones éticas (FM-9), limitaciones de infraestructura (FM-2) y escasez de fondos (FM-6).

Conclusión:. El artículo destaca la necesidad de construir un ecosistema holístico con los recursos disponibles. El estudio en curso aporta varias novedades, como una extensión del AMFE con una dimensión adicional y la agregación IFS-Dombi, utilizando el modelo COBRAC para AMFE, y un enfoque innovador para la evaluación de riesgos en HSQ, que resultan útiles para los responsables de la toma de decisiones y los investigadores.

Palabras claves: *calidad del servicio, instituciones de educación superior, FMEA, conjunto difuso intuicionista, COBRAC, agregación Dombi.*

Новая интуиционистская нечеткая модель FMEA с агрегацией Dombi для повышения качества услуг в эпоху четвертой промышленной революции: применение в высшем образовании

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РУБРИКА ГРНТИ: 27.47.00 Математическая кибернетика,
27.47.19 Исследование операций,
28.17.31 Моделирование процессов управления
ВИД СТАТЬИ: оригинальная научная статья

Резюме:

Введение/цель: Качество услуг высшего образования (КВО) является одной из важнейших областей, пересмотренных в условиях четвертой промышленной революции, которая ставит перед высшими учебными заведениями множество задач. В этом контексте данная статья направлена на достижение двух целей: а) разработать новую систему оценки рисков для анализа режимов и последствий сбоев (FMEA) с использованием интуиционистских нечетких множеств (ИНМ); б) оценить потенциальные факторы *риска или сбоев, с которыми сталкиваются вузы при обеспечении высокого качества КВО в условиях четвертой промышленной революции (I4).*

Методы: В статье используется многокритериальная модель принятия решений (МКМПР), основанная на сравнении ранжированных критериев (COBRAC), с агрегацией Dombi на основе IFS группового принятия решений для разработки нового расширения системы FMEA. В данной статье предлагается инновационный подход, заключающийся во внедрении дополнительного измерения отказоустойчивости в классическую модель FMEA. Виды отказов (FM) определяются с точки зрения атрибутов КВО. В заключении статьи проведена валидация достоверности полученных результатов путем сравнения нескольких моделей МКМПР и анализа чувствительности.

Результаты: На основании мнения 23 экспертов выявлены доминирующие факторы риска: этические вопросы (FM-9), инфраструктурные ограничения (FM-2) и нехватка средств (FM-6).

Вывод: В статье подчеркивается необходимость создания целостной экосистемы с использованием имеющихся ресурсов. Данное исследование содержит несколько новшеств, таких как расширение FMEA за счет дополнительного измерения и агрегации IFS-Dombi с использованием модели COBRAC для FMEA, а также инновационный подход к оценке рисков КВО, которые будут полезными для лиц, принимающих решения, и исследователей.

Ключевые слова: качество услуг, высшие учебные заведения, FMEA, интуиционистское нечеткое множество, COBRAC, агрегация Домби.

Нови интуистички расплинути ФМЕА оквир са Домби агрегацијом за квалитет услуге у индустрији 4.0 – примена у високом образовању

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ОБЛАСТ: математика, операциона истраживања
КАТЕГОРИЈА (ТИП) ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Једна од важних области које се преиспитују у четвртој индустријској револуцији јесте квалитет услуга високог образовања (HSQ), што представља изазов за високошколске установе. У том контексту, овај рад има двоструки циљ: да развије *нови оквир за процену ризика за анализу начина и ефеката отказа (FMEA) помоћу интуитивног фази скупа (IFS), као и да процени потенцијалне факторе ризика или отказа са којима се високошколске установе суочавају при пружању високог квалитета у четвртој индустријској револуцији (I4).*

Методе: У раду је коришћен модел вишекритеријумског одлучивања (MCDM) као што је поређење рангираних критеријума (COBRAC) са Домби агрегацијом заснованом на интуитивном фази скупу за групно одлучивање ради развијања нове екстензије методе FMEA. Предложен је иновативни приступ који укључује тешкоћу контролисања као додатни критеријум у класични модел FMEA. Начини отказа (FM) идентификују се са становишта атрибута HSQ. Такође, испитана је валидност исхода поређењем неколико модела MCDM и анализе осетљивости.

Резултати:На основу мишљења 23 експерта, у раду се утврђују доминантни фактори ризика, као што су етичка питања (FM-9), инфраструктурна ограничења (FM-2) и недостатак финансијских средстава (FM-6).

Закључак: У раду се наглашава потреба за креирањем холистичког екосистема са расположивим средствима. Студија у развоју предлаже неколико новина корисних за доносиоце одлука и истраживаче, као што су проширивање методе FMEA додатним критеријумом и Домби агрегацијом на основу интуитивног фази скупа, коришћење модела COBRAC за FMEA, као и иновативни приступ процени ризика за HSQ.

Кључне речи: квалитет услуге, високошколске установе, FMEA, интуитивни фази скуп, COBRAC, Домби агрегација

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