Assessing Solutions to Overcome Quality 4.0 Barriers: A Decision-Making Framework

Purpose: The industrial revolution changed the market landscape significantly in all industrial sectors. It has a noteworthy impact on enhancing the quality of goods and services. The quality aspect is of utmost concern and determines the success or failure of any product. Therefore, the presented study analyses the key barriers and solutions of Quality 4.0.

Design/Methodology/Approach: Twenty barriers and fifteen solutions were identified using a literature review and investigated using a hybrid approach. Barrier weights were evaluated with the help of the fuzzy-AHP method. Furthermore, the computed weights were used to perform computations in the next step using fuzzy-TOPSIS to prioritize the ranking of identified solutions.

Findings: The research results show that "Lack of applying advanced analytics to uncover Quality 4.0 initiatives" and "Lack of integrating data from various sources across the organization" are the topmost barriers. Furthermore, "Implement a leadership development program focused on Quality 4.0" and "Cross-departmental peer learning environment" are the topmost solutions.

Practical Implications: Managers and industrialists can benefit from Quality 4.0 through improved decision-making, process efficiency, supply chain collaboration, agile quality management, enhanced customer experience, and a culture of continuous improvement. This results in better quality, operational effectiveness, and a competitive edge.

Originality/Value: To our knowledge, solutions need to be mapped with barriers to adopting Quality 4.0. Furthermore, the research results involve novelty by prioritizing the solutions to overcome the anticipated barriers.

Keywords: Quality 4.0; Fuzzy-AHP; Fuzzy-TOPSIS; Continuous improvement

1. Introduction

Quality 4.0 is developing and becoming increasingly important in firms to achieve significant benefits (Antony et al., 2022; Zonnenshain & Kenett, 2020). It gives organizations several significant advantages (Sader et al., 2022). Utilizing cutting-edge technology such as automation, robots, artificial intelligence, and data analytics improves efficiency and production (Antony et al., 2022). Moreover, these technologies improve resource utilization, decrease errors, and streamline procedures. Second, Quality 4.0 facilitates data-driven decision-making by providing timely, precise, and thorough data insights (Broday, 2022). Therefore, organizations must use advanced analytics to uncover trends, identify patterns in their data, and make wise decisions that will lead to continual process improvement (Sony et al., 2020). Third, it also enables early detection of quality concerns through real-time data monitoring and analytics, which supports proactive quality management (Maganga & Taifa, 2022). Additionally, this aids businesses in prompt intervention, defect or nonconformance prevention, and product or service quality improvement.

Additionally, Quality 4.0 greatly improves the client experience (Antony et al., 2023). Organizations may track product performance, gather consumer feedback, and analyse data to understand customer preferences and needs by utilizing technology such as the Internet of Things (IoT). Customization, individualized experiences, and enduring client relationships also become feasible (Nenadál et al., 2022). A further benefit of Quality 4.0 is that it promotes flexibility and adaptability, empowering businesses to react swiftly to shifting market conditions (Brandenburger et al., 2021). By embracing digital technologies and automation, organizations may adapt their operations, launch new products or services more quickly, optimize supply chains, and sustain competitiveness in a business setting (Dias et al., 2022).

Quality 4.0 can further help to optimize supply chain activities, leading to end-to-end visibility and traceability (Javaid et al., 2021). Organizations may track and monitor items using technologies such as blockchain and IoT, ensuring that quality standards are met, lowering the risk of counterfeiting, and improving transparency (Sunny et al., 2020; Ranjith Kumar et al., 2022). This fosters confidence and cooperation with suppliers and partners while enhancing quality control and risk management (Fatorachian & Kazemi, 2021). By giving organizations the tools and capabilities to investigate new possibilities, quality 4.0 also fosters innovations (Emblemsvåg, 2020). Organizations may obtain insights and spot market trends and create creative goods and services by integrating emerging technology and data analytics (Escobar et al., 2021). Adopting Quality 4.0 also makes way for strategic business models such as servitization and outcome-based strategies, in which businesses emphasize providing customers with solutions and value-added services in addition to their products (Emblemsvåg, 2020).

In summary, the emergence of quality 4.0 offers a variety of benefits to various industries, including increased productivity, data-driven decision-making, proactive quality management, improved customer experience, agility and adaptability, supply chain optimization, innovation, and new business models (Kumar et al., 2022). In today's quickly evolving business environment, organizations must stay ahead of competition, satisfy customer expectations, and achieve sustainable growth by implementing Quality 4.0 (Fonseca et al., 2021).

Furthermore, researching these factors enables organizations to customize their approach to align with their unique needs and circumstances, increasing the likelihood of success (Saihi et al., 2023). Organizations can proactively address challenges and seize opportunities by identifying key solutions and barriers (Emblemsvåg, 2020). Additionally, research on assessing barriers and solutions promotes knowledge sharing and collaboration within the industry, facilitating continuous learning and improvement (Nenadál et al., 2022). Ultimately, this research contributes to future readiness and gives organizations a competitive advantage by helping them anticipate emerging trends and successfully align their strategies to adopt Quality 4.0. The presented research is carried out in the emerging economy, India. Specifically, automobile industries were chosen, contributing approximately 7.1% of the nation's GDP (IBEF, 2023). Moreover, the industry catches Foreign Direct Investment (FDI) worth US$ 34.11 billion between 2000 and 2022 (IBEF, 2023). Therefore, it is highly imperative to produce quality products. Therefore, the research objectives are framed as follows:

RO1: To examine barriers to and solutions for adopting Quality 4.0 in an emerging economy context

RO2: To rank the solutions to handle the anticipated barriers and provide managerial implications for effective Quality 4.0 adoption.

The remaining section of the research paper is as follows: Section 2 describes the theoretical background. Section 3 reveals the research methodology for evaluating Quality 4.0 barrier weights and prioritizing the solutions. Section 4 addresses the case illustration and computations involved in the integrated fuzzy-AHP and fuzzy-TOPSIS approaches. The penultimate section discusses the results and managerial implications. Finally, the conclusion and scope for future work are presented in section 6.

2. Theoretical Background

2.1 History of Quality Revolutions

Quality is a relative term defined differently by different quality gurus. Joseph Juram described it as "fitness for purpose," whereas Philip Crosby mentioned it as "conformance to requirements." Similarly, other definitions were put by ISO, Kaoru Ishikawa and others. During the 1970s, there were limited producers but large buyers, and production volume, product variety and innovativeness needed to be improved (Meindl et al., 2021). However, with the passage of time and the introduction of digital transformations, customers have become choosy to buy quality products. Today, products must be of superior quality with a high degree of innovativeness and comply with the required standards (Fonseca et al., 2021).

Over the past century, the concept of quality has undergone significant changes and is now poised for further adaptations (Broday, 2022). When the concept of quality inspections was introduced, the primary concern was to correct product/service defects. Subsequently, Shewhart introduced control charts to manage variability, and organizations began incorporating Total Quality Control (TQC) and studying quality costs (Zonnenshain & Kenett, 2020). Moreover, quality tools and techniques such as Lean and Six Sigma were derived from Total Quality Management (TQM), aimed at eliminating waste and enhancing process performance (Yadav et al., 2021). In the current scenario, the manufacturing industry is experiencing a revolutionary transformation by applying advanced analytics, resulting in significant improvements in product quality (Sariyer et al., 2021).

2.2 Underpinning Theories

2.2.1 Transformational Leadership Theory

Transformational leaders actively support and facilitate employee development and growth individually and as a cohesive team (Birasnav, 2014). They create avenues for learning, offer training opportunities, and promote upskilling initiatives that equip employees with the necessary skills to overcome the barriers of Quality 4.0 (Sony et al., 2020). This commitment to employee development cultivates a culture of continuous improvement and innovation, where individuals are authorized to explore novel ideas, take calculated risks, and contribute their distinct perspectives and insights (Hiebl et al., 2023). By fostering a growth-oriented environment, transformational leaders unleash the full potential of their teams, enabling them to adapt, thrive, and drive quality excellence in the digital era (Birasnav, 2013).

2.2.2 Organizational Culture Theory

Organizational Culture Theory (OCT) holds significant relevance in the context of Quality 4.0, which signifies the role of organizational culture in the integration of digital technologies and data-driven decision-making (Sony et al., 2021). OCT focuses on an organization's shared values, beliefs, and norms that shape its behavior and decision-making procedures (Thekkoote, 2022). In the context of Quality 4.0, OCT assumes a critical role as organizations adapt to the dynamic technological landscape (Maganga & Taifa, 2023). It emphasizes the need to cultivate a culture that promotes quality excellence, continuous improvement, innovation, and adaptability in the digital era (Antony et al., 2023).

2.2.3 *Diversity and Inclusion Theory*

By including individuals from different backgrounds, such as different genders, ethnicities, cultures, and abilities, organizations can tap into a diverse talent pool and benefit from the richness of ideas and perspectives (Otten et al., 2022). Moreover, an inclusive culture within Quality 4.0 initiatives creates an environment where all employees feel valued, respected, and empowered to contribute their best (Ivanov et al., 2018). When individuals feel included and comfortable expressing their ideas, they are more likely to actively participate in quality improvement efforts, collaborate with others, and offer innovative solutions (AlMalki & Durugbo, 2022).

2.2.4 Stakeholder Theory

Stakeholder theory plays a crucial role in Quality 4.0 adoption, which mentions the role of stakeholders in integrating contemporary technologies, data-driven decision-making, and advanced analytics (Antony et al., 2022). Stakeholder theory emphasizes recognizing and managing various stakeholders' interests, needs, and expectations affected by or impacting an organization's activities and outcomes of Quality 4.0 adoption (Fonseca et al., 2021).

Stakeholders in the context of Quality 4.0 may include employees, customers, suppliers, regulatory bodies, communities, and even the environment (Tran et al., 2022). Each stakeholder group possesses unique perspectives, requirements, and expectations regarding the value of products, processes, and facilities (Fonseca et al., 2021). Integrating stakeholder theory into Quality 4.0 initiatives involves identifying and comprehending the needs and expectations of diverse stakeholder clusters (Sony et al., 2020). This can be achieved through active communication, feedback mechanisms, and strategies for stakeholder engagement (Dias et al., 2022). By actively involving stakeholders, organizations gain valuable insights, anticipate potential issues, and align quality initiatives with stakeholder priorities (Awan et al., 2021).

Furthermore, stakeholder theory underscores the importance of striking a balance among the benefits of numerous stakeholders to attain sustainable quality outcomes (Balouei Jamkhaneh et al., 2022). This necessitates that organizations make informed decisions considering the potential impacts on different stakeholder groups and strive to create shared value (Küpper et al., 2019; Chiarini, 2020). For instance, in the context of Quality 4.0, organizations may need to balance the introduction of new technologies with considerations for employee training, customer satisfaction, and regulatory compliance (Nguyen et al., 2023).

2.3 Quality 4.0 Constructs

2.3.1 Leadership and Culture (LC)

A strong commitment from leadership is vital for successful Quality 4.0 adoption (Yadav et al., 2021). With leadership buy-in and support, organizations may be able to allocate resources effectively and drive the necessary changes (Glogovac et al., 2022). Establishing a culture that values quality and continuous improvement is vital, fostering a proactive mindset that encourages innovation and addresses issues quickly (Chiarini & Kumar, 2022). Building diverse and multidisciplinary teams with the right skills and knowledge ensures a comprehensive approach to Quality 4.0 (Antony et al., 2023). Effective communication of the benefits and goals of Quality 4.0 to stakeholders ensures their engagement and support throughout the organization (Sader et al., 2022).

2.3.2 Data and Analytics (DA)

To uncover the full strength of Quality 4.0, organizations must effectively collect and integrate data from various sources across their operations (Bousdekis et al., 2023). It enables a comprehensive view of processes and helps identify areas for improvement (Amat-Lefort et al., 2023). Advanced analytics and machine learning procedures play a crucial role in uncovering valuable insights and opportunities for enhancement (Chiarini, 2020). Organizations can make informed decisions based on data, predict and address quality issues, and optimize their processes accordingly (Sariyer et al., 2021). Real-time data utilization is fundamental, allowing organizations to identify and address potential issues proactively, ensuring high product or service quality (Lee et al., 2019). Robust data governance and security protocols are also essential to protect data integrity and confidentiality (Sureshchandar, 2022).

2.3.3 Technology and Automation (TA)

Adopting Industry 4.0 technologies such as IoT, AI, and robotics is crucial for automating quality processes and enhancing efficiency (Hassoun et al., 2022). Digital quality management systems that seamlessly integrate with other enterprise systems eliminate errors associated with manual data entry and facilitate seamless information sharing across different departments (Gunasekaran et al., 2019). Prioritizing technology interoperability and scalability ensures that organizations can adapt to future growth and changes. Moreover, developing a technology roadmap that aligns with the organization's strategic goals and objectives is crucial (Taylor et al., 2020). It ensures that technology investments support the overall business strategy and enable organizations to stay ahead in the fast-paced world of digital transformations (Maganga & Taifa, 2022).

2.3.4 Collaboration and Stakeholder Engagement (CSE)

Active engagement of stakeholders, including customers, suppliers, and employees, is of utmost importance for the success of Quality 4.0 initiatives (Santos et al., 2021). Without their involvement, organizations may face resistance, limited adoption, and miss out on valuable collaboration opportunities (Javaid et al., 2021). Building cross-functional teams that bring together individuals from different departments or disciplines promotes collaboration and knowledge sharing (Gunasekaran et al., 2019). Additionally, establishing partnerships and collaborations with external organizations can significantly enhance innovation and knowledge exchange (Tran et al., 2022). Moreover, creating feedback loops to capture the insights and ideas of stakeholders is crucial (Antony et al., 2022). Furthermore, regular communication channels and mechanisms require gathering input, addressing concerns, and incorporating valuable suggestions into the Quality 4.0 program (Beard-Gunter et al., 2019). By actively involving stakeholders and fostering a collaborative environment, organizations can leverage diverse perspectives, tap into collective intelligence, and maximize the potential of Quality 4.0 initiatives (Nguyen et al., 2023).

2.3.5 Continuous Learning and Improvement (CLI)

Continuous Learning and Improvement (CLI) is vital to the successful adoption of Quality 4.0 (Javaid et al., 2021). It encompasses several key factors that organizations should address to foster ongoing growth and enhancement (Glogovac et al., 2022). Training and development opportunities are essential for building the skills and knowledge related to Quality 4.0.

Encouraging experimentation and promoting a culture that embraces learning from failures is crucial for driving continuous improvement (Sony et al., 2020). Moreover, establishing a culture of agility and adaptability is paramount to responding effectively to changes in the business landscape (Broday, 2022). Additionally, regular monitoring and evaluation of Quality 4.0 initiatives are essential to identify areas that require improvement, make necessary adjustments, and optimize processes (Antony et al., 2022). Furthermore, organizations can fully embrace the transformative potential of Quality 4.0 and foster a culture of innovation and excellence by prioritizing continual learning and development (Saihi et al., 2023).

2.4 Research Gaps

Researchers (Sony et al., 2020; Antony et al., 2022) have reported that there has been little advancement in quality management models in the last few years. Despite making substantial progress in assessing obstacles to implementing Quality 4.0, solutions to overcome Quality 4.0 barriers still require attention. To improve decision-making in this situation, organized frameworks that consider the substantial impact and viability of various solutions must be developed. Organizations may improve their understanding of Quality 4.0 and considerably boost the likelihood of successful Quality 4.0 adoption by filling these research gaps.

3. Research Methodology

The research methodology is illustrated in three phases. The hierarchical structure of the research methodology is depicted in Figure 1.

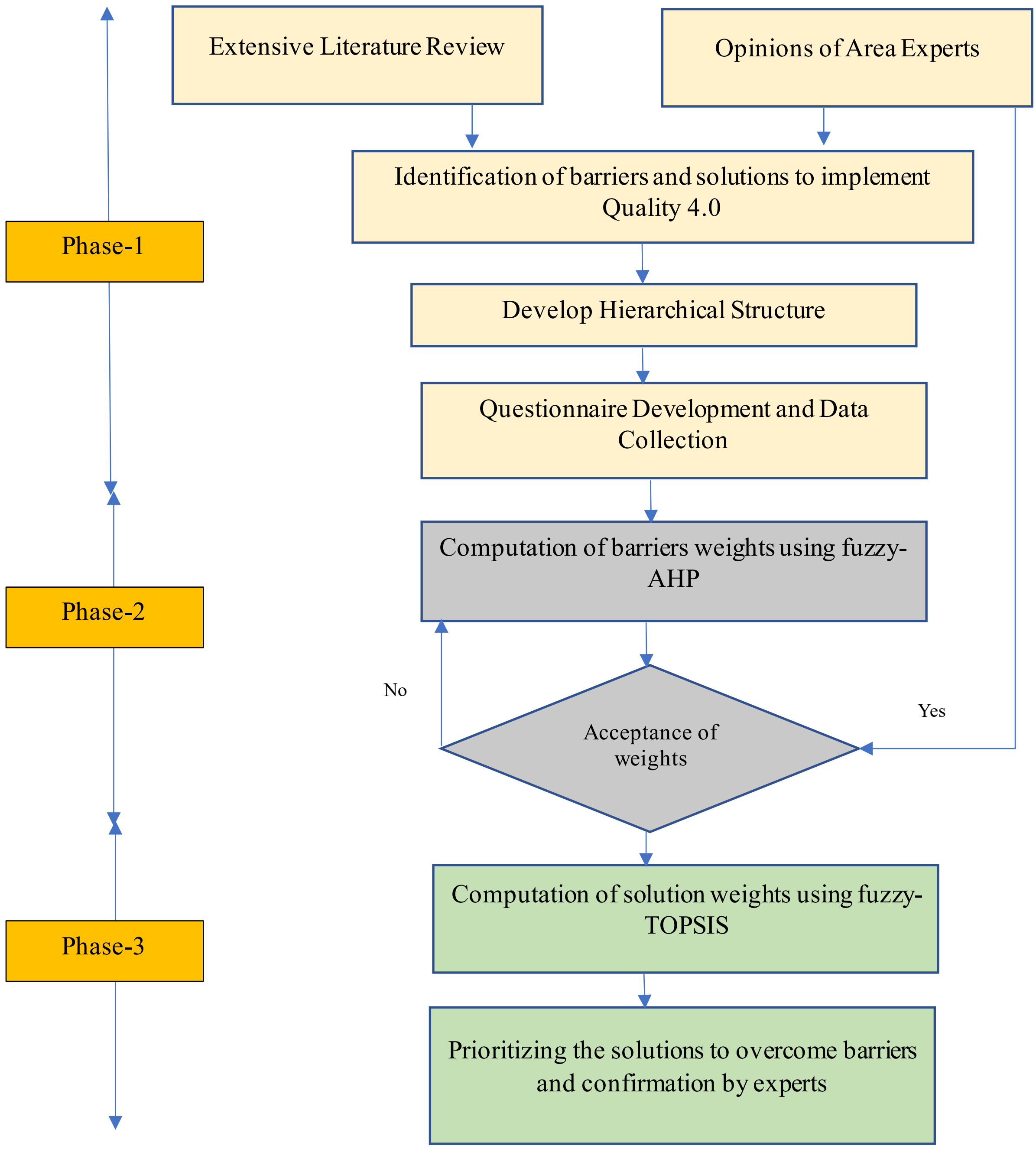


Figure 1: Hierarchical research methodology structure (figure by Authors)

Phase 1: Identification and finalization of Quality 4.0 barriers and solutions

In this phase, twenty key barriers and fifteen solutions were identified through literature review and conformed in discussion with area experts.

Phase 2: Evaluating the barrier weights using fuzzy AHP

Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) is useful in solving complex problems and effective decision-making (Abdul et al., 2023). Moreover, Cebi et al. (2023) discussed that this technique is well suited to overcome inconsistency in experts' opinions and deals with both positivism and negativism. Similar results were discussed by Shi and Lai (2023), who mentioned that fuzzy theory is best suited to overcome ambiguities and vagueness. Linguistic terms are used to develop a pairwise comparison between identified criteria or alternatives (Shi & Lai, 2023). Eventually, this technique gives a crisp weight to analyse the rank of given criteria (Meniz & Özkan, 2023). Fuzzy-AHP methodology is used in a variety of application areas, including project assessment (Bilgen & Şen, 2012), risk valuation (Ilbahar et al., 2018), and critical decision-making (Calabrese et al., 2019). It offers a flexible and effective framework for handling subjective and uncertain judgments in decision-making processes (Lahane & Kant, 2021). A pairwise comparison matrix is developed using a triangular fuzzy number mentioned by (a, b, c). Figure 2 shows a schematic diagram of the intersection among fuzzy numbers.

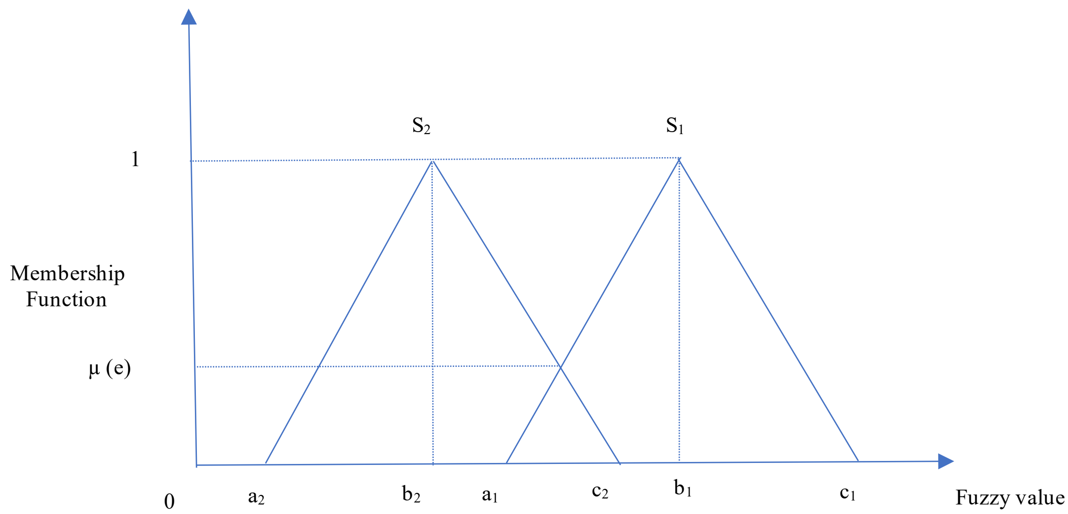


Figure 2: Intersection among fuzzy numbers

(figure by Sirisawat & Kiatcharoenpol, 2018),

The expert scores were taken on the linguistic scale, as shown in Table 1.

Table 1: Linguistic Scale (Table by Patil & Kant, 2014)

Linguistic Term	Triangular Fuzzy Number
Very Low (VL)	(1, 1, 3)
Low (L)	(1, 3, 5)
Medium (M)	(3, 5, 7)
High (H)	(5, 7, 9)
Very High (VH)	(7, 9, 9)

The steps of fuzzy AHP are discussed in Appendix A.

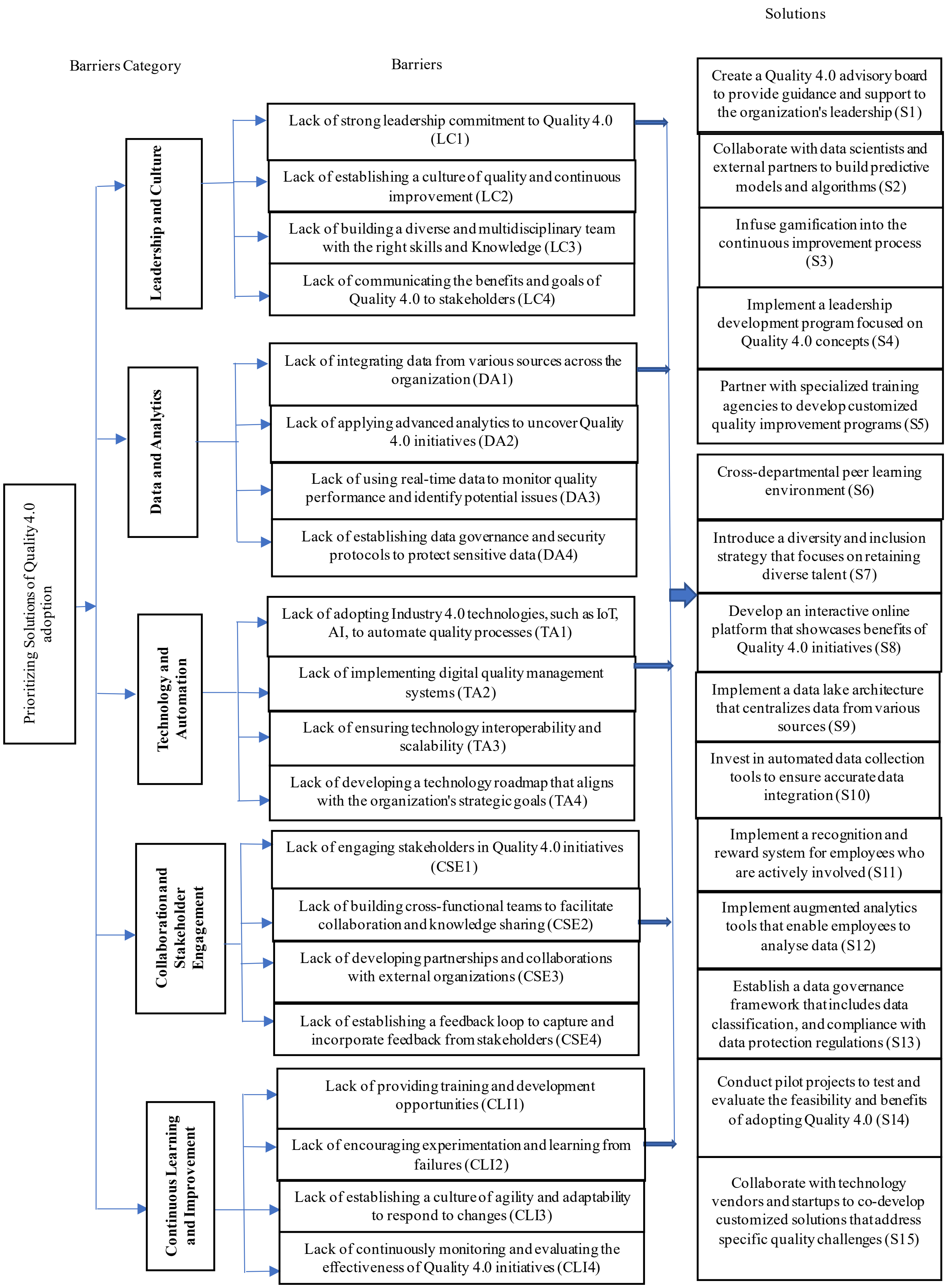
Phase 3: Prioritizing the solutions to tackle identified barriers using Fuzzy-TOPSIS

Fuzzy-TOPSIS, known as the Technique for Order of Preference by Similarity to Ideal Solution, is a robust multicriteria decision-making approach (Hooshangi, 2023). It effectively addresses uncertainties and vagueness inherent in decision-making processes by integrating fuzzy logic principles (Hajiaghaei-Keshteli et al., 2023). Employing fuzzy sets enables the evaluation and comparison of alternatives based on multiple criteria, providing a reliable framework for decision-making under ambiguity (Toker et al., 2023). The proposed research framework is depicted in Figure 3.

[Figure 3 about here]

4. Case Illustration

Our study aimed to analyse barriers to and solutions for implementing Quality 4.0 adoption in the automobile industry in a developing country context, i.e., India. The automobile industry significantly contributes to the country's GDP (Gupta & Raman, 2022). Therefore, reducing waste and defects and providing quality products and services to customers is crucial. India ranks third largest in terms of sales in the automobile market (IBEF, 2023). The advent of digitalization and the rise of new business models have triggered substantial growth and revolutionary changes in multiple industries, including the automotive, electronics, pharmaceutical, and construction sectors (Manavalan & Jayakrishna, 2019). Within the automotive industry, the influence of digital transformations has given rise to disruptive trends, including diverse mobility, autonomous driving, electrification, and connectivity (IBEF, 2023).



Solutions
Barriers Category
Barriers
Prioritizing Solutions of Quality 4.0 adoption
Leadership and Culture
Data and Analytics
Technology and Automation
Collaboration and Stakeholder Engagement
Continuous Learning and Improvement
Lack of strong leadership commitment to Quality 4.0 (LC1)
Lack of establishing a culture of quality and continuous improvement (LC2)
Lack of building a diverse and multidisciplinary team with the right skills and Knowledge (LC3)
Lack of communicating the benefits and goals of Quality 4.0 to stakeholders (LC4)
Lack of integrating data from various sources across the organization (DA1)
Lack of applying advanced analytics to uncover Quality 4.0 initiatives (DA2)
Lack of using real-time data to monitor quality performance and identify potential issues (DA3)
Lack of establishing data governance and security protocols to protect sensitive data (DA4)
Lack of adopting Industry 4.0 technologies, such as IoT, AI, to automate quality processes (TA1)
Lack of implementing digital quality management systems (TA2)
Lack of ensuring technology interoperability and scalability (TA3)
Lack of developing a technology roadmap that aligns with the organization's strategic goals (TA4)
Lack of engaging stakeholders in Quality 4.0 initiatives (CSE1)
Lack of building cross-functional teams to facilitate collaboration and knowledge sharing (CSE2)
Lack of developing partnerships and collaborations with external organizations (CSE3)
Lack of establishing a feedback loop to capture and incorporate feedback from stakeholders (CSE4)
Lack of providing training and development opportunities (CLI1)
Lack of encouraging experimentation and learning from failures (CLI2)
Lack of establishing a culture of agility and adaptability to respond to changes (CLI3)
Lack of continuously monitoring and evaluating the effectiveness of Quality 4.0 initiatives (CLI4)
Create a Quality 4.0 advisory board to provide guidance and support to the organization's leadership (S1)
Collaborate with data scientists and external partners to build predictive models and algorithms (S2)
Infuse gamification into the continuous improvement process (S3)
Implement a leadership development program focused on Quality 4.0 concepts (S4)
Partner with specialized training agencies to develop customized quality improvement programs (S5)
Cross-departmental peer learning environment (S6)
Introduce a diversity and inclusion strategy that focuses on retaining diverse talent (S7)
Develop an interactive online platform that showcases benefits of Quality 4.0 initiatives (S8)
Implement a data lake architecture that centralizes data from various sources (S9)
Invest in automated data collection tools to ensure accurate data integration (S10)
Implement a recognition and reward system for employees who are actively involved (S11)
Implement augmented analytics tools that enable employees to analyse data (S12)
Establish a data governance framework that includes data classification, and compliance with data protection regulations (S13)
Conduct pilot projects to test and evaluate the feasibility and benefits of adopting Quality 4.0 (S14)
Collaborate with technology vendors and startups to co-develop customized solutions that address specific quality challenges (S15)

Figure 3: Research framework to prioritize the solutions to overcome Quality 4.0 barriers (figure by Authors)

A total of 15 area experts were chosen to collect the data. Table 2 shows the experts' profiles.

Table 2: Experts profile (Table by Authors)

Expert	**Designation**	**Qualification**	**Experience (years)**
E-1	Senior Quality Manager	B.Tech	15.4
E-2	Production Manager	B.Tech	13.5
E-3	Research and Development (R&D) Manager	B.Tech	16.2
E-4	Quality Inspector	B.Tech+ M.Tech	18.4
E-5	Quality Assurance Analyst	B.Tech	15.6
E-6	System Integration Specialist	B.Tech+ MBA	16.5
E-7	Production-Head	B.Tech	17.8
E-8	Design Head	B.Tech+ M.Tech	15.3
E-9	Lean manufacturing specialist	B.Tech	14.8
E-10	Plant Head	B.Tech+ M.Tech	20.4
E-11	Manager-Operations	B.Tech	14.7
E-12	Data Analyst	B.Tech	15.9
E-13	SAP-MM consultant	B.Tech+MBA	16.1
E-14	Cyber-security and networking-Head	B.Tech+MBA	14.3
E-15	Technology Analyst	B.Tech+ M.Tech	15.7

All experts were minimum graduates and had good exposure to handling quality issues. The number of experts selected is satisfactory compared to similar previous studies: ten experts (Sirisawat & Kiatcharoenpol, 2018), six experts (Ansari et al., 2019), and fifteen experts (Patil & Kant, 2014). The expert inputs were taken to develop a pairwise comparison matrix at the system and subsystem levels. Moreover, rating values of solutions to overcome barriers were also taken by area experts to prioritize the solutions.

4.1 Computations involved in evaluated barrier weights using Fuzzy-AHP

Standard operation steps were followed to make a pairwise comparison matrix, as mentioned in Appendix A. The aggregated matrix of the barriers category is shown in Table 3.

Table 3: Fuzzy aggregated decision-making matrix of barriers (Table by Authors)

	LC	DA	TA	CSE	CLI	Weight	Rank
LC	(1.00,1.00,1.00)	(0.11,0.17,0.33)	(0.11,5.10,9.00)	(0.11,4.09,7.00)	(0.11,4.57,9.00)	0.2034	3
DA	(3.00,5.94,9.00)	(1.00,1.00,1.00)	(3.00,5.13,9.00)	(0.11,6.70,9.00)	(0.14,4.68,9.00)	0.2189	1
TA	(0.11,0.20,9.00)	(0.11, 0.19, 0.33)	(1.00,1.00,1.00)	(0.11,6.75,9.00)	(0.11,4.51,9.00)	0.2133	2
CSE	(0.14,0.24,9.00)	(0.11,0.15,9.00)	(0.11,0.15,9.00)	(1.00,1.00,1.00)	(0.11,2.08,9.00)	0.2015	4
CLI	(0.11,0.22,9.00)	(0.11,0.21,7.00)	(0.11,0.22,9.00)	(0.11,0.48,9.00)	(1.00,1.00,1.00)	0.1629	5

The barrier weights at the subcategory level are shown in Table 4 to Table 8.

Table 4: Fuzzy aggregated decision-making matrix of LC barriers (Table by Authors)

	LC1	LC2	LC3	LC4	Weight	Rank
LC1	(1.00,1.00,1.00)	(1.00,6.87,9.00)	(0.11,3.14,9.00)	(0.11,5.36,9.00)	0.2757	1
LC2	(0.11,0.15,1.00)	(1.00,1.00,1.00)	(0.11,1.38,9.00)	(3.00,7.93,9.00)	0.2435	3
LC3	(0.11,0.32,9.00)	(0.11,0.72,9.00)	(1.00,1.00,1.00)	(0.11,3.27,9.00)	0.2474	2
LC4	(0.11,0.19,9.00)	(0.11,0.13,0.33)	(0.11,0.31,9.00)	(1.00,1.00,1.00)	0.2240	4

Table 5: Fuzzy aggregated decision-making matrix of DA barriers (Table by Authors)

	DA1	DA2	DA3	DA4	Weight	Rank
DA1	(1.00,1.00,1.00)	(0.11,6.21,9.00)	(0.14,3.93,9.00)	(0.11,2.74,9.00)	0.2583	2
DA2	(0.11,0.16,9.00)	(1.00,1.00,1.00)	(0.11,7.01,9.00)	(1.00,7.13,9.00)	0.2605	1
DA3	(0.11,0.25,7.00)	(0.11,0.14,9.00)	(1.00,1.00,1.00)	(0.14,5.48,9.00)	0.2488	3
DA4	(0.11,0.37,9.00)	(0.11,0.14,1.00)	(0.11,0.18,7.00)	(1.00,1.00,1.00)	0.2323	4

Table 6: Fuzzy aggregated decision-making matrix of TA barriers (Table by Authors)

	TA1	TA2	TA3	TA4	Weight	Rank
TA1	(1.00,1.00,1.00)	(0.11,1.63,9.00)	(0.11,5.56,9.00)	(0.11,5.76,9.00)	0.2613	1
TA2	(0.11,0.61,9.00)	(1.00,1.00,1.00)	(0.14,3.99,9.00)	(0.14,0.79,9.00)	0.2469	3
TA3	(0.11,0.18,9.00)	(0.11,0.25,7.00)	(1.00,1.00,1.00)	(1.00,5.93,9.00)	0.2475	2
TA4	(0.11,0.17,9.00)	(1.27,7.00,7.00)	(0.11,0.17,1.00)	(1.00,1.00,1.00)	0.2442	4

Table 7: Fuzzy aggregated decision-making matrix of CSE barriers (Table by Authors)

	CSE1	CSE2	CSE3	CSE4	Weight	Rank
CSE1	(1.00,1.00,1.00)	(5.00,7.00,9.00)	(0.11,2.54,9.00)	(0.11,2.17,9.00)	0.2785	1
CSE2	(0.11,0.14,0.20)	(1.00,1.00,1.00)	(0.11,1.43,9.00)	(0.11,6.22,9.00)	0.2514	3
CSE3	(0.11,0.39,9.00)	(0.11,0.70,9.00)	(1.00,1.00,1.00)	(7.00,9.00,9.00)	0.2704	2
CSE4	(0.11,0.46,9.00)	(0.11,0.16,9.00)	(0.11,0.11,0.14)	(1.00,1.00,1.00)	0.1997	4

Table 8: Fuzzy aggregated decision-making matrix of CLI barriers (Table by Authors)

	CLI1	CLI2	CLI3	CLI4	Weight	Rank
CLI1	(1.00,1.00,1.00)	(0.11,6.70,6.98)	(0.11,6.09,6.90)	(0.11, 4.07, 5.00)	0.2701	1
CLI2	(0.14,0.15,9.00)	(1.00,1.00,1.00)	(0.11, 1.75, 3.00)	(0.11, 2.54, 5.00)	0.2352	4

CLI3	(0.14,0.16,9.00)	(0.33, 0.57, 9.00)	(1.00,1.00,1.00)	(0.11, 5.74, 9.00)	0.2515	2
CLI4	(0.20,0.25,9.00)	(0.20, 0.39, 9.00)	(0.11, 0.17, 9.00)	(1.00,1.00,1.00)	0.2431	3

Moreover, Table 9 shows the global weights of the barriers.

Table 9: Final ranking of Quality 4.0 barriers (Table by Authors)

S. No.	**Barriers of Quality 4.0 implementation**	**Barrier Category Weights**	**Sub-Barrier**	**Local Weights**	**Global Weight**	**Rank**
1	Leadership and Culture (LC)	0.2034	LC1	0.2757	0.0560	4
2			LC2	0.2435	0.0495	14
3			LC3	0.2474	0.0503	13
4			LC4	0.2240	0.0456	15
5	Data and Analytics (DA)	0.2189	DA1	0.2583	0.0566	2
6			DA2	0.2605	0.0570	1
7			DA3	0.2488	0.0544	7
8			DA4	0.2323	0.0509	11
9	Technology and Automation (TA)	0.2133	TA1	0.2613	0.0558	5
10			TA2	0.2469	0.0527	9
11			TA3	0.2475	0.0528	8
12			TA4	0.2442	0.0521	10
13	Collaboration and Stakeholder Engagement (CSE)	0.2015	CSE1	0.2785	0.0561	3
14			CSE2	0.2514	0.0506	12
15			CSE3	0.2704	0.0545	6
16			CSE4	0.1997	0.0402	18
17	Continuous Learning and Improvement (CLI)	0.1629	CLI1	0.2701	0.0440	16
18			CLI2	0.2352	0.0383	20
19			CLI3	0.2515	0.0410	17
20			CLI4	0.2431	0.0396	19

The sample calculations for computing the weights of different categories of barriers are explained as follows:

S_{LC}= (1.44, 14.93, 26.33) $\otimes$ (1/172.33, 1/56.85,1/13.10)= (0.008, 0.263, 2.011)

S_{DA}= (7.25, 23.45, 37.00) $\otimes$ (1/172.33, 1/56.85,1/13.10)= (0.042, 0.413, 2.825)

S_{TA}= (1.48, 12.71, 37.00) $\otimes$ (1/172.33, 1/56.85,1/13.10)= (0.009, 0.224, 2.825)

S_{CSE}= (1.48, 3.62, 37.00) $\otimes$ (1/172.33, 1/56.85,1/13.10)= (0.009, 0.063, 2.825)

S_{CLI}= (1.44, 2.14, 35.00) $\otimes$ (1/172.33, 1/56.85,1/13.10)= (0.008, 0.038, 2.672)

$V(S_{LC} \geq S_{DA})=0.9292$, $V(S_{LC} \geq S_{TA})=1$, $V(S_{LC} \geq S_{CSE})=1$, $V(S_{LC} \geq S_{CLI})=1$

$V(S_{DA} \geq S_{LC})= 1$, $V(S_{DA} \geq S_{TA})=1$, $V(S_{DA} \geq S_{CSE})=1$, $V(S_{DA} \geq S_{CLI})= 1$

$V(S_{TA} \geq S_{LC})= 0.9863$, $V(S_{TA} \geq S_{DA})= 0.9744$, $V(S_{TA} \geq S_{CSE})=1$, $V(S_{TA} \geq S_{CLI})=1$

$V(S_{CSE} \geq S_{LC})= 0.9314$, $V(S_{CSE} \geq S_{DA})=0.9204$, $V(S_{CSE} \geq S_{TA})=0.9314$, $V(S_{CSE} \geq S_{CLI})=1$

$V(S_{CLI} \geq S_{LC})=0.7568$, $V(S_{CLI} \geq S_{DA})= 0.7440$, $V(S_{CLI} \geq S_{TA})=0.7567$, $V(S_{CLI} \geq S_{CSE})= 0.7567$

d'(LC)= min (0.9292, 1, 1, 1, 1) = 0.9292

d'(DA)= min (1, 1, 1, 1, 1) =1

d'(TA)= min (0.9863, 0.9744, 1, 1, 1)= 0.9744

d'(CSE)= min (0.9314, 0.9204, 0.9314, 1, 1)= 0.9204

d'(CLI)= min (0.7568, 0.7440, 0.7567, 0.7567) = 0.7440

Using Appendix-A, equation (14) and equation (15), the barriers weights are evaluated as (0.2034, 0.2189, 0.2133, 0.2015, 0.1629)

4.2 Computations involved in prioritizing solutions to overcome Quality 4.0 barriers using fuzzy-TOPSIS

The procedure is carried out as follows:

Step 1: Area experts were asked to map the solutions with respect to identified barriers using a linguistic scale as mentioned in Table 1.

Step 2: The aggregated matrix is prepared using Appendix-A, equation (17) and is revealed in Table 10.

Table 10: Aggregated matrix of Quality 4.0 Solutions (Table by Authors)

	Barriers of Quality 4.0 Adoption				
Solution	**LC1**	**LC2**	……………………….	**CLI3**	**CLI4**
S1	(1, 5.00, 9)	(1, 5.93, 9)	……………………….	(1, 4.73, 9)	(1, 5.00, 9)
S2	(1, 7.80, 9)	(1, 5.80, 9)	……………………….	(1, 4.73, 9)	(1, 4.47, 9)
S3	(1, 5.40, 9)	(1, 4.33, 9)	……………………….	(1, 5.27, 9)	(1, 6.87, 9)
S4	(1, 6.20, 9)	(1, 5.53, 9)	……………………….	(1, 5.27, 9)	(1, 5.80, 9)
S5	(1, 4.87, 9)	(1, 5.13, 9)	……………………….	(1, 5.80, 9)	(3, 5.93, 9)
S6	(1, 7.67, 9)	(1, 3.80, 9)	……………………….	(1, 6.33, 9)	(3, 8.60, 9)
S7	(1, 5.53, 9)	(1, 4.87, 9)	……………………….	(1, 4.73, 9)	(1, 5.27, 9)
S8	(1, 7.13, 9)	(1, 5.40, 9)	……………………….	(1, 6.33, 9)	(1, 7.67, 9)
S9	(1, 4.33, 9)	(1, 6.33, 9)	……………………….	(1, 7.27, 9)	(1, 7.13, 9)
S10	(1, 4.33, 9)	(1, 4.60, 9)	……………………….	(1, 5.53, 9)	(1, 3.80, 9)
S11	(1, 7.80, 9)	(1, 4.60, 9)	……………………….	(1, 7.40, 9)	(1, 5.80, 9)
S12	(1, 4.20, 9)	(1, 6.87, 9)	……………………….	(1, 4.47, 9)	(1, 5.00, 9)
S13	(1, 5.27, 9)	(1, 5.93, 9)	……………………….	(1, 5.80, 9)	(1, 5.80, 9)
S14	(1, 4.33, 7)	(1, 4.33, 9)	……………………….	(1, 4.87, 9)	(1, 7.13, 9)
S15	(1, 7.53, 9)	(1, 4.73, 9)	……………………….	(1, 4.73, 9)	(1, 6.60, 9)

Step 3: The normalized matrix is evaluated using Appendix-A, equation (18) to equation (20) and is shown in Table 11.

Table 11: Normalized matrix of Quality 4.0 Solutions (Table by Authors)

S. No.	LC1	LC2	………………….	CLI3	CLI4
S1	(0.11, 0.56, 1.00)	(0.11, 0.66, 1.00)	………………….	(0.11, 0.53, 1.00)	(0.11, 0.56, 1.00)
S2	(0.11, 0.87, 1.00)	(0.11, 0.64, 1.00)	………………….	(0.11, 0.53, 1.00)	(0.11, 0.50, 1.00)
S3	(0.11, 0.60, 1.00)	(0.11, 0.48, 1.00)	………………….	(0.11, 0.59, 1.00)	(0.11, 0.76, 1.00)
S4	(0.11, 0.69, 1.00)	(0.11, 0.61, 1.00)	…………………	(0.11, 0.59, 1.00)	(0.11, 0.64, 1.00)
S5	(0.11, 0.54, 1.00)	(0.11, 0.57, 1.00)	………………….	(0.11, 0.64, 1.00)	(0.33, 0.66, 1.00)
S6	(0.11, 0.85, 1.00)	(0.11, 0.42, 1.00)	………………….	(0.11, 0.70, 1.00)	(0.33, 0.96, 1.00)
S7	(0.11, 0.61, 1.00)	(0.11, 0.54, 1.00)		(0.11, 0.53, 1.00)	(0.11, 0.59, 1.00)
S8	(0.11, 0.79, 1.00)	(0.11, 0.60, 1.00)	………………….	(0.11, 0.70, 1.00)	(0.11, 0.85, 1.00)
S9	(0.11, 0.48, 1.00)	(0.11, 0.70, 1.00)	…………………	(0.11, 0.81, 1.00)	(0.11, 0.79, 1.00)
S10	(0.11, 0.48, 1.00)	(0.11, 0.51, 1.00)	………………….	(0.11, 0.61, 1.00)	(0.11, 0.42, 1.00)
S11	(0.11, 0.87, 1.00)	(0.11, 0.51, 1.00)	………………….	(0.11, 0.82, 1.00)	(0.11, 0.64, 1.00)
S12	(0.11, 0.47, 1.00)	(0.11, 0.76, 1.00)	………………….	(0.11, 0.50, 1.00)	(0.11, 0.56, 1.00)
S13	(0.11, 0.59, 1.00)	(0.11, 0.66, 1.00)	…………………	(0.11, 0.64, 1.00)	(0.11, 0.64, 1.00)
S14	(0.11, 0.48, 0.78)	(0.11, 0.48, 1.00)	………………….	(0.11, 0.54, 1.00)	(0.11, 0.79, 1.00)
S15	(0.11, 0.84, 1.00)	(0.11, 0.53, 1.00)	………………….	(0.11, 0.53, 1.00)	(0.11, 0.73, 1.00)

Step 4: The weighted normalized matrix is computed using Appendix-A, equation (21) and equation (22) and is depicted in Table 12.

Table 12: Weighted normalized matrix of Quality 4.0 Solutions (Table by Authors)

S. No.	LC1	LC2	………………………..	CLI3	CLI4
S1	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.02, 0.04)
S2	(0.01, 0.05, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.02, 0.04)
S3	(0.01, 0.03, 0.06)	(0.01, 0.02, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.03, 0.04)
S4	(0.01, 0.04, 0.06)	(0.01, 0.03, 0.05)	…………………	(0.00, 0.02, 0.04)	(0.00, 0.03, 0.04)
S5	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.03, 0.04)	(0.01, 0.03, 0.04)
S6	(0.01, 0.05, 0.06)	(0.01, 0.02, 0.05)	………………….	(0.00, 0.03, 0.04)	(0.01, 0.04, 0.04)
S7	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)		(0.00, 0.02, 0.04)	(0.00, 0.02, 0.04)
S8	(0.01, 0.04, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.03, 0.04)	(0.00, 0.03, 0.04)
S9	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)	…………………	(0.00, 0.03, 0.04)	(0.00, 0.03, 0.04)
S10	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.03, 0.04)	(0.00, 0.02, 0.04)
S11	(0.01, 0.05, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.03, 0.04)	(0.00, 0.03, 0.04)
S12	(0.01, 0.03, 0.06)	(0.01, 0.04, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.02, 0.04)
S13	(0.01, 0.03, 0.06)	(0.01, 0.03, 0.05)	…………………	(0.00, 0.03, 0.04)	(0.00, 0.03, 0.04)
S14	(0.01, 0.03, 0.04)	(0.01, 0.02, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.03, 0.04)
S15	(0.01, 0.05, 0.06)	(0.01, 0.03, 0.05)	………………….	(0.00, 0.02, 0.04)	(0.00, 0.03, 0.04)

Step 5: The FPIS, FNIS and corresponding distance of each solution are computed using Appendix-A, equation (23) to equation (26)

Step 6: The solutions are prioritized on the basis of closeness coefficient values using Appendix-A, equation (27) and are shown in Table 13.

Table 13: Closeness coefficient values of the Quality 4.0 solutions (Table by Authors)

Solution	e_i^+	e_i^-	$e_i^- + e_i^+$	$e_i^- / (e_i^- + e_i^+)$	**Rank**
S1	0.9319	1.0269	1.9588	0.5241	5
S2	0.9472	1.0349	1.9821	0.5221	6
S3	0.9205	1.0170	1.9375	0.5249	3
S4	0.9321	1.0394	1.9714	0.5272	1
S5	0.9571	1.0053	1.9624	0.5123	11
S6	0.9191	1.0224	1.9416	0.5266	2
S7	0.9509	1.0192	1.9702	0.5173	9
S8	0.9356	1.0310	1.9666	0.5242	4
S9	0.9505	1.0022	1.9527	0.5132	10
S10	0.9407	1.0099	1.9506	0.5177	8
S11	0.9658	0.9913	1.9571	0.5065	13
S12	0.9310	1.0006	1.9315	0.5180	7
S13	0.9574	0.9992	1.9565	0.5107	12
S14	0.9818	0.9852	1.9670	0.5009	15
S15	0.9817	0.9919	1.9735	0.5026	14

4.3 Sensitivity Analysis

Sensitivity analysis is carried out to check the reliability and validity of the computed solutions. The results are shown in Table 14.

Table 14: Sensitivity analysis (Table by Authors)

	T-1	**T-2**	**T-3**	**T-4**	**T-5**	**T-6**	**T-7**	**T-8**	**T-9**	**T-10**	**T-11**	**T-12**	**T-13**	**T-14**	**T-15**
S1	0.548	0.528	0.573	0.537	0.527	0.549	0.529	0.588	0.517	0.566	0.536	0.638	0.530	0.553	0.549
S2	0.543	0.540	0.526	0.508	0.529	0.520	0.527	0.538	0.543	0.524	0.519	0.550	0.537	0.513	0.518
S3	0.579	0.558	0.536	0.565	0.519	0.583	0.660	0.536	0.540	0.528	0.522	0.519	0.543	0.549	0.539
S4	0.657	0.677	0.662	0.667	0.540	0.578	0.521	0.674	0.651	0.651	0.589	0.651	0.658	0.633	0.538
S5	0.537	0.549	0.545	0.508	0.529	0.530	0.535	0.538	0.526	0.556	0.527	0.524	0.529	0.532	0.539
S6	0.584	0.596	0.534	0.603	0.655	0.679	0.532	0.517	0.532	0.541	0.677	0.539	0.547	0.569	0.674
S7	0.546	0.528	0.551	0.563	0.518	0.533	0.565	0.553	0.567	0.559	0.554	0.538	0.529	0.523	0.562
S8	0.577	0.566	0.595	0.564	0.526	0.517	0.522	0.528	0.567	0.511	0.509	0.550	0.496	0.480	0.539
S9	0.540	0.548	0.536	0.538	0.524	0.547	0.529	0.563	0.531	0.545	0.548	0.563	0.550	0.518	0.527
S10	0.542	0.539	0.542	0.559	0.529	0.550	0.511	0.541	0.502	0.536	0.524	0.529	0.530	0.523	0.523
S11	0.555	0.543	0.515	0.538	0.550	0.547	0.572	0.539	0.528	0.534	0.495	0.569	0.526	0.521	0.523

S12	0.545	0.503	0.540	0.506	0.551	0.536	0.535	0.532	0.549	0.596	0.482	0.529	0.556	0.482	0.493
S13	0.542	0.539	0.559	0.519	0.532	0.554	0.556	0.541	0.525	0.539	0.519	0.544	0.524	0.521	0.516
S14	0.546	0.546	0.570	0.528	0.543	0.568	0.548	0.569	0.557	0.564	0.572	0.579	0.556	0.551	0.484
S15	0.529	0.526	0.532	0.517	0.519	0.533	0.521	0.530	0.519	0.521	0.511	0.521	0.516	0.506	0.507

In Trial-1, the barrier B1 was assigned a higher weight of 0.5, while the remaining barriers were assigned a weight value equal to 0.0263. Similarly, in the second trial, barrier B2 was assigned a weight value of 0.5, while the remaining barriers were assigned a weight value of 0.0263. The process was repeated for 13 trials. In the fourteenth trial, the first ten barriers were assigned a weight value of 0.1, while the remaining barriers were assigned zero weight. In the 15th experiment, all barriers were assigned equal weight values, i.e., 0.05. The ranking of solutions varied slightly, which confirms the reliability and validity of the solutions. Additionally, the sensitivity analysis is graphically represented in Figure 4.

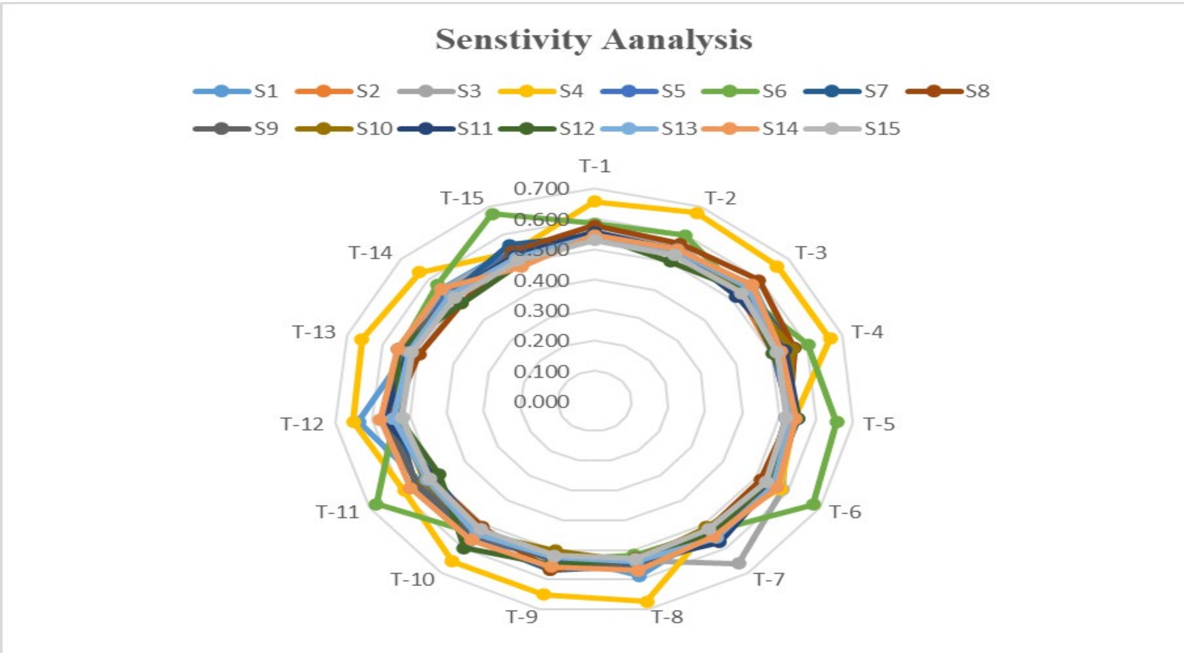


Figure 4: Sensitivity analysis (figure by Authors)

5. Discussion of Findings

"Lack of applying advanced analytics to uncover Quality 4.0 initiatives" ranks first among the identified barriers. It can bring significant benefits to organizations. Quality 4.0 involves leveraging technologies such as AI, IoT, big data analytics, and automation to enhance quality management systems. Similar findings were discussed by Singh et al. (2022), who emphasized that digital technologies are the cornerstone of future manufacturing. Organizations can unlock valuable insights and identify improvement opportunities in quality-related processes by utilizing advanced analytics and machine learning. It allows for a comprehensive view of quality-related factors across the organization. Predictive analytics, powered by machine learning algorithms, can further be applied to historical data to identify anticipated patterns and trends. Organizations can take proactive measures to prevent defects or failures by predicting quality issues before they occur.

Predictive anomaly detection helps organizations address potential issues promptly. Moreover, machine learning algorithms can assess root causes by analysing complex data sets. They can identify the underlying factors contributing to quality problems, allowing organizations to address the root causes rather than treat symptoms. Real-time monitoring is made possible through advanced analytics and machine learning. Organizations can gain immediate insights into quality performance by continuously analysing data streams, detecting deviations from set thresholds, and triggering timely responses or alerts. It enables quick intervention and corrective actions. Process optimization is another area where advanced analytics and machine learning play a vital role. By analysing production data, machine learning algorithms can identify optimal process parameters, leading to improved quality outcomes and reduced variability.

To implement Quality 4.0, organizations must "collect and integrate data from various sources across the organization," ranked second among barriers. Chiarini and Kumar (2022) also discussed that integration across distinct equipment makes the production system resilient and flexible, thus enhancing operational performance. The process begins by defining the data requirements and assessing existing sources such as Quality Management Systems (QMS), Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) systems, and customer feedback platforms. Effective data integration methods such as Extract, Transform and Load (ETL) processes, Application Programming interfaces (APIs), or middleware platforms must be identified. Implementing data capture mechanisms, centralizing data storage, and standardizing formats enable a unified view of quality-related data. Moreover, data cleansing and transformation improve accuracy, while analytics tools analyse and visualize the integrated data. Real-time monitoring systems facilitate the timely identification of issues, and a feedback loop ensures continuous improvement. "Lack of engaging stakeholders in Quality 4.0 initiatives" is ranked third among the barriers. Küpper et al. (2019) mentioned that a lack of stakeholder involvement and engagement may result in potential setbacks. Organizations can create a collaborative environment that drives quality enhancement and overall performance by actively engaging stakeholders. On the other hand, disagreement between stakeholders may result in working in silos and restricting the seamless integration among distinct processes and sections.

In the context of Quality 4.0 adoption, "Lack of strong leadership commitment to Quality 4.0" ranks fourth among the barriers. Many significant roadblocks, including a lack of motivation and employee engagement and resistance to change, confront quality 4.0. As such, effective leadership plays a crucial role in overcoming these issues. Furthermore, leaders must create an environment where employees feel empowered to explore new ideas. Innovative solutions can emerge by permitting employees to experiment, driving quality management practices forward. Equally important is cultivating a mindset that views failures as valuable lessons rather than setbacks. When failures occur, a thorough analysis of their root causes can provide insights for improvement. Sharing and applying these insights to future endeavours enables organizations to continually adapt, learn, and enhance their quality processes, ultimately promoting a culture of continuous improvement.

“Implementing a leadership development program focused on Quality 4.0” ranks first among solutions. It is important to assess the organization's specific needs regarding Quality 4.0 and identify the leadership skills and competencies required for successful adoption. Leaders' strategic vision and mission help organizations set the pathway toward successful Quality 4.0 adoption. Moreover, the proper direction keeps the employees intact and helps overcome the anticipated barriers. "Cross-departmental peer learning environment" holds the second position among the solutions. Leveraging employees' collective knowledge and experiences promotes cross-departmental collaboration, fosters a culture of continuous learning, and enhances the organization's understanding and application of Quality 4.0 concepts.

"Infuse gamification into the continuous improvement process" ranks third among the solutions. By gamification of the process, employees actively embrace Quality 4.0, fostering a culture of continuous improvement. Gamification helps improve the learning experience of employees, which eventually helps enhance performance (Adhiatma et al., 2022). Hammadi et al. (2017) presented similar findings and highlighted that gamification helps to engage employees effectively, creating their interest and enthusiasm to work dedicatedly and sincerely.

"Develop an interactive online platform that showcases benefits of Quality 4.0 initiatives" ranks fourth among solutions. Creating an interactive online platform provides a dynamic showcase of the real-time advantages of Quality 4.0 initiatives. This platform enables users to explore how digital technologies enhance decision-making, process efficiency, supply chain collaboration, customer experience, and overall quality management. Through interactive dashboards, data visualizations, and case studies, the platform helps to bring the tangible outcomes of Quality 4.0 adoption. Users can engage with real-time data, interactive simulations, and valuable resources, fostering a deeper understanding of the practical implications and inspiring wider adoption of Quality 4.0 across organizations.

5.1 Managerial Implications

Several managerial measures are needed to ensure Quality 4.0 adoption in industries. To implement Quality 4.0, managers must create a clear strategic vision, outlining goals and anticipated results. Managers must thoroughly analyse their existing quality management procedures and make the appropriate technological investments including data analytics, AI capabilities. Moreover, developing data collection methods and analytics capabilities are essential milestones. Managers should encourage cross-functional teams and collaboration while dismantling departmental silos. Programs for upskilling the workforce in digital technology and data analysis should be available. It is also crucial to give cybersecurity and data privacy safeguards a priority. Moreover, managers must continually modify and enhance their strategies in alignment with new technological developments.

Business model optimization for Quality 4.0 is crucial in the digital era to meet customer demands, improve quality control, enhance customer satisfaction, and drive competitive advantage. By integrating digital technologies and data analytics, organizations can proactively address quality issues, tailor products to customer needs, ensure supply chain visibility, make data-driven decisions, and foster continuous improvement and innovation. These initiatives enable companies to deliver superior quality, stay ahead in the market, and meet the expectations of digitally empowered customers.

Building cross-functional teams is essential for facilitating collaboration and knowledge sharing in the context of Quality 4.0 adoption. These teams bring together individuals from various departments, including quality management, operations, IT, engineering, and data analytics, to ensure a holistic approach to adopting Quality 4.0 initiatives. By harnessing diverse perspectives, cross-functional teams enhance problem-solving capabilities and decision-making processes. Team members can share their specialized knowledge and experiences, promoting continuous learning and a comprehensive understanding of Quality 4.0 technologies and best practices. Collaborating within cross-functional teams enables effective coordination and integration of different technologies, ensuring alignment with Quality 4.0 objectives. Moreover, these teams contribute to effective change management by engaging stakeholders from various departments, fostering a shared vision, and addressing resistance to change. Building cross-functional teams encourages collaboration, knowledge sharing, and successful Quality 4.0 adoption in organizations. Furthermore, conducting training programs, using collaboration platforms, and providing regular updates and progress reports keep stakeholders informed and involved.

6. Conclusion and Scope for Future Work

In the Volatile, Uncertain, Complex, and Ambiguous (VUCA) environment, manufacturing firms must upgrade themselves to survive in a competitive marketplace. Effective Quality 4.0 adoption in industries requires a systematic approach encompassing technology, process optimization, and cultural transformation. Organizations should establish a clear vision and align it with their overall business strategy, defining specific outcomes to be achieved through Quality 4.0 initiatives. Moreover. conducting a comprehensive assessment of current quality management practices and technologies is essential for identifying areas that need improvement and determining how Quality 4.0 can address existing challenges. Selecting suitable technologies such as IoT devices, data analytics, and artificial intelligence enables real-time data collection, analysis, and decision-making for improved quality monitoring and process optimization. Furthermore, building a robust data infrastructure ensures the integrity and analysis of quality-related data, facilitating continuous improvement.

Additionally, optimizing processes through lean and Six Sigma methodologies and fostering a culture of quality and innovation are critical. Additionally, change management strategies should be implemented to communicate the benefits of Quality 4.0 effectively and address resistance. Continuous monitoring, feedback, and adjustment ensure ongoing improvement in Quality 4.0 implementation. By adopting these steps, industries can successfully embrace Quality 4.0, resulting in enhanced product quality, increased efficiency, and sustained competitiveness. Moreover, Kaizen can help organizations continually enhance their processes and services by involving employees in problem-solving and fostering a culture of ongoing improvement. It can increase efficiency, reduce costs, and improve employee’s satisfaction. Overall, adopting Quality 4.0 can enable organizations in all sectors to navigate disruptive times by improving their processes, products, and services.

To explore the future scope and social implications of Quality 4.0, researchers can examine Quality 4.0 aspects using advanced MCDM techniques such as interval-valued, T-spherical, and q-rung ortho fuzzy sets. Additionally, future studies can analyse the results of presented study using an empirical model and verify the results. Furthermore, the current study was conducted in India, a similar investigation can be conducted in other parts of the world**.**

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Appendix-A

Fuzzy Numbers

The triangular fuzzy number can be represented as (a, b, c). A fuzzy number N on R is stated by (a, b, c) and can be represented using equation (1).

$$\mu_N(y) = \begin{Bmatrix} \left(\dfrac{y-a}{b-a}\right) & y \in [a, b] \\ \left(\dfrac{y-c}{b-c}\right) & y \in [b, c] \\ 0 & otherwise \end{Bmatrix} \tag{1}$$

where a, b and c represent the lower, middle and upper limit values of fuzzy number such as $a \le b \le c$.

Let P and Q be two fuzzy numbers $P = (a_1, b_1, c_1)$, and $Q = (a_2, b_2, c_2)$. The computations of fuzzy numbers are performed using equations (2-5) as follows:

$$\begin{aligned} P+Q &= (a_1,b_1,c_1)+(a_2,b_2,c_2) \\ &= (a_1+a_2, b_1+b_2, c_1+c_2) \\ &\text{for } a_1a_2>0, b_1b_2>0, c_1c_2>0 \end{aligned} \quad (2)$$

$$\begin{aligned} P-Q &= (a_1,b_1,c_1)-(a_2,b_2,c_2) \\ &= (a_1-c_2, b_1-b_2, \mathrm{c}_1-a_2) \\ &\text{for } a_1a_2>0, b_1b_2>0, c_1c_2>0 \end{aligned} \quad (3)$$

$$\begin{aligned} PXQ &= (a_1,b_1,c_1)\,\mathrm{X}(a_2,b_2,c_2) \\ &= (a_1\,\mathrm{a}_2, b_1b_2, \mathrm{c}_1\,c_2) \\ &\text{for } a_1a_2>0, b_1b_2>0, c_1c_2>0 \end{aligned} \quad (4)$$

$$\begin{aligned} P/Q &= (a_1,b_1,c_1)\div(a_2,b_2,c_2) \\ &= (a_1/c_2, b_1/b_2, \mathrm{c}_1/a_2) \\ &\text{for } a_1a_2>0, b_1b_2>0, c_1c_2>0 \end{aligned} \quad (5)$$

Steps Involved in Fuzzy AHP

Step 1: The judgmental matrix is represented as

$$\tilde{B} = \begin{bmatrix} 1 & \tilde{b}_{12} & .... & .... & \tilde{b}_{1n} \\ \tilde{b}_{21} & 1 & .... & .... & \tilde{b}_{2n} \\ .... & .... & .... & .... & .... \\ .... & .... & .... & .... & .... \\ \tilde{b}_{n1} & \tilde{b}_{n2} & .... & .... & 1 \end{bmatrix} \quad (6)$$

Step 2: Evaluate the fuzzy synthetic extent with respect to the ith barrier using equation (7-9), which is defined as

$$R_i = \sum_{j=1}^{m} S_{gi}{}^{j} x \left[\sum_{i=1}^{n} \sum_{j=1}^{m} S_{gi}{}^{j} \right] \quad (7)$$

where $\sum_{j=1}^{m} S_{gi}{}^{j} = \left(\sum_{j=1}^{m} a_{ij}, \sum_{j=1}^{m} b_{ij}, \sum_{j=1}^{m} c_{ij} \right)$ (8)

$$\sum_{i=1}^{n} \sum_{j=1}^{m} S_{gi}{}^{j} = \left(\frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} c_{ij}}, \frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} b_{ij}}, \frac{1}{\sum_{n}^{i=1} \sum_{m}^{j=1} a_{ij}} \right) \quad (9)$$

a, b and c represent lower, middle and upper limit values

Step 3: The possibility degree of $V(S_2 \geq S_1) = hgt\left(S_2 \cap S1\right) = \mu(e)$ (10)

$$
= \begin{Bmatrix} 1 & if\, b_2 \geq b_1 \\ 0 & if\, a_2 \geq c_2 \\ \dfrac{a_1 - c_2}{(\mathrm{b}_2 - c_2)(b_1 - a_1)} & otherwise \end{Bmatrix} \tag{11}
$$

$where\ \mu(e)\ represents\ hightest$ intersection $between\ two\ fuzzy\ numbers$

To match S1 and S2, a comparison is made between $V(S_1 \geq S_2)$ and $V(S_2 \geq S_1)$. For the probability that the convex fuzzy numbers are greater than q fuzzy numbers, Si, (i=1,2,3,………..q), can be defined as:

$$
\begin{aligned} V(S \geq S1, S2, S3, S4.......Sq) &= \mathrm{V}(\mathrm{S} \geq S1), \mathrm{V}(\mathrm{S} \geq S2)................\mathrm{V}(\mathrm{S} \geq Sq) \\ &= \min \mathrm{V}(\mathrm{S} \geq S1), i = 1,2,3........\mathrm{q} \end{aligned} \tag{12}
$$

It is assumed that $d'(\mathrm{B_i}) = \min \mathrm{V}(\mathrm{S_i} \geq S_q)$ (13)

For q=1, 2, 3, 4, 5,…………n (q≠i), the weight vector is represented as

$$
\begin{aligned} &W' = \left(d'(B_1), d'(B_2), ...d'(B_n)\right)^T \\ &where\ B_i\ (i = 1,2,3,4,5,.........n)\ \text{reveals n barriers} \end{aligned} \tag{14}
$$

Step 4: The normalized weight vectors of the barriers are evaluated as

$$
W = \left(d(B_1), d(B_2)...............d(B_n)\right)^T \tag{15}
$$

where W is a nonfuzzy number

Steps Involved in Fuzzy-TOPSIS

Step 1: Map the solutions with respect to identified barriers. In this, weights determined in the previous section (using fuzzy AHP) are used.

Step 2: Develop a fuzzy matrix for solutions using a team of k area experts, having m number of solutions $(\mathrm{S}_1, \mathrm{S}_2, ...\mathrm{S}_m)$ and n number of barriers $(B_1, B_2, ...B_n)$

$$
C = \begin{array}{c c} & \begin{array}{cccc} B_1 & B_2 & & B_n \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ \\ S_m \end{array} & \begin{pmatrix} a_{11} & a_{12} & .... & a_{1n} \\ a_{21} & a_{22} & .... & a_{2n} \\ .... & .... & .... & .... \\ a_{m1} & a_{m2} & .... & a_{mn} \end{pmatrix} \end{array} \tag{16}
$$

where a_{mn} represents the rating of solution S_m with respect to barrier B_n

Step 3: Develop aggregate fuzzy values for identified solutions

For N decision makers, the aggregated fuzzy matrix is evaluated as

$$d = \min_{N}\{a_{rsN}\},\; e = \frac{1}{N}\sum_{n=1}^{N} b_{rsN},\; f = \max_{N}\{c_{rsN}\} \qquad (17)$$
$$where\, r = 1,2,3,.......m\; and\; s = 1,2,3,..........n$$

Step 4: Normalization of the fuzzy decision-making matrix is computed as

$$D = \left[q_{ij}\right]_{mxn} \qquad (18)$$
$$where\, i = 1,2,3............\text{m and j} = 1,2,3............n$$

$$\tilde{q} = \left(\frac{l_{ij}}{n_j^*}, \frac{m_{ij}}{n_j^*}, \frac{n_{ij}}{n_j^*}\right), where\, n_j^* = \max n_{ij}\; (benefit\; criteria) \qquad (19)$$
$$\tilde{q} = \left(\frac{l_j^-}{n_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), where\, l_j^- = \min l_{ij}\; (\text{cost}\; criteria) \qquad (20)$$

Step 5: Evaluate the weighted normalized decision-making matrix

$$\tilde{T} = \left[\tilde{t}_{ij}\right]_{mxn}, where\, i = 1,2,3...........m\; and\; j = 1,2,3..................n \qquad (21)$$

where $\tilde{T} = \tilde{q}_{ij}\, x\, w_j$ (22)

Step 6: Evaluate the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

$$S^+ = \left\{t_1^+, \text{t}_2^+, ...\text{t}_\text{n}^+\right\},\; where\, tj^+ = \left\{\max(t_{ij})\right\} \qquad (23)$$
$$S^- = \left\{t_1^-, \text{t}_2^-, ...\text{t}_\text{n}^-\right\},\; where\, tj^- = \left\{\min(t_{ij})\right\} \qquad (24)$$
$$j = 1,2,3...............n$$

Step 7: Calculate the distance of each identified solution from FPIS and FPIN

$$e_i^+ = \left\{\sum_{j=1}^{n}(t_{ij} - t_{ij}^+)^2\right\}^{1/2} \qquad (25)$$
$$e_i^- = \left\{\sum_{j=1}^{n}(t_{ij} - t_{ij}^-)^2\right\}^{1/2} \qquad (26)$$
$$where\, i = 1,2,3..........m\; and\; j = 1,2,3...............n$$

Step 8: Evaluate the closeness coefficient CC_i as follows:

$$CCi = \frac{e_i^-}{e_i^- + e_i^+} \tag{27}$$

Step 9: Rank the solutions on the basis of closeness coefficient value