Ranking the Enablers of Supply Chain Digitization in Pakistan using a Novel Triangular Fuzzy Best Worst Method: A Case Study of Fertilizer Industry

Umer Javaid

MS-L&SCM 2k20

A thesis submitted to NUST Business School for the partial fulfillment of the degree of Master of Science in Logistics & Supply Chain Management

2022

Ranking the Enablers of Supply Chain Digitization in Pakistan using a Novel Triangular Fuzzy Best Worst Method: A Case Study of Fertilizer Industry

Umer Javaid

MS-L&SCM 2k20

Dr. Waqas Ahmed

A thesis submitted to NUST Business School for the partial fulfillment of the degree of Master of Science in Logistics & Supply Chain Management

2022

THESIS ACCEPTANCE CERTIFICATE

It is certified that the final copy of MS L&SCM thesis written by Mr/ Umer Javaid Registration No. 330315 has been vetted by the undersigned, found complete in all aspects as per NUST Statutes/Regulations/MS Policy, and is free of plagiarism, errors, and mistakes and is accepted as fulfillment for the award of MS degree. It is further certified that necessary amendments as pointed out by GEC members and foreign/local evaluators of the scholar have also been incorporated in the said thesis.

Signature of Supervisor with Stamp:________________________________

Date:____

Program Head Signature with Stamp:_______________________________

Date: ____

Signature of HOD with Stamp: ___________________________________

Date:____

Countersigned by

Signature (Dean/Principal):_____________________

Date:______________________________________

I hereby state that no portion of the work referred to in this dissertation has been submitted in support of an application for another degree or qualification of this or any other University or other institutes of learning.

Student’s Name:____________________

Signature:_________________________

Date:______________________________

Dedication and Acknowledgment

First and undoubtedly most important, I thank Allah the Almighty, for bestowing his immeasurable blessings, which have aided me at every turn in completing my research successfully. I write my dissertation as a tribute to my numerous friends and family. A special sentiment of thanks to my devoted parents, whose words of support and push for persistence still reverberate in my ears. I dedicate this work to my father, and I especially appreciate him for supporting me during the whole master's program. I also want to thank my supervisor, Dr. Waqas Ahmed, and my GEC members, Dr. Mujtaba Hassan Agha and Dr. Faran Ahmed, for their help and guidance throughout the process. I will always be grateful for everything they did, especially for the hours and the effort put in by Dr. Waqas Ahmed in rehearsing and revising my presentations and documentation.

Table of Contents

List of Tables

List of Figures

List of Notations and Abbreviations

IT	Information Technology
SCM	Supply Chain Management
SCRM	Supply Chain Risk Management
FMCG	Fast Moving Consumer Goods
IoT	Internet of Things
BCT	Blockchain Technology
BDA	Big Data Analytics
IDY	Industry 4.0
BWM	Best Worst Method
FMCDM	Fuzzy Multi Criteria Decision Making
AHP	Analytical Hierarchy Process
GTFN	Generalized Triangular Fuzzy Number
TFN	Triangular Fuzzy Number
SC	Supply Chain
AI	Artificial Intelligence
JIT	Just in Time
IIoT	Industrial Internet of Things
AM	Additive Manufacturing
ALM	Additive Layer Manufacturing
RFID	Radio Frequency Identification
WSN	Wireless Sensor Networks
NFC	Near field Communication
QR	Quick Response Code
LPWAN	Low Power Wide Area Networks
MTC	Machine Type Communications
SDN	Software Defined Networking
NFV	Network Function Virtualization
GSN	Global Sensor Networks
Wi-Fi	Wireless Fidelity

ZigBee	Zonal Intercommunication Global Standard
6LOWPAN	IPv6 over Low-Power Wireless Personal Area Networks
SMEs	Small and Medium Sized Enterprises
API	Application Programming Interface
MADM	Multi Attributive Decision Making
MODM	Multi Objective Decision Making
OR	Operations Research
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
ELECTRE	Elimination Et Choix Traduisant la REalité ("Elimination and Choice Translating Reality"
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
SSCM	Sustainable Supply Chain Management
SWOT	Strength, Weakness, Opportunity and Threat Analysis
MULTIMOORA	Multiple Objective Optimization on the basis of Ratio Analysis plus Full Multiplicative Form
MABAC	Multi-Attributive Border Approximation Area Comparison
FBWM	Fuzzy Best Worst Method
DM	Decision Maker
FST	Fuzzy Set Theory
CoCoSo	Combined Compromised Solution
GMIR	Graded Mean Integration Representation
TQM	Total Quality Management
CR	Consistency Ratio
CI	Consistency Index
VIKOR	Multi-criteria Optimization and Compromise Solution
MBO	Monarch Butterfly Optimization
EWA	Earthworm Optimization
EHO	Elephant Herding Optimization
MS	Moth Search

Abstract:

Crisp values of criteria may not be sufficient to accurately depict real-world multi-criteria decision-making problems, given the ambiguity typically present in decision data because of incomplete information and the ambiguity resulting from the decision-makers qualitative opinion. The best-worst method, the most recent multi criteria decision making technique technique, was expanded to the fuzzy environment in this work, using generalized triangular fuzzy numbers and the weights of criteria and alternatives with regard to various criteria were then calculated in a fuzzy environment using the graded mean integration representation approach. Three cases were studied to demonstrate the viability and efficacy of the suggested fuzzy best worst method. The results show that the proposed fuzzy best worst method can not only obtain reasonable preference ranking for alternatives but also has higher comparison consistency than the best worst method and a higher distinguishing power than normalized triangular fuzzy best worst method. Additionally, a list of important digitization enablers that can enhance supply chain management is identified and prioritized in this study. Companies have been compelled to go beyond the traditional decision-making process, which is based on intuition and prior experience, due to the intense market rivalry. The primary IT and digitization enablers helpful for enhancing supply chain performance have been evaluated, ranked, and prioritized using the Best Worst Method functioning in the fuzzy domain. The same is carried out using best worst method and normalized triangular fuzzy best worst method, and the results are compared in terms of rankings and weights. There are a total of 26 essential enablers, and they have all been rated. The results showed that the top three digitalization and IT enablers on which enterprises should concentrate heavily to enhance their supply chain performance are "transparency and visibility," "effective management of technologies," and "automation via smart contracts." The results of this study will assist firms in concentrating on digitalization technologies to enhance the performance of their supply chain and provides a multi criteria decision making tool to rank different criteria and sub-criteria.

1 Introduction:

In this chapter, the suggested research topic is introduced, and the framework of the research is established by tying together the background information and requirement of the research problem. The research objectives and questions are explained in detailed followed by the theoretical and empirical significance of the study. The chapter also includes the introduction of how the methodology developed in this research is going to be implemented to answer the research questions.

1.1 Supply Chain and Organization Performance:

Supply chains in this globalized world are often distributed in large geographical areas which makes the efficient flow of products and information quite difficult. This can be improved using information technology (IT) or tools of digitization (Liu & Chiu, 2021). The use of IT has led to the betterment of supply chain processes when employed in the manufacturing sector in America. It has led to a reduction in cycle time, provided on-time delivery of products to customers, improved supply chain agility, and resulted in higher efficiency throughout the supply chain (Hennelly et al., 2020). The adoption of digitization in supply chain management (SCM) has resulted in improving the performance of the organization (Jabbour et al., 2020).

One of the purposes of an organization's existence is to enhance its profit generation. For this purpose, an organization must attain a competitive advantage. This is attained by improving the supply chain performance of an organization. In today's global scenario the performance of an organization is linked to its supply chain performance. When the performance of the supply chain increases it increases the performance of the organization (Kalyar et al., 2020). Kumar in his study found out that supply chain management practices namely i) Sharing of Information/Data, ii) Developing a better relationship with suppliers, iii) Improving logistics operations, improves organizational performance (Kumar et al., 2020).

Cloud-based supply chain management systems improve the performance of the supply chain of a company which in turn enhances the performance of an organization (Lin et al., 2021). SCM provides a competitive advantage and increases the performance of an organization by improving financial and marketing operations (Isnaini et al., 2020). A positive relationship was found between supply chain management and organizational performance (Saragih et al., 2020).

It is therefore of imperative importance that supply chain performance be enhanced so that organizational performance is made better. Digitization can improve supply chain performance by managing external environmental factors like extreme weather events, currency exchange rates, etc. (Jabbour et al., 2020).

1.2 Digitization of Supply Chain:

Supply chains today are no longer local but span multiple localities and regions. In such a scenario it is at times difficult to ensure the smooth, efficient, and effective flow of products and information. This can be achieved by the use of IT or digitization Firms can enhance their performance by investing in digitization by developing and storing data that is used to improve their services to customers (Huo et al., 2021). Reducing risk or mitigating it can help an organization in achieving a competitive advantage. To reduce risk or mitigate it, supply chain risk management (SCRM) is of imperative importance. Digitization can help an organization in improving its supply chain risk management (Schlüter et al., 2019).

Digitization plays a key role in improving food supply chains. Consumers are now more aware of the food they are to consume therefore safety of the food and excellent quality is at the top of their mind. This can be achieved through real-time data sharing using digitization. Food companies in Thailand have applied sensors for monitoring and feeding chicks which has resulted in improving the productivity and supply chains in the poultry industry (Kittipanya-Ngam & Tan, 2020). Logistics is one of the most important aspects of a supply chain. In the case of fast-moving consumer good (FMCG) companies operating in Turkey delivery times, flexibility issues, and inventories were reduced by the use of digitization (Kayikci, 2018).

To achieve lower costs and higher profits, visibility through a supply chain is of immense importance which is achieved through digitization. No company or department can operate in isolation; hence to improve an organization's performance standardization of processes within the supply chain is necessary. This can be achieved through digitization (Agrawal & Narain, 2018). To enhance organizational performance IT or digitization plays a key role. This fact is further strengthened by the fierce competition in the market due to globalization. No organization can now compete in the global market if it does not invest in digitization as by not doing so it is depriving itself of competitive advantage.

This will result in the loss of sales for the organization hence leading to financial risk. Digitization can help any organization improve its performance. A similar study was carried out by McKinsey, the study estimated that digitization of the supply chain can help in reducing operational expenses by 30% and 75% less lost sales (Alicke et al., 2017). The use and adoption of digital technologies in the supply chain will provide more and more opportunities, benefits, and gains once each entity involved in the supply chain, including but not limited to suppliers, partners, customers, etc., works together to coproduce and cocreate value (Ganbold et al., 2021). It is in the interest and benefit of organizations to invest in IT so that the supply chain processes are improved and standardized leading to an increase in the company's performance.

1.3 Technologies/Enablers of Digitization:

Digitization primarily helps in moving from paper-based systems to digital systems. This has numerous advantages i) Reduces operating expense by reducing labor costs, ii) Helps in reducing order picking time in warehouses thereby improving efficiency, iii) Improves productivity, iv) Customer orders are timely delivered as compared to paper-based systems, iv) Improves perfect order fulfillment parameter (the percent of orders that have been fulfilled perfectly), especially in case of e-commerce (Koul, 2018). Many tools of digitization do exist, the implementation of which is to provide improvements in supply chains and resultantly enhance organizational performance.

Internet of Things (IoT), Blockchain (BCT), Big Data Analytics (BDA), Automation and 3D printing, Robotics, and Machine Learning (Industry 4.0) are the top 4 digitization tools that will overhaul supply chain management in the years to come and provide its users with competitive advantage according to MIT Management Sloan School (Stackpole, 2020). World Economic Forum in 2017 reported that technologies central to Industry 4.0 (IDY) revolution like AI, robotics, automation, etc. are transforming businesses and supply chains across various industries. To take advantage of this industrial revolution organizations will have to understand the opportunities provided by such technologies not only in their sector or domain but also in the vast domain of customers, suppliers, and adjoining markets (Tjahjono et al., 2017).

Gupta in his study found four leading technologies that will have an impact on enhancing supply chain performance for organizations. These are big data analytics, block chain technology, industry 4.0, internet of things (Gupta et al., 2021). Often IoT is considered a sub-technology of the industry 4.0 but the difference lies in the requirement for application, hardware, software, and complete systems as well as security features. IoT is more concerned with the day-to-day activities in daily life whereas industry 4.0 is applied to influence and optimize the production processes. It was also noted that a primary difference is in the goal that is to be achieved using these technologies. The primary goal for IoT is to have a connected future by trying to bridge the gap between the real and cyber world, whereas for industry 4.0 the goals to be achieved are primarily optimization of production, improvement of quality and improvement of materials management, etc. (Blankenberg, 2016)

1.4 Significance of the study:

All of this develops the importance of digitization to enhance supply chain performance which will improve organizational performance. However, many companies are not able to reap the benefits discussed in the preceding sections. One of the reasons for this is that companies especially in developing countries do not realize the enablers that are necessary for the implementation of these technologies. This research is conducted to identify such technologies that have an impact on improving supply chain performance.

1.4.1 Theoretical Significance:

Gupta in his study has consolidated key digital tools such as BDA, IDY, IOT and BCT as the key enablers/technologies of digitization and has also enlisted the subcategory enablers of each technology/main enabler. His study claims that these enablers may help in improving the supply chain performance of organizations (Gupta et al., 2021). To check the efficacy of these enablers, ranks were established using best worst method (BWM) (Rezaei, 2015), however, it has been noted that his research does miss out on some key subcategory enablers. As Korherr and Kanbach in their research found that to reap benefits from big data there must be an interconnection of technology, people, and the firm environment (Korherr & Kanbach, 2021). This according to them is a digitization enabler. Similarly, organizational openness is another enabler for big data analytics, the presence of which is necessary for improving supply chain performance (Papa et al., 2021). These further warrants that research is conducted to determine the enablers and subcategory enablers of digitization.

1.4.2 Empirical Significance:

Data collection is an important aspect of any research conducted as it is likely to influence all results or inferences drawn from the study conducted. The study conducted by Gupta establishes the ranking of the digitization enablers based on data collected from a panel of nine industrial and academic experts. However, the data collected by Gupta to establish the relative grading of the digitization enablers was conducted using crisp values collected from experts and no mechanism was adopted to account for the uncertainty associated with the use of experts for data collection. For this purpose, the study aims to develop and use a fuzzy multi-criteria decision-making method (FMCDM). Fuzzy was introduced by Zadeh to account for uncertainty associated with the use of experts for data collection in 1965 (Dubois & Prade, 2012).

For this study, the multi-criteria decision-making tool to be used is the best worst method (BWM). This method was introduced by Rezaei in 2015 and has numerous advantages over other MCDM techniques such as the analytical hierarchy process (AHP), which is discussed in Section 2.11 (Rezaei, 2015) To account for the uncertainty associated with the data collected from experts and to manage it better this study plans to use generalized triangular fuzzy numbers (GTFN) with BWM. The perceived advantages and comparison with BWM and fuzzy BWM using normalized triangular fuzzy numbers (TFN) are explained in later Sections of the report (Guo & Zhao, 2017).

1.5 Research Question:

Limited research has been found that consolidates all the enablers of digitization in a single study, especially in the case of companies operating in developing countries and no study has been found that accounts for the uncertainty associated with the use of multi-criteria decision-making tools (MCDM) in case of establishing the relative importance of digitization tools available to enhance or improve supply chain performance. The main questions to be addressed by this study are as follows:

1. What are the ranks of the key digitization technologies/enablers and subcategory enablers which improve supply chain performance?
2. How can uncertainty associated with the use of human judgment for ranking using MCDM tools be tackled more effectively by utilizing fuzzy numbers?

1.6 Research Objective:

The research objectives to be attained by this proposal/study are as follows:

1. Establish a relative grading of the key digitization enabler that has the most impact in enhancing the performance of the supply chain, of the companies by using a fuzzy MCDM technique i.e., Generalized triangular fuzzy best worst method.
2. Establish a relative grading of the subcategory enablers that function as a mediator by helping in the implementation of the key digitization enablers using the generalized triangular fuzzy best-worst method (BWM).
3. Use generalized triangular fuzzy with the best worst method to account for the uncertainty associated with the use of experts for data collection and compare with previous approaches of BWM.

1.7 Outline of the Proposal:

The next Sections discuss the following in the same order. Chapter 2 enlists the literature review of the past studies to identify the enablers and subcategory enablers of digitization. The same is again carried out to identify the research carried out in the field of MCDM and the research conducted using best worst method and then a critical analysis of the literature to identify the shortcomings of BWM and how they are to be addressed by the methodology developed in this research. Chapter 3 enlists the methodology developed in this research primarily the concepts of the methodology developed i.e., generalized triangular fuzzy number best worst method (GTFN-BWM). The methodology implementation to rank the enablers and subcategory enablers of digitization are listed in the chapter 4. Chapter 5 lists down the weights and ranks obtained using GTFN-BWM, BWM and TFN-BWM, followed by discussion on the results obtained and the efficacy of the methodology developed in chapter 6. The chapter 7 uses the methodology developed in this research on 3 case studies identified from literature to develop the importance of GTFN-BWM. and lastly chapter 8 lists down the findings of this study along with the conclusion and limitations of this research and also directions for future research are listed down.

2 Literature Review:

This chapter presents a brief overview of supply chain management, performance measurement of supply chain processes, the use of IT in the supply chain, the perceived benefits of digitizing the supply chain, technologies/enablers of digitization of the supply chain, the impacts and benefits of digital technologies for supply chain, the subcategory enablers of big data analytics, internet of things, industry 4.0 and blockchain technologies, the comparison of BWM with AHP, the shortcomings of BWM and comparative analysis with normalized fuzzy BWM. The Section also enlists the shortcomings of fuzzy BWM which are to be solved by the methodology enlisted in chapter 4.

2.1 Supply Chain Management:

Supply chain management (SCM) covers the planning and management of all resources that participate in logistics, procurement, locating, and altering of all activities of management. It also includes coordination and collaboration with supply chain partners such as suppliers, intermediaries, customers, and third-party service providers (Min et al., 2019). SCM over the past few decades has helped in attaining a sustainable competitive advantage. It has shown considerable changes, most of which are owed to technological advancements that took place with the changing times (Tarofder et al., 2017). Supply chain strategies are adopted by organizations as a means for generating and sustaining strategic competitive advantage (Madhani, 2019; Min et al., 2019). Fawcett claims that such an arrangement is crucial to yield all the benefits associated with the management of the supply chain. These benefits comprise better delivery services, inventory reduction, and also reduces large product development cycles (Fawcett et al., 2008).

2.2 Performance Measurement of Supply Chain Management:

Performance measurement can simply be defined as a process of measuring the efficiency and efficacy of any given process (Garengo & Sardi, 2021). Janvier explains effectiveness as a measure of the level of customer satisfaction whereas efficiency can be defined as the means to achieve the pre-determined satisfaction level of the customers e.g. cost-effectiveness and exploitation of resources (Janvier-James, 2012) Some of the main reasons behind the emphasis on the effectiveness of SCM are escalating competition, globalization of the market, and organizations prioritizing what customers demand (Ali et al., 2019). Tigga asserts that the measurement of time along with quality can certainly judge the supply chain's (SC) capability of providing better services to the end users whereas innovations and flexibility in an SC show the ability to handle rapid disparities in supply and demand (Tigga et al., 2021). Therefore, it is evident from the discussion in the previous sections that to enhance an organization's SC and performance, the use of digital and IT tools is required (Jiang et al., 2020).

2.3 Digitization of Supply Chain Management:

Digitization refers to "the increasing penetration of digital technologies in society with the associated changes in the connection of individuals and their behavior"(Agrawal & Narain, 2018). Many organizations consider becoming more "digital" because they have witnessed the value and `criticality of digital technologies for the growth of their businesses. Also, the support from management for such initiatives is growing now more than ever (Rodríguez et al., 2020). Although strategic, and operational aspects of the supply chain are highly valued, this study focuses on the technological side of the SCM, more specifically, the digitization of the SCM. Also, it centers on identifying and exploring the digital/technological features that function as enablers to the SCM in the context of digitization.

The digital supply chain can be demarcated from the standard supply chain practices due to its involvement in the development of information systems and the adoption of innovative technologies that strengthen the integration and the agility of the supply chain and thus results in improving customer service and sustainable performance of the organization (Ageron et al., 2020; Farajpour et al., 2022; Haddud & Khare, 2020). However, Jagtap & Rahimifard argued that digitizing the organizations requires a meticulous understanding of the digital applications and features that would act as enablers contributing toward major benefits for business (Jagtap & Rahimifard, 2019) Complex problems in SC can be addressed by digitization. Nevertheless, for an organization to achieve the target level of digitization through the formation of practical implementation is still a challenging topic.

2.4 Benefits of Digitization of Supply Chain:

In supply chain practices, the flow of accurate real-time information is considered as important as the flow of goods. Not only does information sharing provides flexibility but also improves the responsiveness of the supply chain (Huo et al., 2021). The information shared may include order status, sales forecasts, end-customer demand, inventory levels, lead times, capacity availability, and quality. Sharing information may also improve transparency, speed up payment cycles, avoid lost sales, reduce inventories, create trust and avoid overproduction, hence, helping in the overall gain of the organization (Lee et al., 2022).

This discussion emphasizes the significance of sharing real-time information to improve the supply chain. This is why most firms improve their SC by adopting digitization (Taboada & Shee, 2021). Though Huo argued that the digitization of organizations is challenging as organizational, functional, and technological factors need to be aligned to reap benefits (Huo et al., 2021). Digital technologies can transform organizational activities by offering new capabilities and opportunities for organizations. They also offer some functional benefits such as less cost of operations, less labor required, enhances accuracy of work, and improved communication among business partners. More specifically, digital technologies benefit the supply chain in various ways such as (R. Novais et al., 2019);

1. It facilitates in offering a new medium for the distribution of services.
2. It provides organizations with a platform for communication with their partners and allows for real-time data sharing.
3. It designs an organization’s transactional system in a way that facilitates the customer’s preferences.
4. It provides a central and standardized business platform.
5. It allows end users to customize their needs online anytime and anywhere.

2.5 Technologies of Digitization of Supply Chain:

Irfan arguably claims that despite of heavy cash invested in IT and the indication of positive effects from the acceptance of IT, many organizations have not been able to achieve the promised results in their SC (Irfan et al., 2022). It has been noted that this is the result of organizations not identifying the enablers of the implemented technologies, which are essential in enhancing the performance of SC. Many researchers in their studies have identified various digital transformation enablers for supply chain performance. This study, however, has selected four key enablers that are new, and they provide huge scope for further research the impact, benefits, and subcategory enablers of which are explained in the sections that follow.

Table 2.1 Main Enablers of Digitization that improve Supply Chain Performance

Key Enablers	Sources
Big Data Analytics	(Agrawal & Narain, 2018; Attaran, 2020; de Assis Santos & Marques, 2022; Fang et al., 2022; Gupta et al., 2021)
Industry 4.0	(Agrawal & Narain, 2018; Attaran, 2020; Bag et al., 2021; Gupta et al., 2021; Rad et al., 2022; Tortorella et al., 2020)
Internet of Things	(Agrawal & Narain, 2018; Attaran, 2020; Evtodieva et al., 2019; Gupta et al., 2021; Sestino et al., 2020)
Blockchain Technology	(Agrawal & Narain, 2018; Attaran, 2020; Gupta et al., 2021; Gurtu & Johny, 2019)

2.6 Big Data Analytics:

Research carried out by industry professionals defines big data analytics (BDA) as data that is generated in large quantities, due to the use of digitization technologies, so that traditional methods cannot be applied to it and specific algorithms need to be developed for it to answer the research question (Favaretto et al., 2020). Tech America Foundation defines big data analytics (BDA) as follows: “Big data is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information.” Many researchers argue that data generated more than 300 terabytes in a week is called big data (Al Hadwer et al., 2019).

2.6.1 Impact/Benefits of Big Data Analytics for Supply Chain:

The traceability and visibility of products can be improved by using digital technologies like big data, thus improving the SC performance and as a result enhancing the overall performance of the organization (Maheshwari et al., 2021). It has allowed to increase production capacity and efficiency and has also improved customer satisfaction levels (Sakao & Neramballi, 2020). Competitive advantage and low costs were the results of the implementation of BDA in the case of the production and service industry (Agrawal & Narain, 2018). Organizations today “consider digital SCs disruptive and important for performance improvement”(Gupta et al., 2021). Research evaluating the role of BDA in SCM seems to have been left behind. BDA can support professionals in more effective decision-making and in managing work in general.

Several studies have been carried out to determine the role BDA plays for SCM, focusing largely on the traditional techniques of BDA and the impact they have on supply chain management (Ageron et al., 2020). It has been noted that the role of BDA and its impact on SCM needs to be studied deeply by researchers. Many authors are of the view that the competition now is about the supply chain of firms and not what it was traditionally thought out to be i.e. between firms (Guan et al., 2020). As a result of this, organizations are now formulating new strategies to compete with other firms (Oh et al., 2019). Firms should use technologies and data to their advantage. Korherr and Kanbach (Korherr & Kanbach, 2021) compared big data to the digital transformation that took place in the 1990s when organizations changed their core strategies and processes. They claimed that big data holds such an impact if taken seriously by firms and it will soon result in better strategies for the firms who have adopted BDA.

Subsequently, BDA is vital for the storage, analysis, and acquisition of data in modern supply chain practices (Aryal et al., 2020). Additionally, BDA is essential in producing quality data in supply chain processes (Chehbi-Gamoura et al., 2020). Lamba & Singh have identified change management, data science/big data skills, and big data initiatives as enablers for an effective BDA utility in an organization (Lamba & Singh, 2018). It helps in demand forecasting, improves end-to-end supply chain visibility, and enhances productivity and efficiency (Maheshwari et al., 2021). BDA maintains a positive relationship with supply chain sustainability. It has improved the pharmaceutical sector operating out of Iran (Shokouhyar et al., 2020). BDA helps in improving inventory, warehouse, and logistics management all of which contribute to enhancing the performance of the supply chain (Alotaibi et al., 2020).

2.6.2 Sub-Category Enablers for Big Data Analytics:

IT enablers, the presence of which is to have a significant impact in improving the performance of big data analytics, thereby enhancing the performance of the supply chain are documented as follows:

1. Data capturing and storage is the process of collecting, formatting, arranging, and storing data electronically in ways that make it easy to search for information and retrieve the data as needed. Data capturing and storage techniques serve as another subcategory enabler of BDA. At times data is present in raw form. To extract meaningful information from the data, Smart filters are used to perform data capturing and storage, which extracts

meaningful data from inconsistent one (Sivarajah et al., 2017). Data being used for big data analytics needs to be of good quality, should be reliable, and shouldn't have incomplete or empty values (Côrte-Real et al., 2020).

2. Data security protects data from compromise by external attackers and malicious insiders. Data privacy governs how data is collected, shared, and used. With organizations shifting their focus to data-driven processes, data security and privacy are becoming more important. Data security and privacy is an important sub-category enabler that if provided will provide better results in the case of BDA (Mengke et al., 2016).
3. Integration of technology with data is another important sub-category enabler which shows that data is not be collected at some set stages but after every stage and process in the SC network and integrate it, for BDA to provide better results (Asri et al., 2015).
4. Change management is a systematic approach to dealing with the transition or transformation of an organization's goals, processes, or technologies. Change management of the processes and the commitment of the top-tier managers illustrates that only those people be employed by the organization who have an understanding of the technology and the problem, and how to use the technology to address the existing problem (Lamba & Singh, 2018). People who are skilled in Big Data/Data Science Skills should be employed by the companies if they want to reap the benefits of BDA and improve their supply chain performance (Davenport & Patil, 2012).
5. For the adoption of BDA, feasibility studies need to be carried out, as it is a big investment for organizations, therefore feasibility study must be carried out before moving towards BDA, as it may not be beneficial for all organizations (Lamba & Singh, 2018; Sivarajah et al., 2017).
6. Organizational openness is an across-organization philosophy that emphasizes transparency in all areas and free unrestricted access to knowledge. Organizational openness to the acceptance of BDA is another enabler for big data analytics the presence of which is necessary to reap the benefits of big data in improving Supply Chain Performance (Papa et al., 2021). Korherr and Kanbach in their research found out that to reap benefits from big data there must be an interconnection of technology, people, and the firm environment (Korherr & Kanbach, 2021).

7. Synchronization of processes is defined as the process of establishing consistency among data from a source to a target data storage and vice versa and the continuous harmonization of the data over time. BDA processes should be coordinated in a way that helps supply chain firms to develop synchronization of operations with one another to aid response in a unified and speedy manner (Wu & Lin, 2018).
8. Sejahtera subcategorized adequate system capabilities, established culture of collaboration, good working attitude, and champions as enablers of BDA (Sejahtera et al., 2018).

2.7 Industry 4.0:

Industry 4.0 is defined as the digitization of businesses through the use of intelligent machine learning techniques, artificial intelligence (AI), robotics, and computer (Culot et al., 2020). Industry 4.0 can be described as a mechanism where the manufacturing environment of an organization is increasingly digitized and automated, as well as the creation of digital value chains that enable communication between manufacturers, their environment, and business partners (Dallasega et al., 2018). Lean manufacturing introduced in 1991 by James P Womack has been of immense importance in the manufacturing sector. Rosin in his study found out that Industry 4.0 supports Just in time (JIT) and Jidoka (quality to be built into the production process) strategies, which are central to lean manufacturing (Rosin et al., 2020).

2.7.1 Role of Industry 4.0 Technologies in Management of Supply Chain:

Supply chains today through the use of technologies primarily Industry 4.0 is striving to make supply chain processes like procurement, manufacturing, planning, logistics, etc. more efficient, resilient, and adaptive (Ghadge et al., 2020). Industry 4.0 provides organizations with opportunities to improve their supply chains by providing real-time data. Ralston found out that supply chain performance and resilience were improved through the use of smart systems, made possible by the use of Industry 4.0 technologies (Ralston & Blackhurst, 2020). It is known as the main influencer of the fourth industrial revolution as it includes technologies such as the Industrial Internet of Things (IIoT) and cloud computing (Bag et al., 2021).

Dallasega has emphasized that after mechanization, electrification, and computerization Industry 4.0 is the new revolution termed the fourth industrial revolution (Dallasega et al., 2018).

The main drivers of Industry 4.0 are the Industrial Internet of Things (IIoT), Cloud-based computing, and smart manufacturing which are responsible for transforming the supply chain process into a fully digitized and intelligent one (Vaidya et al., 2018). Many researchers assert that industry 4.0 has enhanced the productivity and efficacy of organizations (Agrawal & Narain, 2018; Attaran, 2020; Büyüközkan & Göçer, 2018). While there have been studies in all domains, research on the impact of smart technology on firms is lagging. Bag also mentions in their study that Industry 4.0 has redefined business by starting a revolution. These components of Industry 4.0 indicate that it is dependent on systems enabled through digital technologies (Bag et al., 2021). This is why firms must focus on developing good IT security and infrastructure to attain a sustainable and successful supply chain network (Benias & Markopoulos, 2017).

2.7.2 Sub-Category Enablers for Industry 4.0:

Industry 4.0 subcategory enablers are characterized as:

1. E-Supply chain management states that to move towards Industry 4.0 an organization must implement technologies that will help them to utilize the internet in their operations e.g. e-business can help the organization reach its customers through the internet. Effective management of these technologies is essential to reap benefits from Industry 4.0, thus playing the role of a sub-category enabler (Cheng et al., 2010).
2. Supply chains today span multiple countries and continents, in such a case, Tracking the products and modifying the product to achieve product localization throughout the supply chain is of immense importance, otherwise, the cost incurred may result in financial bankruptcy. This acts as another subcategory enabler that if achieved provides the benefit of implementing Industry 4.0 (Danys et al., 2022).
3. Additive manufacturing (AM) or additive layer manufacturing (ALM) is the industrial production name for 3D printing, a computer-controlled process that creates three-dimensional objects by depositing materials, usually in layers. Additive manufacturing and 3D Printing act as important sub-category enablers of digitization as they allow for reducing the lead time thereby improving the supply chain performance through Industry 4.0 (Kothman & Faber, 2016).

4. Implementation and development of business models that support innovation are essential to improve the company processes. This acts as an enabler of industry 4.0 (Gottge et al., 2020; Stock & Seliger, 2016).
5. Software is the key enabler of Industry 4.0 initiatives. Most of the new Industry 4.0 job profiles are related to the development and operation of software systems. Effective Management of these technologies is another important enabler (Wan et al., 2016).

2.8 Internet of Things:

The Internet of things (IoT) is concerned with the network of things and people that are connected and collect and share data about how they operate and the environment in which they operate (Goumagias et al., 2021). Internet of Things (IoT) can be referred to as "a new IT revolution that has improved SC communication by another level. The IoT is a network formed by connecting a very large number of things to the Internet with the help of wireless communication"(McRae et al., 2018). Dorsemaine in their study define IoT as a "Group of infrastructures and interconnected objects and allowing their management, data mining and the access to the data they generate." (Boyes et al., 2018).

2.8.1 Impact of Internet of Things on Management of Supply Chain:

IoT has numerous applications as it provides easy access to a wide variety of IoT devices (Kassab & Darabkh, 2020). IoT finds its application in optimizing supply chains and thereby enhancing an organization's performance. IoT finds its application in the food supply chain. It provides the following benefits i) Improves operations and production, ii) Provides a better understanding of external and internal factors and environment, iii) Improves logistics through the use of robotics and automation, iv) Improves traceability, and v) Increases supply chain sustainability (Ben-Daya et al., 2020). Dr. Siva Kumar found out that in India IoT helps in enhancing quality, and security and reduces lead times when used by freight forwarders to improve their logistics (Sivakumar et al., 2020).

IoT can be categorized as a digital technology that has drastically improved communication along the supply chain (Gupta et al., 2021). IoT can improve agility, adaptability, visibility, and adaptability to deal with the many challenges faced in SCM. The main enablers of IoT are radio frequency identification (RIFD) and wireless sensor networks (WSN) (Ben-Daya et al., 2019). IoT has the following benefits when applied in SC (Aich et al., 2019):

1. Reduction of operational costs can enhance the responsiveness of the SC.
2. Tracking real-time data exchange.
3. Simplifying the process of information flow can improve the agility of the SC.

2.8.2 Sub-Category Enablers for Internet of Things:

Subcategory enablers for IoT are further subcategorized as:

1. Cloud-centric IoT for different SCM operations that include Logistics and systems for manufacturing allows organizations to achieve intelligent manufacturing that can be remotely monitored to enhance productivity thereby acting as a sub-category enabler (Atlam et al., 2017; Khayer et al., 2020).
2. The process of understanding and modeling an enterprise business aiming to improve its performance which includes the modeling of the relevant business domain, business processes, and business information is called enterprise modelling. Enterprise modeling/manufacturing provides live data that will improve company performance and enhance IoT performance (Lim et al., 2020).
3. Radio frequency identification (RFID) refers to a wireless system comprised of two components: tags and readers. Tags, which use radio waves to communicate their identity and other information to nearby readers, can be passive or active. Radio frequency identification helps in the transfer of data through the use of wireless networks, which provides easy tracking of products (Costa et al., 2021).
4. A sensor network is a group of sensors where each sensor monitors data in a different location and sends that data to a central location for storage, viewing, and analysis. A sensor network that integrates all the sensors and provides live data from the sensors is essential to achieve better results from IoT (Rayes & Salam, 2022).
5. In another study, near-field communication (NFC), quick response codes (QR), structured data, beacons, and Bluetooth are stated as enablers of the internet of things (Trappey et al., 2017).
6. A study that has forecasted the future of IoT has documented Low power wide area networks (LPWAN) and machine type communications (MTC) as key enablers for the

future of IoT. The author also pointed out software defined networking (SDN) and network function virtualization (NFV) as enablers for limited IoT applications (Palattella et al., 2016). SDN is a network architecture approach that enables the network to be intelligently and centrally controlled, or 'programmed,' using software applications. This helps operators manage the entire network consistently and holistically, regardless of the underlying network technology. In a comparative study, Raju identified RFID, WSN, cloud computing, global sensor networks (GSN), wireless fidelity (Wi-Fi), Bluetooth, zonal intercommunication global standard (ZigBee), IPv6 over Low-power wireless personal area networks (6LOWPAN) as sub-technologies and enablers of IoT (Raju et al., 2020).

7. The internet of things employs big data-supported manufacturing to help increase productivity by reducing facility downtime (Voss et al., 2017).

2.9 Blockchain Technology:

Blockchain is a distributed database of records that has information on all the transactions made and shared among all participating groups (Crosby et al., 2015). Blockchain as a technology has provided decentralization by providing peer-to-peer connection and improved transparency (Bigini et al., 2020). Block Chain is defined as "a shared ledger that allows for unchangeable storage of data via a verified transaction" (Li et al., 2021)**.** BCT provides for trust development between the parties involved and it is one of the most important elements required for partnership development in a Supply Chain (Kwon & Suh, 2004)**.** Tapscott claims that BCT is "the most important invention since the Internet" (Radziwill, 2018). This is why, interest in this field concerning its application in SC is on the rise (Kshetri, 2018).

2.9.1 Role of Blockchain Technology in Supply Chain Management:

Blockchain can improve supply chain transparency as compared to traditional monitoring mechanisms, which leads to better financing options being available to small and medium-sized enterprises (SMEs), especially in developing countries (Chod et al., 2020). Smart contracts lower administrative costs and minimize legal disputes. A study on this behalf has been conducted by Zgraggen which entails the benefits blockchain can provide in reducing political risks in the case of insurance-based smart contracts (Zgraggen, 2020). Value creation in operations and the supply chain are enhanced by the use of blockchain (Wamba & Queiroz, 2020).

Blockchain technology removes third parties thereby establishing and enhancing trust among its users. As a result, the auditing of organizations can be improved and it also decreases the overall cost incurred (Di Vaio & Varriale, 2020). Before the selection of suppliers, they are assessed over multiple criteria, an area that has been redefined by BDA by providing real-time access to checks and balances developed for different suppliers. Also, the shipping industry is streamlining its processes using blockchain technology. Many studies claim that BCT has improved SC by (Appelbaum & Smith, 2018; Kshetri, 2018)**:**

1. Providing consistent and reliable information about SC.
2. Improving SC coordination, visibility through the SC, and traceability of products.
3. Reducing errors and attacks.
4. Improving contract management thereby making it easier to study and improve the SC.
5. Minimizing complexity in SC processes.
6. Providing room for innovation thus allowing for the restructuring of SC

Gurtu & Johny conclude in their study that the value of blockchain technology can be analyzed by focusing on three primary areas: smart contracts, supply chain finance, and increased supply chain visibility and traceability (Gurtu & Johny, 2019).

2.9.2 Sub-Category Enablers for Blockchain Technology:

Subcategory enablers for block chain technology are:

1. Transparency and visibility throughout the supply chain enhance organization performance, this can be achieved through the use of blockchain technology as it acts as a distributed ledger, instead of a centralized one (Babich & Hilary, 2020).
2. Validation of data and transactions allows the organization to enter into a contract with no preferred suppliers, thereby decreasing the risk associated with this (Christidis & Devetsikiotis, 2016).
3. Automation through the use of smart contracts is another enabler that will provide a competitive edge to the organization through the use of BCT (Chen, 2018).
4. The integrity of the products can be easily maintained through the use of BCT, as it provides organizations with information about their products, and any fraudulent activities or transactions can be detected and removed (Babich & Hilary, 2020).

5. Another study confirmed that standardization and automation are the most prominent enablers of blockchain technology (Seebacher & Schüritz, 2017).
6. Real-time information is regarded as another digitization enabler for blockchain technology (Nowicka, 2018). Helo in his study is of the view that the development of accessible data and application programming interface (API), facilitate the success of the full potential of the blockchain whereas peer-to-peer networks hold extreme importance in cryptographic models (Helo & Shamsuzzoha, 2020).

2.10 Multi-Criteria Decision-Making Tools:

The selection of the best alternative/criterion from a given set of alternatives/criteria is referred to as decision-making (Plous, 1993). Multi-Criteria Decision Making (MCDM) is defined as considering multiple criteria in decision-making (Yalcin et al., 2022). MCDM can be broadly classified into two categories: namely Multi-Attribute Decision Making (MADM) which considers the variables to be discrete and the number of alternatives to be limited and Multi-Objective Decision Making (MODM) which considers continuous variables and the number of alternatives in this approach are unlimited (Guo & Zhao, 2017). Ever since Operations Research (OR) was pioneered in 1957 by Churchman, Arnoff, and Ackoff it has made great achievements be developing theory and enlisting new methods (Gass & Assad, 2005).

In the past years, several methods have been established in MCDM such as TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), AHP (Analytical Hierarchy Process), ELECTRE (Elimination EtChoix Traduisant la REalite'), PROMETHEE (Preference Ranking Organization Method For Enrichment Evaluation)., Grey Theory among others (Aruldoss et al., 2013). As the latest MCDM tool, Rezaei developed the Best Worst Method (BWM) to find out the weights of different criteria from a set of given criteria and alternatives based on pair-wise comparison with less number of pairwise comparisons (Rezaei, 2015).

2.11 Advantages of Best Worst Method over other MCDM tools:

It was developed by Rezaei as a multi-criteria decision-making tool (MCDM). This method has numerous advantages over other multi-criteria decision-making tools. Analytical Hierarchy Programming (AHP) was formerly used in such a scenario but the disadvantage of using it occurs in the later stages when the process of making pairwise comparisons becomes complicated as compared to that of BWM. AHP is a matrix-based comparison method that requires n (n-1)/2 comparisons, whereas BWM is a vector-based multi-criteria decision-making tool that requires 2n-3 comparisons. In BWM, the final weights obtained are highly reliable as it provides more consistent comparisons compared to AHP.

While in most MCDM methods like AHP, the consistency ratio is a measure to check if the comparisons are reliable or not. Whereas, in BWM consistency ratio is used to see the level of reliability as the output of BWM is always consistent. Another advantage of BWM is that it cannot only be used to derive the weights independently but can also be combined with other MCDM methods. In the case of AHP pairwise comparisons are used in which integers and fractions are used to determine the weight whereas in the case of BWM only integers are used. This makes the calculations much easier as compared to AHP (Rezaei, 2015).

2.12 Stand Alone Applications of Best Worst Method:

BWM has been used in several applications. Rezaei used capabilities and willingness as two dimensions of supplier evaluation and segmentation with BWM. This segmentation was then used to develop different strategies for supplier development (Rezaei, 2015). A ranking of external forces affecting sustainable supply chain management (SSCM) practices in the oil and gas industry using BWM was carried out by Sadaghiani (Sadaghiani et al., 2015). BWM was used to rank enablers of technological innovation in the case of medium and micro-small-scale enterprises in India (Gupta & Barua, 2016). Vendor selection based on multiple criteria is another application of BWM (Setyono & Sarno, 2018). BWM was used to evaluate and rank sustainable supply chain management criteria for manufacturing industries in Pakistan (Khokhar et al., 2020). It was used to rank enablers of digitization that improve supply chain performance (Gupta et al., 2021).

2.13 Integration of Best Worst Method with other techniques:

BWM can be used together with other MCDM techniques. BWM was integrated with SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis to find the weight of the supplier's resilience score (Vahidi et al., 2018). Integration of the Interval MULTIMOORA (Multiple Objective Optimization on the basis of Ratio Analysis plus Full Multiplicative Form) method and Interval Borda Rule with BWM was carried out for the selection of hybrid engines

(Hafezalkotob et al., 2019). A fuzzy model was integrated with BWM for the evaluation and selection of suppliers who had a primary focus on sustainability (Amiri et al., 2021). BWM was integrated with TOPSIS to find out the green image weight of suppliers, which was further used to design a supply chain network (Lahri et al., 2021). BWM was integrated with Multi Attributive Border Approximation Area Comparison (MABAC) to evaluate and select providers at an initial stage to find the optimum point of view of all participants in a supply chain (Muravev & Mijic, 2020).

2.14 Fuzzy Best Worst Method v/s Best Worst Method:

To solve a non-linear model, BWM works by deriving the relative weights using pairwise comparisons. Reference comparison is the "preference degree of the best criteria among the other criteria" in comparison and "the preference degree of all criteria over the worst criterion." As a result, preferring linguistic variables over crisp values can serve in comprehending pairwise comparisons. This technique as compared to others is rather much easier, more precise, and more efficient as, the secondary comparisons which can make the process slow and redundant are not required in this technique (Rezaei, 2015). Conversely, it has been observed that human judgments most likely comprise uncertainty and ambiguity this is why, Guo & Zhao proposed a FBWM (fuzzy-based BWM method) which makes even fewer comparisons and is favored to find the weights of the criteria (Guo & Zhao, 2017). Ecer & Parmucar, proved in their research that FBWM can deliver more reliable results by making even lesser comparisons and can obtain crisp weights by the means of the FBWM method (Ecer & Pamucar, 2020).

The fuzzy set theory was introduced by Zadeh in 1965 to account for the uncertainty associated with human judgment (Dubois & Prade, 2012). BWM was established in fuzzy environments to solve real-world decision-making problems to cater to the ambiguity that comes from the shortage of sufficient and precise information and judgment of the decision makers (DM). Recent studies on FBWM, suggest that to deal with human judgments, the fuzzy set theory (FST) is more efficient than a BWM. Moreover, several studies have shown that the inconsistency level of FBWM is much lower to a BWM (Guo & Zhao, 2017). BWM cannot overcome the challenge of ambiguity and uncertainty of the expert's judgment. To solve this issue, the capability of fuzzy numbers is used (Khan et al., 2021). In case the number of criteria is greater than three multi optimality results by the use of BWM which cannot lead to effective ranking results whereas fuzzy BWM provides a single optimal solution (Guo & Zhao, 2017). All this establishes that fuzzy BWM is much better equipped to deal with ambiguity and uncertainty associated with the use of human judgment as it provides optimal high-consistency results as compared to BWM.

2.15 Applications of Fuzzy BWM:

Fuzzy BWM has been used in several applications. It has been used to aggregate the linguistic preferences of the decision makers (DM) to obtain optimal weights in the design of a single-part reconfigurable flow line (Kumar et al., 2022). Barriers facing solar energy development in Iran were ranked by the use of fuzzy BWM which ranked economic factors as the primary barrier to solar energy development (Mostafaeipour et al., 2021). A strategy canvas was drawn by the use of fuzzy BWM to determine the best approach for strategy making and innovation with a prime focus on sustainable performance and company growth (Khanmohammadi et al., 2019). Risk in halal supply chains was ranked by the use of fuzzy BWM in a study carried out on the halal supply chain industry (Khan et al., 2021).

2.16 Integration of Fuzzy BWM with other Techniques:

Fuzzy BWM has been integrated with other techniques. Fuzzy BWM has been integrated with combined compromise solution (CoCoSo) and Bonferroni mean function for the selection of sustainable suppliers (Ecer & Pamucar, 2020). The optimal illumination system for the control room of a power plant based on the operator’s cognitive performance was ranked using Fuzzy BWM and QUALIFLEX (Zare et al., 2020). Fuzzy BWM was used to weigh the sustainable supplier selection criteria and a piecewise linear value function was used to rank the suppliers (Jafarzadeh Ghoushchi et al., 2019). The energy security performance of 30 Chinese provinces from 2008-2017 was ranked using fuzzy BWM, data envelopment analysis, and assurance regions (Huang et al., 2021). Fuzzy BWM was integrated with generalized interval-valued trapezoidal fuzzy numbers and was then used in the selection of transport mode, selection of a high-cost performance car, and supplier selection with a focus on supplier development (Ali & Rashid, 2020).

2.17 Short Comings of the Fuzzy BWM Method:

The FBWM Method used by Guo deals with normalized triangular fuzzy numbers, and it is not a method that can support the use of non-normalized triangular fuzzy numbers. Palash Dutta and Dash proved in their medical decision-making research that the use of generalized triangular fuzzy numbers instead of normalized fuzzy numbers provides slightly better results (Dutta & Dash, 2018). The same was also proved by Asif Ali and Tabbasm Rashid in their research that the use of generalized interval-based fuzzy numbers provides either the same results or slightly better results as compared to the results obtained by the use of normalized triangular fuzzy numbers (Ali & Rashid, 2020).

This study proposes the use of a non-normalized triangular fuzzy number with BWM for ranking purposes. Using non-normalized or generalized triangular fuzzy numbers the degree of confidence of the decision maker is made part of the final model. The final proposed methodology for this study is to combine Chen’s (Chen, 1985) Generalized Fuzzy Numbers arithmetic model with the BWM methodology used by Rezaei in their research (Rezaei, 2015). This proposed methodology is to provide better ranking of alternatives as compared to other multicriteria decision making techniques. For comparison purposes this research compares the results obtained using GTFN-BWM with those obtained by the use of BWM and normalized triangular fuzzy BWM to determine the efficacy of the methodology developed.

3 Fuzzy Best Worst Method Using Generalized Triangular Fuzzy Numbers:

This chapter lists down the basic concepts of BWM and normalized fuzzy BWM. This chapter enlists down the details of the concepts and the methods used in developing the methodology i.e., generalized triangular fuzzy best worst method. The chapter provides the non-linearly constrained optimization model for the methodology and steps on how to obtain weights and ranks of alternatives using the methodology developed. The consistency index of the fuzzy reference comparisons and the consistency ratio is also developed in this chapter.

3.1 Generalized Triangular Fuzzy Numbers:

Chen (Chen, 1985) introduced the concept of generalized fuzzy numbers. A generalized triangular fuzzy number is a number $\tilde{a}$, which is a fuzzy subset of real line R, whose membership function $\mu_{\tilde{a}}(x)$ consists of following conditions.

1- $\mu_{\tilde{a}}(x)$ is a continuous mapping from R to the closed interval $[0, w], 0 < w \leq 1$
2- $\mu_{\tilde{a}}(x) = 0$, where $-\infty < x \leq l$
3- $\mu_{\tilde{a}}(x)$ is strictly increasing with a constant rate on $l \leq x < m$
4- $\mu_{\tilde{a}}(x) = w$, where $x = m$
5- $\mu_{\tilde{a}}(x)$ is strictly decreasing with a constant rate on $m \leq x < u$
6- $\mu_{\tilde{a}}(x) = 0$, where $u \leq x < \infty$

A generalized triangular fuzzy membership function is shown in Equation 3.1, where, $\tilde{a} = (l, m, u;\ w)$, where all l, m, u are real numbers and w is the core value (Pathinathan et al., 2015).

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 & x < l \\ \dfrac{w(x-l)}{m-l} & l \leq x < m \\ \dfrac{w(u-x)}{u-m} & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{3.1}$$

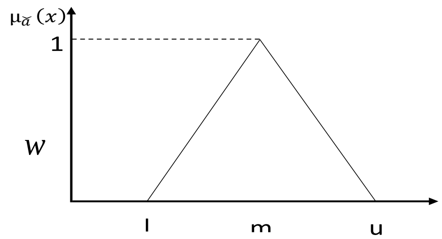

Figure 3.1 GTFN Membership Function

GTFN holds an advantage over TFN because it considers the degree of confidence of decision-makers about a particular issue while considering each individual's perception (Chen & Chen, 2003a; Pathinathan et al., 2015). Also, GTFN helps in better expression of incomplete and inconsistent information while solving a MCDM problem (Aikhuele & Odofin, 2017). This explains that by using GTFN, more precise results can be obtained as compared to TFNs which do not consider the degree of confidence of decision makers' opinions.

3.2 GTFN Defuzzification:

Chen and Hsieh showed in their study that the graded mean integration function (GMIR) for both normalized and non-normalized TFN is the same (Chen & Hsieh, 2000; Chen & Wang, 2006). This study, therefore, uses the GMIR equation to obtain the rank of GTFNs. The equation of GMIR to obtain the rank of fuzzy number $\tilde{a}_i = (l_i, m_i, u_i; w)$ is listed as equation 3.2

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \tag{3.2}$$

3.3 Steps of Best Worst Method with Generalized TFNs:

The steps of GTFN BWM are based on the steps of BWM presented by Rezaei and modified by Guo for fuzzy BWM (Guo & Zhao, 2017; Rezaei, 2015). The five steps of finding the optimal fuzzy weights are as follows:

Step 1

Determine the set of criteria $\{c_1, c_2, ...c_n\}$.

Step 2

Determine the best criteria c_b and the worst criteria c_w from the list of given criteria.

Step 3

Execute the fuzzy reference comparisons for the best criteria to determine the best to other vector $\tilde{a}_b = \{a_{b1}, a_{b2}, ...a_{bn}\}$.

Step 4

Execute the fuzzy reference comparisons for the worst criteria to determine the other to worst vector $\tilde{a}_w = \{a_{1w}, a_{2w}, ...a_{nw}\}$.

Step 5

Find the optimal fuzzy weights $\tilde{w}_1^*, \tilde{w}_2^*, ...\tilde{w}_n^*$.

3.4 Optimality Condition:

The optimality condition for BWM with generalized TFNs is based on the same principles presented by Rezaei for BWM and by Guo for fuzzy BWM i.e. the optimal weight for the criteria *j* is the one where for each pair of $\tilde{w}_b / \tilde{w}_j$ and $\tilde{w}_j / \tilde{w}_w$ the following condition is satisfied (Rezaei, 2015).

$$\frac{\tilde{w}_b}{\tilde{w}_j} = \tilde{a}_{bj} \tag{3.3}$$

$$\frac{\tilde{w}_j}{\tilde{w}_w} = \tilde{a}_{jw} \tag{3.4}$$

Where,

- $\tilde{w}_b$ is the weight of the best criteria.
- $\tilde{w}_w$ is the weight of the worst criteria.
- $\tilde{w}_w$ is the weight of the *j* criteria.
- $\tilde{a}_{bj}$ is the fuzzy comparison of the best criteria with all other criteria.

- $\tilde{a}_{jw}$ is the fuzzy comparison of the other criteria with the worst criteria.

To satisfy this condition listed in Equation 3.3 and 3.4 for all criteria j the solution is to be obtained where the maximum absolute differences i.e., $\left|\frac{\tilde{w}_b}{\tilde{w}_j} - \tilde{a}_{bj}\right|$ and $\left|\frac{\tilde{w}_j}{\tilde{w}_w} - \tilde{a}_{jw}\right|$ is minimized for all criteria.

3.5 Constrained Optimization Problem:

Based on the steps listed in Section 3.3. and the optimality condition listed in Section 3.4 the constrained optimization problem for finding the generalized fuzzy weights is listed in Equation 3.5. $\tilde{w}_b, \tilde{w}_w, \tilde{w}_j, \tilde{a}_{bj}, \tilde{a}_{jw}$ are all generalized triangular fuzzy numbers.

$$\begin{aligned}
&\min \max_j \left\{ \left|\frac{\tilde{w}_b}{\tilde{w}_j} - \tilde{a}_{bj}\right| \left|\frac{\tilde{w}_j}{\tilde{w}_w} - \tilde{a}_{jw}\right| \right\} \\
&s.t. \\
&\sum_j^n R(\tilde{w}_j) = 1 \\
&l_j \le m_j \le u_j \\
&0 \le \tilde{w}_j \le 1 \\
&l_j \ge 0 \\
&j = 1, 2, ..., n
\end{aligned} \tag{3.5}$$

Where,

- $\sum_j^n R(\tilde{w}_j) = 1$ enlists that the sum of the rank obtained by using the GMIR of all fuzzy numbers should be equal to 1.
- $l_j \le m_j \le u_j$ represents the linearity condition of fuzzy numbers (Chutia et al., 2013).
- $0 \le \tilde{w}_j \le 1$ represents that the height of any fuzzy number is within the range of [0,1].
- $l_j \ge 0$ represents the non-negativity condition for fuzzy numbers.

The equation 3.5 can be transformed into the following nonlinearly constrained optimization problem by using ξ which is also a generalized triangular fuzzy number and the following conditions.

$$\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{\tilde{w}_b}{\tilde{w}_j} - \tilde{a}_{bj} \right| \le \xi \\
&\left| \frac{\tilde{w}_j}{\tilde{w}_w} - \tilde{a}_{jw} \right| \le \xi \\
&\sum_{j}^{n} R(\tilde{w}_j) = 1 \\
&l_j \le m_j \le u_j \\
&0 \le \tilde{w}_j \le 1 \\
&l_j \ge 0 \\
&j = 1, 2, ..., n
\end{aligned} \tag{3.6}$$

Where,

$$\begin{aligned}
\tilde{w}_b &= (l_b, m_b, u_b; w_b) \\
\tilde{w}_w &= (l_w, m_w, u_w; w_w) \\
\tilde{w}_j &= (l_j, m_j, u_j; w_j) \\
\tilde{a}_{bj} &= (l_{bj}, m_{bj}, u_{bj}; w_{bj}) \\
\tilde{a}_{jw} &= (l_{jw}, m_{jw}, u_{jw}; w_{jw}) \\
\xi &= (k, k, k; k)
\end{aligned} \tag{3.7}$$

3.6 Data Collection:

For this study data collection was conducted using experts. The number of experts to be used has been a matter of debate among researchers. For this purpose, a literature review of past studies using the same methodology was conducted. Gupta in his study used a total of nine experts from both industry and academia. They had been involved in the digitization of supply chains in companies. All experts from whom data was collected had an experience of at least ten years in this field (Gupta et al., 2021). A study was conducted to identify the enablers of technological innovation for Indian MSMEs. For this study, a total of sixteen experts, eight from industry and eight from academia, were used. All experts used had a minimum of 10 years of experience (Gupta & Barua, 2016). A similar study carried out in Iran for the selection of sustainable suppliers for the automobile sector used a total of three experts (Amiri et al., 2021). The best worst method with the multi-attributive border approximation area comparison (MABAC) model was used to conduct a study by Muravev & Mijic which involved four experts each having at least 10 years of experience in supply chain evaluation (Muravev & Mijic, 2020). BWM was used for location selection, which involved nine experts for data collection (Liang et al., 2021).

A panel of eight experts was used to apply BWM to find a ranking of the critical success factors for sustainable entrepreneurship in the Pakistani telecommunication industry (Muneeb et al., 2020). Three experts were part of the panel which helped in determining the best to others and worst to other vector in the case of a study that aimed at developing a supplier risk assessment matrix for the manufacturing sector (Er Kara & Oktay Fırat, 2018). Data used for determining the weights of the criteria used in the selection of sustainable materials for manufacturing automotive products were collected from a panel of eight experts (Wakeel et al., 2021). To collect data for ranking total quality management enablers in the healthcare industry using BWM a panel of six experts, having immense experience and expertise in total quality management (TQM) was used (Talib et al., 2019). For this study, a panel of six experts will be used, following the same pattern as the past studies. Lastly, what is seen as common in the literature was that all the experts that participated in the research had at least 10 years of experience if not more. This requirement was put into special consideration while choosing the experts for this study.

3.6.1 Development of Questionnaire:

The questionnaire (refer to Appendix A) used in this study was adapted from similar pattern research done by Rezaei (Rezaei, 2015). It consists of 5 sections where each section represents the best to other vector and other to worst vector value for main category enablers, big data analytics, internet of things, industry 4.0 and block chain technology respectively. It was distributed by hand to a panel of six experts Details of each of these experts are mentioned in Table 3.1.

Table 3.1 Qualifications of Panel of Experts used for Data Collection

S. No.	Expert Number	Field	Years in the Industry	Public/ Private/ Academic
1	Expert 1	Supply Chain & Planning	17	Private
2	Expert 2	Supply Chain & Logistics	15	Private
3	Expert 3	Supply Chain & Logistics	11	Private
4	Expert 4	Supply Chain	15	Public
5	Expert 5	Supply Chain	12	Private
6	Expert 6	Supply Chain	11	Private

3.6.2 Development of the Linguistic Scale:

It has been noted that in 1-9 scales, the decision maker feels very confused while making comparisons of the alternatives as the scale is too detailed. It is hard for the decision-maker to make adjacent comparisons and distinguish between each of those comparisons. This is why contrary to BWM using 1-9 scales, the proposed generalized TFN BWM only uses five granularities of linguistic terms, which can help the decision-maker make reference comparisons more accurately and easily (Guo & Zhao, 2017) which are enlisted in Table 3.2.

Table 3.2 Linguistic Scale with Membership Function Values

S. No.	Linguistic Term	Normalized Membership Function	Generalized Membership Function
1	Equally Important	(1, 1, 1)	(1, 1, 1; w)
2	Weakly Important	(2/3, 1, 3/2)	(2/3, 1, 3/2; w)
3	Fairly Important	(3/2, 2, 5/2)	(3/2, 2, 5/2; w)
4	Very Important	(5/2, 3, 7/2)	(5/2, 3, 7/2; w)
5	Absolutely Important	(7/2, 4, 9/2)	(7/2, 4, 9/2; w)

The inclusion of *w*, the confidence of the decision maker in the Generalized Membership function for linguistic variables is based on the study of Chen in which a fuzzy risk analysis was carried out using generalized trapezoidal fuzzy numbers (Chen & Chen, 2003a). Since the generalized triangular fuzzy number is a special case of trapezoidal fuzzy number *(a, b, c, d; w)*. To convert a generalized trapezoidal fuzzy number into a generalized triangular fuzzy number the following condition must hold i.e. *b=c*, therefore for a generalized triangular fuzzy number *(l, m, u; w)* the same rule has been adopted, and applied, where every linguistic term can have different values of *w* (Pathinathan et al., 2015).

3.6.3 Data Collection from Experts:

The responses of the decision makers were collected on paper which was later assorted and presented in the Tables (refer to Appendix B). Each expert first selected the best criterion and the worst criterion from a given set of criteria. The best criterion was then compared with all the given criteria to develop the best to other vectors. Similarly, the worst criteria selected were also compared with all the other criteria to develop the other to worst vector. This activity was conducted for the main enablers and the subcategory enablers. The Linguistic terms used for comparison are enlisted in Section 3.2 where EI is 'Equally Important, WI is 'Weakly Important,' FI is 'Fairly Important,' VI is 'Very Important, and AI is 'Absolutely Important.'

3.7 GTFN-FBWM Consistency Index and Ratio:

A fuzzy comparison is fully consistent when $\tilde{a}_{bj} \times \tilde{a}_{jw} = \tilde{a}_{bw}$, and where.

- $\tilde{a}_{bj}$ is the fuzzy preference of the best criterion over the criterion j.
- $\tilde{a}_{jw}$ is the fuzzy preference of the criterion j over the worst criterion.
- $\tilde{a}_{jw}$ is the fuzzy preference of the best criterion over the worst criterion.

In practice, there may exist inconsistency for criterion *j* related to pairwise comparison. The consistency ratio is employed to check how consistent a fuzzy pairwise comparison is.

A five-point linguistic scale was used by Guo (Guo & Zhao, 2017) where the maximum possible fuzzy value of $\tilde{a}_{bw}$ is (7/2, 4, 9/2), which corresponds to the linguistic term 'Absolutely important (AI)' given by the decision-maker. The linguistic scale used in this study is enlisted in Section 3.6.2. When $\tilde{a}_{bj} \times \tilde{a}_{jw} \neq \tilde{a}_{bw}$ which means $\tilde{a}_{bj} \times \tilde{a}_{jw}$ may be higher or lower than, $\tilde{a}_{bw}$ the inconsistency of fuzzy pairwise comparison will occur. When both $\tilde{a}_{bj}$ and $\tilde{a}_{jw}$ are equal to $\tilde{a}_{bw}$, the inequality will reach the greatest this results in ξ. Thus, ξ should be subtracted from both $\tilde{a}_{bj}$ and $\tilde{a}_{jw}$ added to $\tilde{a}_{bw}$. Considering the occurrence of the greatest inequality, according to the equality relation

$$\frac{\tilde{w}_b}{\tilde{w}_j} \times \frac{\tilde{w}_j}{\tilde{w}_w} = \frac{\tilde{w}_b}{\tilde{w}_w} \tag{3.8}$$

The following equation will be obtained:

$$(\tilde{a}_{bj} - \xi) \times (\tilde{a}_{jw} - \xi) = (\tilde{a}_{bw} + \xi) \tag{3.9}$$

As for the maximum fuzzy inconsistency $\tilde{a}_{bj} = \tilde{a}_{jw} = \tilde{a}_{bw}$, the Equation 3.9 can be written as.

$$(\tilde{a}_{bw} - \xi) \times (\tilde{a}_{bw} - \xi) = (\tilde{a}_{bw} + \xi) \tag{3.10}$$

Finally, it can be derived as.

$$\xi^2 - (1 + 2\tilde{a}_{bw})\xi + (\tilde{a}_{bw}^2 - \tilde{a}_{bw}) = 0 \tag{3.11}$$

For $\tilde{a}_{bw}$, the maximum possible fuzzy value is (7/2, 4, 9/2), which indicates $l_{bw} = 7/2;\ m_{bw} = 4$ and $u_{bw} = 9/2$. It shows that the maximum value of l_{bw}, m_{bw} and u_{bw} cannot exceed 9/2. In this case, the upper boundary u_{bw} is used to calculate the consistency index because u_{bw} is the largest in the interval $[l_{bw}, u_{bw}]$ and therefore the fuzzy consistency ratio remains effective. The other linguistic values used by (Guo) correspond to the following linguistic conversions where the following values of $\tilde{a}_{bw}$ are possible.

$$\begin{aligned} \tilde{a}_{bw} &= (5/2, 3, 7/2) \\ \tilde{a}_{bw} &= (3/2, 2, 5/2) \\ \tilde{a}_{bw} &= (2/3, 1, 3/2) \\ \tilde{a}_{bw} &= (1, 1, 1) \end{aligned} \tag{3.12}$$

Therefore, the previous CR equation can be transferred to.

$$\xi^2 - (1 + 2\tilde{u}_{bw})\xi + (\tilde{u}_{bw}^2 - \tilde{u}_{bw}) = 0 \tag{3.13}$$

Where,

$$\begin{aligned} u_{bw} &= 1 \\ u_{bw} &= 3/2 \\ u_{bw} &= 5/2 \\ u_{bw} &= 7/2 \\ u_{bw} &= 9/2 \end{aligned} \tag{3.14}$$

After solving for these values of u_{bw}, the maximum value of ξ for each case is obtained. The maximum value of ξ is considered the consistency index.

Table 3.3 GTFN-BWM Consistency Index Values for Linguistic Terms

Linguistic Terms	Equally Importance (EI)	Weakly Important (WI)	Fairly Important (FI)	Very Important (VI)	Absolutely Important (AI)
$\tilde{a}_{bw}$	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)
CI	3.00	3.80	5.29	6.69	8.04

The consistency ratio is to be calculated using the formula listed as equation 3.15 (Guo & Zhao, 2017; Rezaei, 2015)

$$\text{Consistency Ratio} = \frac{\xi}{\text{Consistency Index}} \tag{3.15}$$

4 GTFN-FBWM Model Implementation:

The model presented in chapter 3 is implemented using Python language for optimization. Based on the data collected form experts and listed in Appendix B, models can be created to rank the main and subcategory enablers. This section lists the model of main category enablers based on the data collected from expert one. The model for data collected from the remaining five experts to rank the main and subcategory enablers can be presented on the same line and principles.

4.1 Model for Main Category Enablers:

For the main category enablers, the set of criteria consists of four criteria i.e., criteria 1 is big data analytics, criteria 2 is the internet of things, criteria 3 is industry 4.0, and criteria 4 is blockchain technology. Data collected for the main category enablers from expert one is as follows:

Table 4.1 Expert 1 Best to Other Vector Values for Main Category Enablers

Best & Worst Criteria	**Comparison of Best Criteria with other criteria**			
	BDA	IOT	IDY	BCT
Big Data Analytics	EI	VI	FI	WI
	(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.9)	(2/3,1,3/2;0.8)
Internet of Things	VI	EI	WI	FI
	(5/2,3,7/2;0.8)	(1,1,1;1)	(2/3,1/3/2;0.9)	(3/2,2,5/2;0.8)

The consistency index can be checked by constructing the consistency check table. The Table 4.2 shows the consistency of comparisons. The crisp value of the data collected is calculated using the GMIR equation enlisted in Section 3.2.

Table 4.2 Expert 1 Consistency Check for Main Category Enablers

Crisp Weight of Best to Worst Comparison	A_{b1}	A_{b2}	A_{b3}	A_{b4}
	1.00	3.00	2.00	1.00
	A_{1w}	A_{2w}	A_{3w}	A_{4w}
3.00	3.00	1.00	1.00	2.00
	$A_{b1} \times A_{1w}$	$A_{b2} \times A_{2w}$	$A_{b3} \times A_{3w}$	$A_{b4} \times A_{4w}$
	3.00	3.00	2.00	2.00

The Table 4.2 shows that for criteria 1 and 2 i.e., Big Data Analytics and Internet of Things the comparison is fully consistent i.e. $\tilde{a}_{bj} \times \tilde{a}_{jw} = \tilde{a}_{bw}$ For the other two criteria i. e Industry 4.0 and Block Chain Technology the comparison is not fully consistent i.e. $\tilde{a}_{bj} \times \tilde{a}_{jw} \neq \tilde{a}_{bw}$. To find the consistency for this comparison Table 3.3 shows the max value of ξ, for which these comparisons are consistent. In this case, a_{bw} has a value of 'Very Important' which gives a max value of ξ as 6.69. The non-linearly constrained optimization model is listed in equation 4.1.

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_1, m_1, u_1; w_1)} - (l_{11}, m_{11}, u_{11}; w_{11}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_2, m_2, u_2; w_2)} - (l_{12}, m_{12}, u_{12}; w_{12}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_3, m_3, u_3; w_3)} - (l_{13}, m_{13}, u_{13}; w_{13}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_4, m_4, u_4; w_4)} - (l_{14}, m_{14}, u_{14}; w_{14}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_2, m_2, u_2; w_2)} - (l_{12}, m_{12}, u_{12}; w_{12}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_2, m_2, u_2; w_2)} - (l_{22}, m_{22}, u_{22}; w_{22}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_2, m_2, u_2; w_2)} - (l_{32}, m_{32}, u_{32}; w_{32}) \right| \leq (k, k, k; k) \\
&\left| \frac{(l_4, m_4, u_4; w_4)}{(l_2, m_2, u_2; w_2)} - (l_{42}, m_{42}, u_{42}; w_{42}) \right| \leq (k, k, k; k) \\
&\sum_{j=1}^{4} R(\tilde{w}_j) = 1 \\
&l_j \leq m_j \leq u_j \\
&0 \leq \tilde{w}_1 \leq 1;\ 0 \leq \tilde{w}_2 \leq 1;\ 0 \leq \tilde{w}_3 \leq 1;\ 0 \leq \tilde{w}_4 \leq 1 \\
&l_j \geq 0 \\
&j = 1, 2, 3, 4
\end{aligned}
\tag{4.1}
$$

Then the same problem can be represented by the following nonlinearly constrained optimization problem using concrete numbers (Ali & Rashid, 2020; Guo & Zhao, 2017).

$$
\begin{aligned}
&\min k \\
&s.t. \\
&l_1-(2.5\times u_2)\le (k\times u_2); \qquad l_1-(2.5\times u_2)\ge -(k\times u_2) \\
&m_1-(3\times m_2)\le (k\times m_2); \qquad m_1-(3\times m_2)\ge -(k\times m_2) \\
&u_1-(3.5\times l_2)\le (k\times l_2); \qquad u_1-(3.5\times l_2)\ge -(k\times l_2) \\
&\min(\min(w_1,w_2),0.8)\le k; \qquad \min(\min(w_1,w_2),0.8)\ge -k \\
&l_1-(1.5\times u_3)\le (k\times u_3); \qquad l_1-(1.5\times u_3)\ge -(k\times u_3) \\
&m_1-(2\times m_3)\le (k\times m_3); \qquad m_1-(2\times m_3)\ge -(k\times m_3) \\
&u_1-(2.5\times l_3)\le (k\times l_3); \qquad u_1-(2.5\times l_3)\ge -(k\times l_3) \\
&\min(\min(w_1,w_3),0.9)\le k; \qquad \min(\min(w_1,w_3),0.9)\ge -k \\
&l_1-(0.67\times u_4)\le (k\times u_4); \qquad l_1-(0.67\times u_4)\ge -(k\times u_4) \\
&m_1-(1\times m_4)\le (k\times m_4); \qquad m_1-(1\times m_4)\ge -(k\times m_4) \\
&u_1-(1.5\times l_4)\le (k\times l_4); \qquad u_1-(1.5\times l_4)\ge -(k\times l_4) \\
&\min(\min(w_1,w_4),0.8)\le k; \qquad \min(\min(w_1,w_4),0.8)\ge -k \\
&l_3-(0.67\times u_2)\le (k\times u_2); \qquad l_3-(0.67\times u_2)\ge -(k\times u_2) \\
&m_3-(1\times m_2)\le (k\times m_2); \qquad m_3-(1\times m_2)\ge -(k\times m_2) \\
&u_3-(1.5\times l_2)\le (k\times l_2); \qquad u_3-(1.5\times l_2)\ge -(k\times l_2) \\
&\min(\min(w_3,w_2),0.9)\le k; \qquad \min(\min(w_3,w_2),0.9)\ge -k \\
&l_4-(0.67\times u_2)\le (k\times u_2); \qquad l_4-(0.67\times u_2)\ge -(k\times u_2) \\
&m_4-(1\times m_2)\le (k\times m_2); \qquad m_4-(1\times m_2)\ge -(k\times m_2) \\
&u_4-(1.5\times l_2)\le (k\times l_2); \qquad u_4-(1.5\times l_2)\ge -(k\times l_2) \\
&\min(\min(w_4,w_2),0.8)\le k; \qquad \min(\min(w_4,w_2),0.8)\ge -k \\
&((l_1+(4\times m_1)+u_1)/6+(l_2+(4\times m_2)+u_2)/6+(l_3+(4\times \\
&m_3)+u_3)/6+(l_4+(4\times m_4)+u_4)/6)=1 \\
&l_1\le m_1\le u_1; l_2\le m_2\le u_2; l_3\le m_3\le u_3; l_4\le m_4\le u_4 \\
&0\le w_1\le 1; 0\le w_2\le 1; 0\le w_3\le 1; 0\le w_4\le 1 \\
&l_1\ge 0; l_2\ge 0; l_3\ge 0; l_4\ge 0; k\ge 0
\end{aligned}
\tag{4.2}
$$

The non-linearly constrained optimization model using crisp numbers presented by Equation 4.2 was implemented using Python the results of which are enlisted in the chapter 5. All other models for subcategory enablers based on the data collected from Expert 1 can be created on the same lines. Models and python codes for data collected for the remaining experts are created along the same lines.

5 Weights and Ranks of Main and Subcategory Enablers:

The results obtained from the data collected from all six experts for main and subcategory enablers are listed in this chapter along with the results are obtained using BWM, and fuzzy BWM by Guo. This chapter lists down the individual and the global weights obtained using each methodology. The individual and global weights and ranks of all the main and subcategory enablers are noted down for all the three methodologies.

5.1 Individual Weights and Ranks for Main Category Enablers:

This section lists down the results obtained for the main category enabler for all six experts using GTFN BWM, TFN BWM, and BWM. The consistency index using the value of best to worst comparison is also enlisted and based on this and the value of ξ obtained by solving the model consistency ratio is calculated and listed The GMIR difference for the best and the worst comparison is calculated for TFN-BWM and GTFN-BWM. The criteria set for main category enablers is as follows:

1. Criteria 1 is big data analytics (C_1).
2. Criteria 2 is the internet of things (C_2)
3. Criteria 3 is industry 4.0 (C_3)
4. Criteria 4 is blockchain technology (C_4).

For the main category enablers, the weights of all the four criteria obtained for BWM, TFN-BWM and GTFN-BWM are shown in Figure 5.1 to 5.6. The weights along with the ranks and the value of ξ, consistency index (CI), consistency ratio (CR) and GMIR difference of the best and the worst ranked criteria obtained for all the criteria using BWM and TFN-BWM for all six experts is shown in Table 5.1. The weights along with the value of ξ, consistency index, consistency ratio and GMIR difference of the best and the worst ranked criteria obtained using GTFN-BWM for all main category enablers are listed down in Table 5.2.

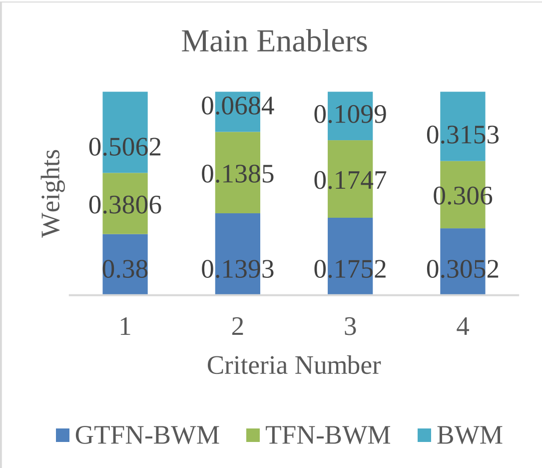

Figure 5.1 Weight of Main Category Enablers for Expert 1

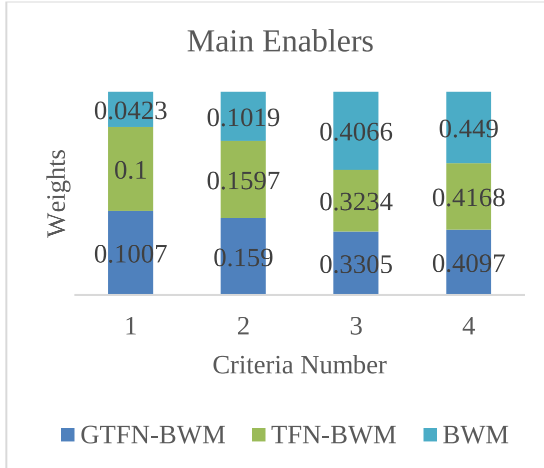

Figure 5.2 Expert 2 Weights for Main Category Enablers

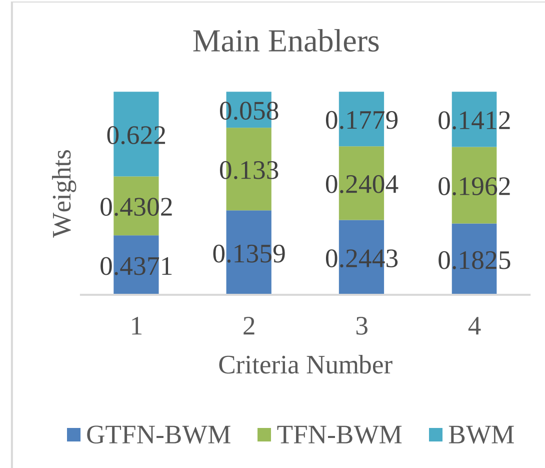

Figure 5.3 Expert 3 Weights for Main Category Enablers

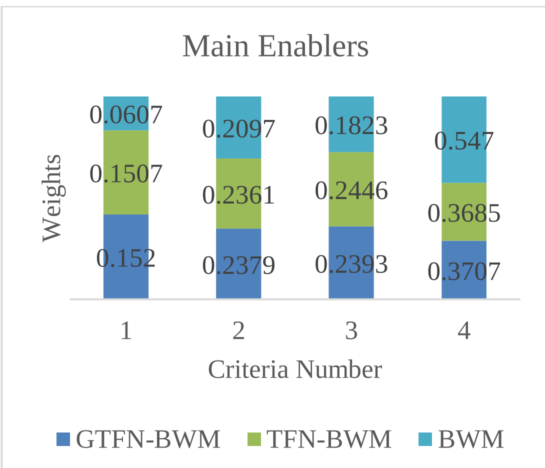

Figure 5.4 Expert 4 Weights for Main Category Enablers

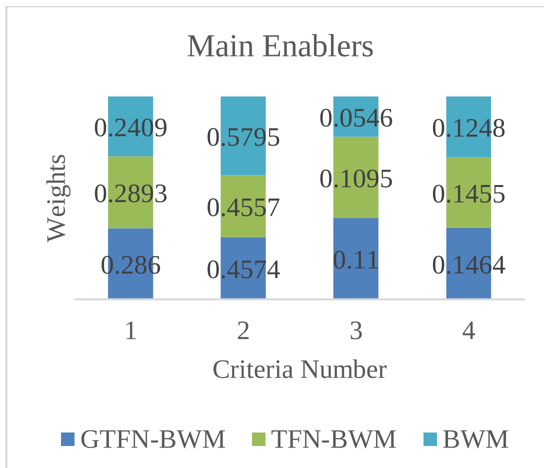

Figure 5.5 Expert 5 Weights for Main Category Enablers

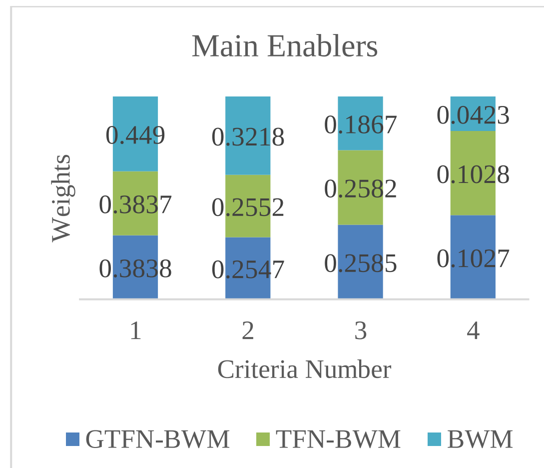

Figure 5.6 Expert 6 Weights for Main Category Enablers

Table 5.1 Weights and Ranks for Main Category Enablers using BWM and TFN-BWM

Values	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		Expert 6	
	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM
Criteria 1	0.5062 1st	0.3806 1st	0.0423 4th	0.1000 4th	0.6220 1st	0.4302 1st	0.0607 4th	0.1507 4th	0.2409 2nd	0.2893 2nd	0.4490 1st	0.3837 1st
Criteria 2	0.0684 4th	0.1385 4th	0.1019 3rd	0.1597 3rd	0.0580 4th	0.1330 4th	0.2097 2nd	0.2361 3rd	0.5795 1st	0.4557 1st	0.3218 2nd	0.2552 3rd
Criteria 3	0.1099 3rd	0.1747 3rd	0.4066 2nd	0.3234 2nd	0.1779 2nd	0.2404 2nd	0.1823 3rd	0.2446 2nd	0.0546 4th	0.1095 4th	0.1867 3rd	0.2582 2nd
Criteria 4	0.3153 2nd	0.3060 2nd	0.4490 1st	0.4168 1st	0.1412 3rd	0.1962 3rd	0.5470 1st	0.3685 1st	0.1248 3rd	0.1455 3rd	0.0423 4th	0.1028 4th
Zeta	0.3944	0.2868	2.594	0.4258	2.594	0.7912	1.999	0.5615	2.594	0.4258	2.594	0.5000
CI	3.73	6.69	4.47	8.04	4.47	8.04	3.73	6.69	4.47	8.04	4.47	8.04
CR	0.1057	0.0428	0.5803	0.0529	0.5803	0.0984	0.5359	0.0839	0.5803	0.0529	0.5803	0.0621
GMIR Difference	---	0.2422	---	0.3168	---	0.2972	---	0.2170	---	0.3462	---	0.2810

Table 5.2 Weights and Ranks for Main Category Enablers using GTFN-BWM

Values	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Criteria 1	0.3800 1st	0.1007 4th	0.4371 1st	0.1520 4th	0.2860 2nd	0.3838 1st
Criteria 2	0.1393 4th	0.1590 3rd	0.1359 4th	0.2379 3rd	0.4574 1st	0.2547 3rd
Criteria 3	0.1752 3rd	0.3305 2nd	0.2443 2nd	0.2393 2nd	0.1100 4th	0.2585 2nd
Criteria 4	0.3052 2nd	0.4097 1st	0.1825 3rd	0.3707 1st	0.1464 3rd	0.1027 4th
Zeta	0.2868	0.4258	0.7912	0.5615	0.4258	0.4999
CI	6.69	8.04	8.04	6.69	8.04	8.04
CR	0.0428	0.0529	0.0984	0.0839	0.0529	0.0621
GMIR Difference	0.2407	0.3089	0.3013	0.2180	0.3474	0.2811

The Table 5.1 and 5.2 and the Figure 5.1 – 5.6 above show that the ranks obtained for expert one using BWM, TFN-BWM, and GTFN-BWM are the same i.e., big data analytics has the first rank, followed by blockchain technology, industry 4.0, and the internet of things. The ranks obtained for expert two using BWM, TFN-BWM, and GTFN-BWM are the same i.e., blockchain technology has the first rank, followed by industry 4.0, internet of things, and big data analytics. The ranks obtained for expert three using BWM, TFN-BWM, and GTFN-BWM are the same i.e., big data analytics has the first rank, followed by industry 4.0, blockchain technology, and the internet of things. The ranks obtained for expert 4 using BWM are blockchain technology, followed by the internet of things, industry 4.0, and big data analytics whereas the ranks obtained by TFN-BWM and GTFN-BWM are the same i.e., blockchain technology has the first rank, followed by industry 4.0, internet of things, and big data analytics. The ranks obtained for expert five using BWM, TFN-BWM, and GTFN-BWM are the same i.e., the internet of things has the first rank, followed by big data analytics, blockchain technology, and industry 4.0. the ranks obtained for expert 6 using BWM are big data analytics has the first rank followed by the internet of things, industry 4.0, and blockchain technology, whereas the ranks obtained by TFN-BWM and GTFN-BWM are the same i.e., big data analytics has the first rank, followed by industry 4.0, internet of things, and blockchain technology.

The CR obtained using GTFN-BWM is much lower as obtained using BWM which develops that the methodology developed in this research provides much better results as compared to BWM. The comparison with fuzzy BWM cannot be conducted based on CR as it is based on the defuzzification method used, the shortcomings of which are explained in detail in chapter 6, however the GMIR difference value obtained by the comparison of the best and the worst ranked criteria is used to compare GTNF-BWM with TFN-BWM. In each case, the GMIR difference values obtained by both methodologies are enlisted in the Table 5.1 and 5.2.

5.2 Individual Weights and Ranks for Subcategory Enablers of BDA:

This section lists down the results obtained for the Big Data Analytics subcategory enabler for all six experts using GTFN BWM, TFN BWM, and BWM. The consistency index using the value of best to worst comparison is also enlisted and the value of ξ obtained by solving the model is also enlisted. The consistency ratio is calculated and enlisted in this section. Similarly, the GMIR difference for the best and the worst comparison is calculated for TFN-BWM and GTFN-BWM are also enlisted. The criteria set for subcategory enablers of big data analytics are listed below:

1. Criteria 1 is data capturing and storage (C_1)
2. Criteria 2 is data security and privacy (C_2)
3. Criteria 3 is data and information technology integration (C_3)
4. Criteria 4 is change management (C_4)
5. Criteria 5 is feasibility study on big data analytics (C_5)
6. Criteria 6 is organizational openness (C_6)
7. Criteria 7 is the synchronization of processes (C_7)
8. Criteria 8 is adequate system capabilities (C_8).

For the subcategory enablers, the weights of all the eight criteria obtained for BWM, TFN-BWM and GTFN-BWM are shown in Figure 5.7 to 5.12. The weights along with the ranks and the value of ξ, consistency index (CI), consistency ratio (CR) and GMIR difference of the best and the worst ranked criteria obtained for all the criteria using BWM and TFN-BWM for all six experts is shown in Table 5.3. The weights along with the value of ξ, consistency index, consistency ratio and GMIR difference of the best and the worst ranked criteria obtained using GTFN-BWM for all main category enablers are listed down in Table 5.4.

Figure 5.7 Expert 1 Weights for Subcategory Enablers for BDA

Figure 5.8 Expert 2 Weights for Subcategory Enablers for BDA

Figure 5.9 Expert 3 Weights for Subcategory Enablers for BDA

Figure 5.10 Expert 4 Weights for Subcategory Enablers for BDA

Figure 5.11 Expert 5 Weights for Subcategory Enablers for BDA

Figure 5.12 Expert 6 Weights for Subcategory Enablers for BDA

Table 5.3 Weights and Ranks for Subcategory Enablers of BDA using BWM and TFN-BWM

Values	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		Expert 6	
	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM
Criteria 1	0.1183	0.1481	0.1747	0.1482	0.0810	0.1172	0.0944	0.0771	0.1945	0.1961	0.2226	0.1904
	3rd / 4th	3rd	3rd /4th	3rd / 4th	5th / 6th / 7th	6th	6th	6th	1st	1st	1st	1st
Criteria 2	0.2847	0.2405	0.1749	0.1555	0.0810	0.0902	0.2066	0.1731	0.1771	0.1623	0.0505	0.0746
	1st	1st	2nd	2nd	5th / 6th / 7th	7th	2nd /3rd	2nd /3rd	2nd/3rd/4th	2nd	7th	7th
Criteria 3	0.0645	0.0718	0.0747	0.0875	0.2432	0.1813	0.2287	0.1848	0.1771	0.1575	0.2015	0.1764
	7th	7th	6th / 7th	6th / 7th	1st	1st	1st	1st	2nd/3rd/4th	3rd /4th	2nd	2nd
Criteria 4	0.0646	0.0903	0.2258	0.1887	0.0270	0.0777	0.0215	0.0487	0.1435	0.1300	0.1595	0.1260
	5th / 6th	5th / 6th	1st	1st	8th	8th	8th	8th	5th	5th	3rd / 4th	4th / 5th
Criteria 5	0.2578	0.1821	0.0251	0.0691	0.1891	0.1425	0.0950	0.1330	0.0167	0.0527	0.0210	0.0507
	2nd	2nd	8th	8th	2nd / 3rd	3rd	4th / 5th	4th / 5th	8th	8th	8th	8th
Criteria 6	0.0646	0.0903	0.0747	0.0875	0.1891	0.1525	0.0519	0.0766	0.1771	0.1575	0.0925	0.1300
	5th / 6th	5th / 6th	6th / 7th	6th / 7th	2nd / 3rd	2nd	7th	7th	2nd/3rd/4th	3rd / 4th	5th /6th	3rd
Criteria 7	0.0268	0.0552	0.0752	0.1152	0.0810	0.1123	0.0950	0.1330	0.0566	0.0780	0.0925	0.1256
	8th	8th	5th	5th	5th / 6th / 7th	5th	4th / 5th	4th / 5th	7th	6th	5th /6th	6th
Criteria 8	0.1183	0.1213	0.1747	0.1482	0.1080	0.1256	0.2066	0.1731	0.0571	0.0654	0.1595	0.1260
	3rd /4th	4th	3rd / 4th	3rd / 4th	4th	4th	2nd / 3rd	2nd / 3rd	6th	7th	3rd / 4th	4th / 5th
Zeta	2.594	0.4411	1.999	0.3461	1.999	0.6793	2.59	0.5599	3.59	0.5599	2.594	0.4999
CI	4.47	8.04	3.73	6.69	3.73	6.69	4.47	8.04	4.47	8.04	4.47	8.04
CR	0.5803	0.0054	0.5359	0.0517	0.5359	0.1015	0.5794	0.0696	0.8031	0.0696	0.5803	0.0621
GMIR Difference	---	0.1853	---	0.1196	---	0.1037	---	0.1361	---	0.1434	---	0.1397

Table 5.4 Weights and Ranks for Subcategory Enablers of BDA using GTFN-BWM

Values	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Criteria 1	0.1498 3^{rd}	0.1453 3^{rd} / 4^{th}	0.1164 5^{th}	0.0807 6^{th}	0.1960 1^{st}	0.1997 1^{st}
Criteria 2	0.2415 1^{st}	0.1582 2^{nd}	0.0921 7^{th}	0.1596 2^{nd} / 3^{rd}	0.1620 2^{nd}	0.0678 7^{th}
Criteria 3	0.0733 7^{th}	0.0883 7^{th}	0.1781 1^{st}	0.2001 1^{st}	0.1574 3^{rd} / 4^{th}	0.1674 2^{nd}
Criteria 4	0.0912 5^{th} /6^{th}	0.1889 1^{st}	0.0750 8^{th}	0.0522 8^{th}	0.1297 5^{th}	0.1333 4^{th} / 5^{th}
Criteria 5	0.1774 2^{nd}	0.0695 8^{th}	0.1507 3^{rd}	0.1343 4^{th} / 5^{th}	0.0529 8^{th}	0.0537 8^{th}
Criteria 6	0.0912 5^{th} / 6^{th}	00.0884 6^{th}	0.1544 2^{nd}	0.0789 7^{th}	0.1574 3^{rd} / 4^{th}	0.1355 3^{rd}
Criteria 7	0.0561 8^{th}	0.1159 5^{th}	0.1100 6^{th}	0.1343 4^{th} / 5^{th}	0.0782 6^{th}	0.1093 6^{th}
Criteria 8	0.1192 4^{th}	0.1453 3^{rd} / 4^{th}	0.1231 4^{th}	0.1596 2^{nd} / 3^{rd}	0.0660 7^{th}	0.1333 4^{th} / 5^{th}
Zeta	0.4411	0.3461	0.6793	0.5599	0.5599	0.4999
CI	8.04	6.69	6.69	8.04	8.04	8.04
CR	0.0054	0.0517	0.1015	0.0696	0.0696	0.0621
GMIR Difference	0.1854	0.1194	0.1031	0.1479	0.1431	0.1460

The Table 5.3 and 5.4 and the Figure 5.7 – 5.12 show that the ranks obtained for all experts using BWM, TFN-BWM and GTFN-BWM have the same best and worst criteria whereas the other ranks for all three methodologies. The CR obtained using GTFN-BWM is much lower as obtained using BWM which develops that the methodology developed in this research provides much better results as compared to BWM. The comparison with fuzzy BWM cannot be conducted based on CR as it is based on the defuzzification method used, the shortcomings of which are explained in detail in chapter 6, however the GMIR difference value obtained by the comparison of the best and the worst ranked criteria is used to compare GTNF-BWM with TFN-BWM. In each case, the GMIR difference values obtained by both methodologies are enlisted in the Table 5.3 and 5.4.

5.3 Individual Weights and Ranks of Subcategory Enablers of IOT:

This section lists down the results obtained for the Internet of Things (IoT) subcategory enabler for all six experts using GTFN BWM, TFN BWM, and BWM. The consistency index and the value of ξ obtained by solving the model are also enlisted. The consistency ratio and, the GMIR difference for the best and the worst comparison are calculated for TFN-BWM and GTFN-BWM and enlisted. The criteria set for subcategory enablers for Internet of things is: Criteria 1 is cloud-centric IoT for logistics and manufacturing (C_1), criteria 2 is enterprise modeling/manufacturing (C_2), criteria 3 is radio frequency identification (C_3), criteria 4 is sensor networks (C_4), criteria 5 is NFC, QR codes, structured data beacons and Bluetooth (C_5), criteria 6 is software-defined networking (C_6), and criteria 7 is big data supported manufacturing (C_7).

For the subcategory enablers, the weights of all the eight criteria obtained for BWM, TFN-BWM and GTFN-BWM are shown in Figure 5.13 to 5.18. The weights along with the ranks and the value of ξ, consistency index (CI), consistency ratio (CR) and GMIR difference of the best and the worst ranked criteria obtained for all the criteria using BWM and TFN-BWM for all six experts is shown in Table 5.5. The weights along with the value of ξ, consistency index, consistency ratio and GMIR difference of the best and the worst ranked criteria obtained using GTFN-BWM for all main category enablers are listed down in Table 5.6.

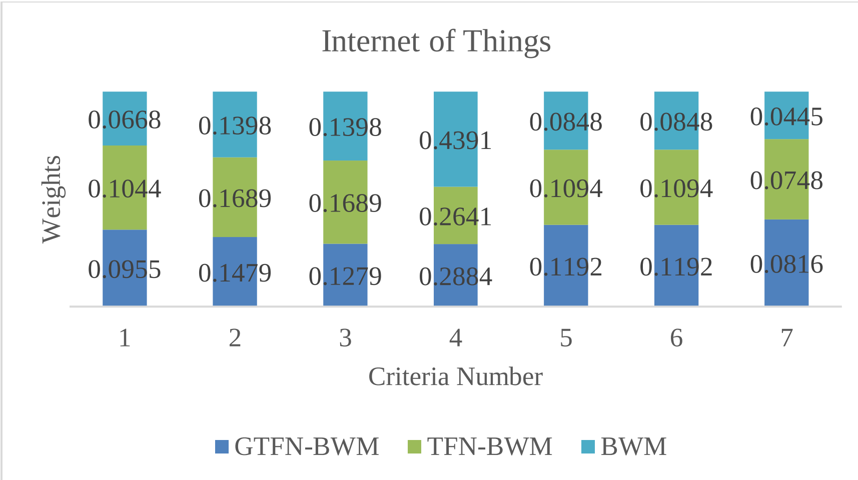

Figure 5.13 Expert 1 Weights for Subcategory Enablers of IOT

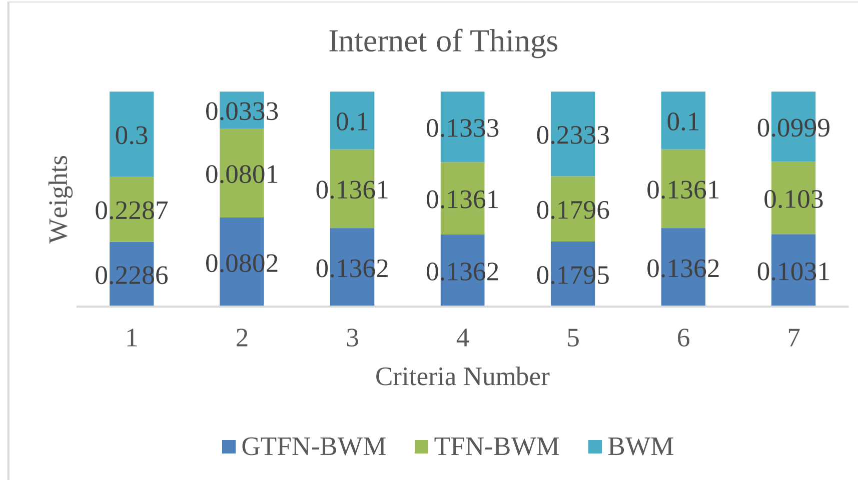

Figure 5.14 Expert 2 Weights for Subcategory Enablers of IOT

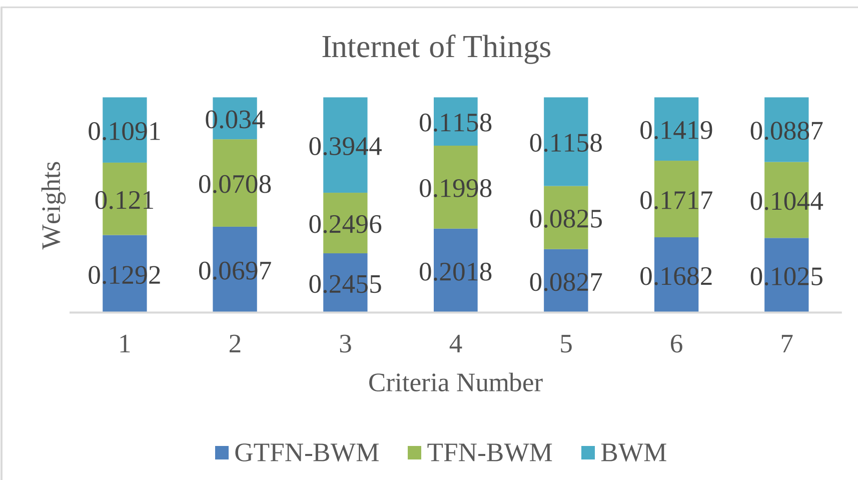

Figure 5.15 Expert 3 Weights for Subcategory Enablers of IOT

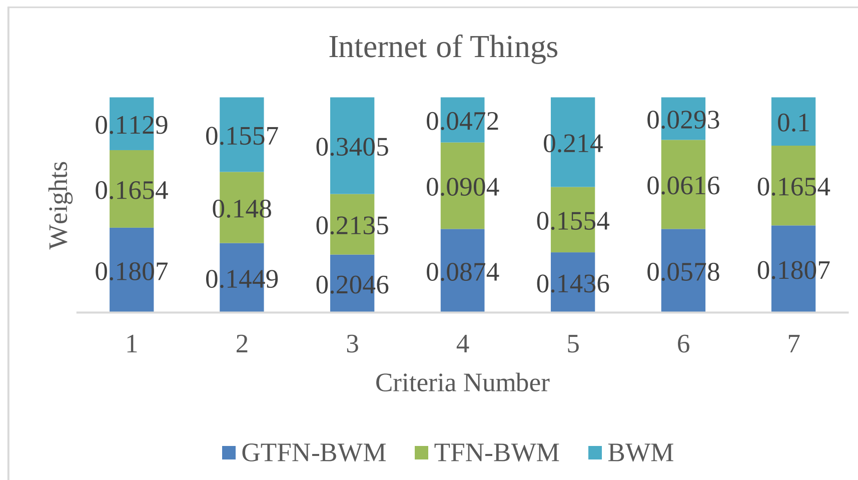

Figure 5.16 Expert 4 Weights for Subcategory Enablers of IOT

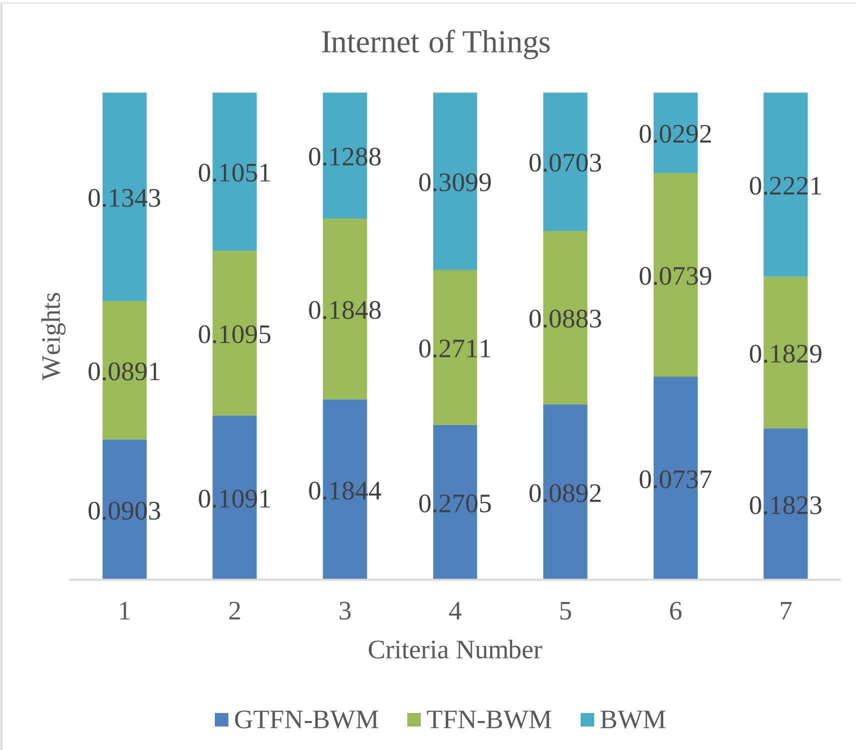

Figure 5.17 Expert 5 Weights for Subcategory Enablers of IOT

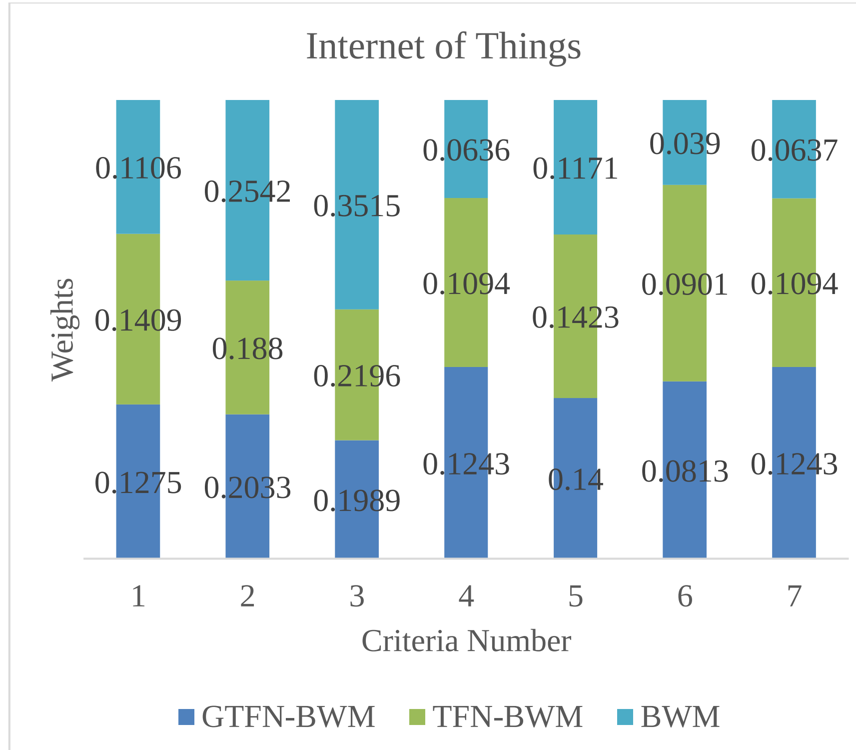

Figure 5.18 Expert 6 Weights for Subcategory Enablers of IOT

Table 5.5 Weights and Ranks for Subcategory Enablers of IOT using BWM and TFN-BWM

Values	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		Expert 6	
	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM
Criteria 1	0.0668 6th	0.1044 6th	0.3000 1st	0.2287 1st	0.1091 5th	0.1210 4th	0.1129 4th	0.1654 2nd / 3rd	0.1343 3rd	0.0891 5th	0.1106 4th	0.1409 4th
Criteria 2	0.1398 2nd / 3rd	0.1689 2nd / 3rd	0.0333 7th	0.0801 6th	0.0340 7th	0.0708 7th	0.1557 3rd	0.1480 5th	0.1051 5th	0.1095 4th	0.2542 2nd	0.1880 2nd
Criteria 3	0.1398 2nd / 3rd	0.1689 2nd / 3rd	0.1000 4th / 5th	0.1361 3rd/4th/5th	0.3944 1st	0.2496 1st	0.3405 1st	0.2135 1st	0.1288 4th	0.1848 2nd	0.3515 1st	0.2196 1st
Criteria 4	0.4391 1st	0.2641 1st	0.1333 3rd	0.1361 3rd/4th/5th	0.1158 3rd /4th	0.1998 2nd	0.0472 6th	0.0904 6th	0.3099 1st	0.2711 1st	0.0636 6th	0.1094 5th / 6th
Criteria 5	0.0848 4th / 5th	0.1094 4th / 5th	0.2333 2nd	0.1796 2nd	0.1158 3rd /4th	0.0825 6th	0.2140 2nd	0.1554 4th	0.0703 6th	0.0883 6th	0.1171 3rd	0.1423 3rd
Criteria 6	0.0848 4th / 5th	0.1094 4th / 5th	0.1000 4th / 5th	0.1361 3rd/4th/5th	0.1419 2nd	0.1717 3rd	0.0293 7th	0.0616 7th	0.0292 7th	0.0739 7th	0.0390 7th	0.0901 7th
Criteria 7	0.0445 7th	0.0748 7th	0.0999 6th	0.1030 7th	0.0887 6th	0.1044 5th	0.1000 5th	0.1654 2nd / 3rd	0.2221 2nd	0.1829 3rd	0.0637 5th	0.1094 5th / 6th
Zeta	1.8599	0.4494	1.999	0.2894	3.594	0.4911	3.594	0.6333	2.594	0.5000	1.999	0.5615
CI	4.47	8.04	3.73	6.69	4.47	8.04	4.47	8.04	4.47	8.04	3.73	6.69
CR	0.4160	0.0558	0.5359	0.0432	0.8040	0.0610	0.8040	0.0787	0.5803	0.0621	0.5359	0.0839
GMIR Difference	---	0.1893	---	0.1257	---	0.1788	---	0.1519	---	0.1972	---	0.1295

Table 5.6 Weights and Ranks for Subcategory Enablers of IOT using GTFN-BWM

Values	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Criteria 1	0.0955 6^{th}	0.2286 1^{st}	0.1292 4^{th}	0.1807 2^{nd} / 3^{rd}	0.0903 5^{th}	0.1275 4^{th}
Criteria 2	0.1479 2^{nd}	0.0802 7^{th}	0.0697 7^{th}	0.1449 4^{th}	0.1091 4^{th}	0.2033 1^{st}
Criteria 3	0.1279 3^{rd}	0.1362 3^{rd} /4^{th} / 5^{th}	0.2455 1^{st}	0.2046 1^{st}	0.1844 2^{nd}	0.1989 2^{nd}
Criteria 4	0.2884 1^{st}	0.1362 3^{rd} /4^{th} / 5^{th}	0.2018 2^{nd}	0.0874 6^{th}	0.2705 1^{st}	0.1243 5^{th} / 6^{th}
Criteria 5	0.1192 4^{th} / 5^{th}	0.1795 2^{nd}	0.0827 6^{th}	0.1436 5^{th}	0.0892 6^{th}	0.1400 3^{rd}
Criteria 6	0.1192 4^{th} / 5^{th}	0.1362 3^{rd} /4^{th} / 5^{th}	0.1682 3^{rd}	0.0578 7^{th}	0.0737 7^{th}	0.0813 7^{th}
Criteria 7	0.0816 7^{th}	0.1031 6^{th}	0.1025 5^{th}	0.1807 2^{nd} / 3^{rd}	0.1823 3^{rd}	0.1243 5^{th} / 6^{th}
Zeta	0.4494	0.2894	0.4911	0.6333	0.4999	0.5615
CI	8.04	6.69	8.04	8.04	8.04	6.69
CR	0.0558	0.0432	0.0610	0.0787	0.0621	0.0839
GMIR Difference	0.2068	0.1484	0.1758	0.1468	0.1968	0.1220

The Tables 5.5 and 5.6 along with the Figures 5.13 - 5.18 enlist down the results. For expert 1 the result obtained show that the same ranks are obtained using BWM and TFN-BWM whereas different ranks are obtained by GTFN-BWM. For expert 2 the result of GTFN BWM, TFN BWM, and BWM show that different ranks are obtained for every method. For expert 3 the results enlisted in Table 5.5 and 5.6 of GTFN BWM, TFN BWM, and BWM show that same ranks are obtained using GTFN-BWM and TFN-BWM whereas different ranks are obtained using BWM. For expert 4 the result obtained shows that different ranks are obtained for GTFN BWM, TFN BWM, and BWM. For expert 5 the result obtained have the same ranks for GTFN BWM and TFN BWM, whereas different ranks are obtained for BWM. Lastly, for expert six the result obtained shows that different ranks are obtained for GTFN BWM, TFN BWM, and BWM.

The CR obtained using GTFN-BWM is much lower as obtained using BWM which develops that the methodology developed in this research provides much better results as compared to BWM. The comparison with fuzzy BWM cannot be conducted based on CR as it is based on the defuzzification method used, the shortcomings of which are explained in detail in chapter 6, however the GMIR difference value obtained by the comparison of the best and the worst ranked criteria is used to compare GTNF-BWM with TFN-BWM. In each case, the GMIR difference values obtained by both methodologies are enlisted in the Table 5.5 and 5.6.

5.4 Individual Weights and Ranks of Subcategory Enablers of Industry 4.0:

This section lists down the results obtained for Industry 4.0 subcategory enabler for all six experts using GTFN BWM, TFN BWM, and BWM. The weights obtained are shown in Figure 5.19 – 5.24. The Tables 5.7 enlist the weights and ranks obtained using BWM and TFN-BWM including the consistency index, the value of ξ, consistency ratio and the GMIR difference value for the best and the worst ranked criteria. Table 5.8 enlists the weights, ranks, ξ, CI, CR and GMIR difference of the best and worst ranked criteria using GTFN-BWM. The criteria set for subcategory enablers of IDY are Criteria 1 is e-supply chain management (C_1), criteria 2 is tracking and localization of products (C_2), criteria 3 is additive manufacturing and 3D printing (C_3), criteria 4 is innovative business models (C_4), and criteria 5 is effective management of technologies.

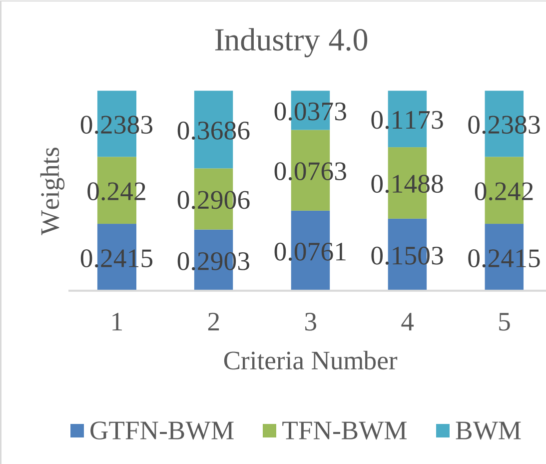

Figure 5.19 Expert 1 Weights for Subcategory Enablers of IDY

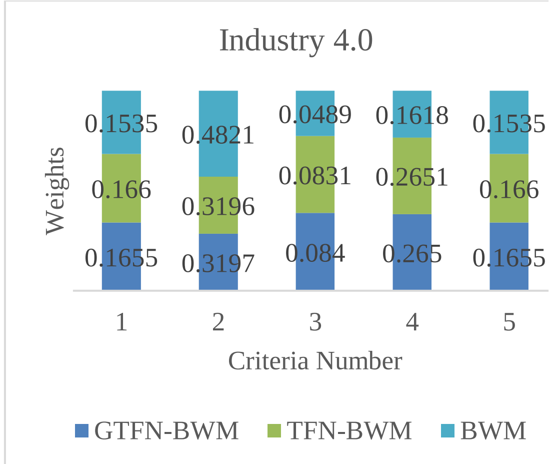

Figure 5.20 Expert 2 Weights for Subcategory Enablers of IDY

Figure 5.21 Expert 3 Weights for Subcategory Enablers of IDY

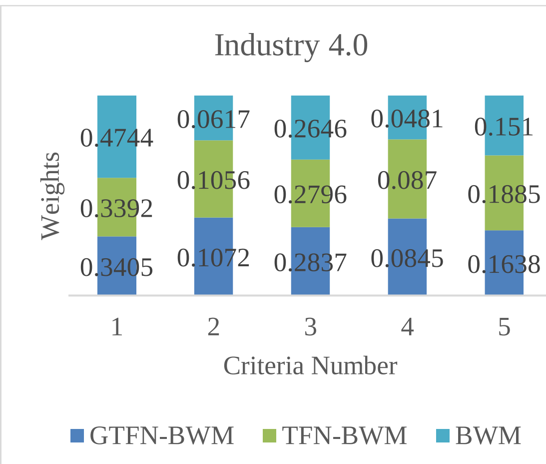

Figure 5.22 Expert 4 Weights for Subcategory Enablers of IDY

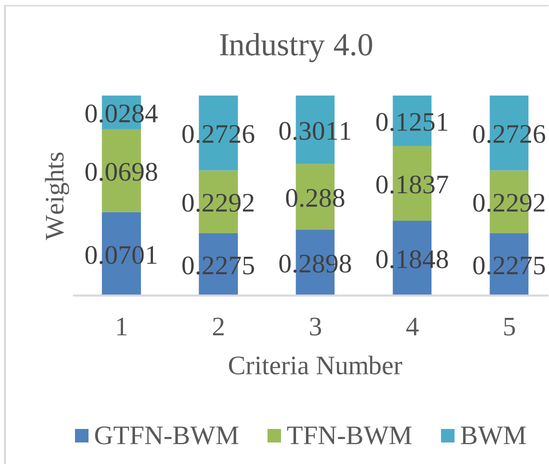

Figure 5.23 Expert 5 Weights for Subcategory Enablers of IDY

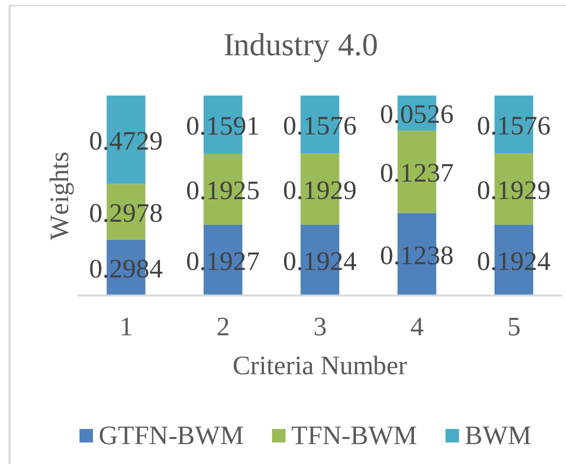

Figure 5.24 Expert 6 Weights for Subcategory Enablers of IDY

Table 5.7 Weights and Ranks for Subcategory Enablers of IDY using BWM and TFN-BWM

Values	**Expert 1**		**Expert 2**		**Expert 3**		**Expert 4**		**Expert 5**		**Expert 6**	
	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM
Criteria 1	0.2383 2^{nd} / 3^{rd}	0.2420 2^{nd} / 3^{rd}	0.1535 3^{rd} / 4^{th}	0.1660 3^{rd}/4^{th}	0.1054 4^{th}	0.1451 4^{th}	0.4744 1^{st}	0.3392 1^{st}	0.0284 5^{th}	0.0698 5^{th}	0.4729 1^{st}	0.2978 1^{st}
Criteria 2	0.3686 1^{st}	0.2906 1^{st}	0.4821 1^{st}	0.3196 1^{st}	0.1930 3^{rd}	0.1468 3^{rd}	0.0617 4^{th}	0.1056 4^{th}	0.2726 2^{nd}/3^{rd}	0.2292 1^{st}/2^{nd}	0.1591 2^{nd}	0.1925 4^{th}
Criteria 3	0.0373 5^{th}	0.0763 5^{th}	0.0489 5^{th}	0.0831 5^{th}	0.1931 2^{nd}	0.2522 2^{nd}	0.2646 2^{nd}	0.2796 2^{nd}	0.3011 1^{st}	0.2880 3^{rd}	0.1576 3^{rd} /4^{th}	0.1929 2^{nd} /3^{rd}
Criteria 4	0.1173 4^{th}	0.1488 4^{th}	0.1618 2^{nd}	0.2651 2^{nd}	0.0438 5^{th}	0.0944 5^{th}	0.0481 5^{th}	0.0870 5^{th}	0.1251 4^{th}	0.1837 4^{th}	0.0526 5^{th}	0.1237 5^{th}
Criteria 5	0.2383 2^{nd} / 3^{rd}	0.2420 2^{nd} / 3^{rd}	0.1535 3^{rd} / 4^{th}	0.1660 3^{rd}/4^{th}	0.4645 1^{st}	0.3613 1^{st}	0.1510 3^{rd}	0.1885 3^{rd}	0.2726 2^{nd}/3^{rd}	0.2992 1^{st}/2^{nd}	0.1576 3^{rd} /4^{th}	0.1929 2^{nd} /3^{rd}
Zeta	1.8599	0.2145	1.8599	0.2145	2.594	0.5599	1.8599	0.2145	2.594	0.4411	2	0.5655
CI	4.47	8.04	4.47	8.04	4.47	8.04	4.47	8.04	4.47	8.04	3.73	6.69
CR	0.4160	0.0266	0.4160	0.0266	0.5803	0.0696	0.4160	0.0266	0.5803	0.0548	0.5361	0.0845
GMIR Difference	---	0.2143	---	0.2365	---	0.2669	---	0.2522	---	0.1594	---	0.1741

Table 5.8 Weights and Ranks for Subcategory Enablers of IDY using GTFN-BWM

Values	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Criteria 1	0.2145 2nd / 3rd	0.1655 3rd / 4th	0.1426 4th	0.3405 1st	0.0701 5th	0.2984 1st
Criteria 2	0.2903 1st	0.3197 1st	0.1479 3rd	0.1072 4th	0.2275 2nd / 3rd	0.1927 2nd
Criteria 3	0.0761 5th	0.0840 5th	0.2467 2nd	0.2837 2nd	0.2898 1st	0.1924 3rd / 4th
Criteria 4	0.1503 4th	0.2650 2nd	0.0948 5th	0.0845 5th	0.1848 4th	0.1238 5th
Criteria 5	0.2415 2nd / 3rd	0.1655 3rd / 4th	0.3678 1st	0.1638 3rd	0.2275 2nd / 3rd	0.1924 3rd / 4th
Zeta	0.2145	0.2145	0.5599	0.2145	0.4411	0.5655
CI	8.04	8.04	8.04	8.04	8.04	6.69
CR	0.0266	0.0266	0.0696	0.0266	0.0548	0.0845
GMIR Difference	0.2142	0.2357	0.2730	0.2560	0.2197	0.1746

The results obtained for expert 1 as shown in Table 5.7 and 5.8 show that same ranks are obtained for all three methodologies i.e., BWM, TFN-BWM and GTFN-BWM. The results obtained for expert 2 show that same ranks are obtained using all three methodologies however the individual weights for all criteria differ. Same ranks are obtained for expert 3 and expert 4 whereas different ranks are obtained for each methodology for expert 5 as listed in Table 5.7 and 5.8. Similarly for all three methodologies the weights and ranks obtained for expert 6 are different. The CR obtained using GTFN-BWM is much lower as obtained using BWM which develops that the methodology developed in this research provides much better results as compared to BWM. The comparison with fuzzy BWM cannot be conducted based on CR as it is based on the defuzzification method used, the shortcomings of which are explained in detail in chapter 6, however the GMIR difference value obtained by the comparison of the best and the worst ranked criteria is used to compare GTNF-BWM with TFN-BWM. In each case, the GMIR difference values obtained by both methodologies are enlisted in the Table 5.7 and 5.8.

5.5 Individual Weights and Ranks of Subcategory Enablers of BCT:

This section lists down the results obtained for the Blockchain Technology subcategory enabler for all six experts using GTFN BWM, TFN BWM, and BWM. The weights obtained are shown in Figure 5.25 – 5.30. The Tables 5.9 enlist the weights and ranks obtained using BWM and TFN-BWM including the consistency index, the value of ξ, consistency ratio and the GMIR difference value for the best and the worst ranked criteria. Table 5.10 enlists the weights, ranks, ξ, CI, CR and GMIR difference of the best and worst ranked criteria using GTFN-BWM. The criteria set for subcategory enablers of BCT are:

1. Criteria 1 is transparency and visibility (C_1)
2. Criteria 2 is validation of data and transactions (C_2)
3. Criteria 3 is automation using smart contracts (C_3)
4. Criteria 4 is the integrity of the products (C_4)
5. Criteria 5 is standardization and automation of processes (C_5)
6. Criteria 6 is real-time information (C_6).

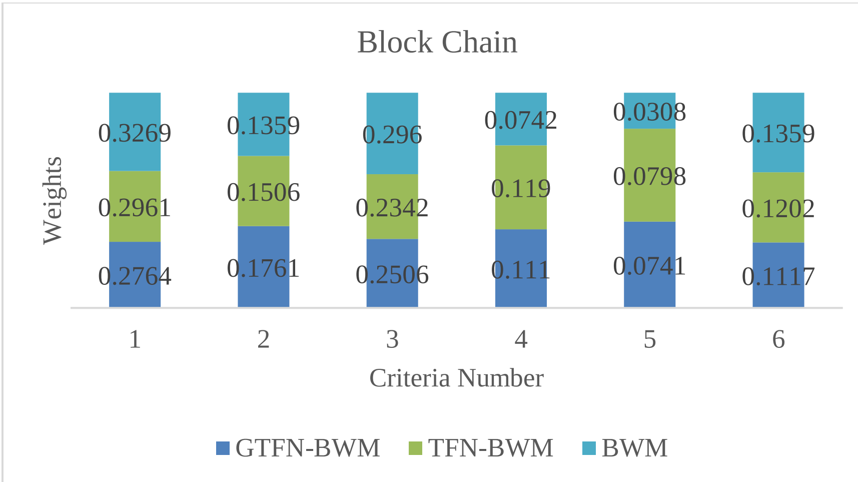

Figure 5.25 Expert 1 Weights for Subcategory Enablers of BCT

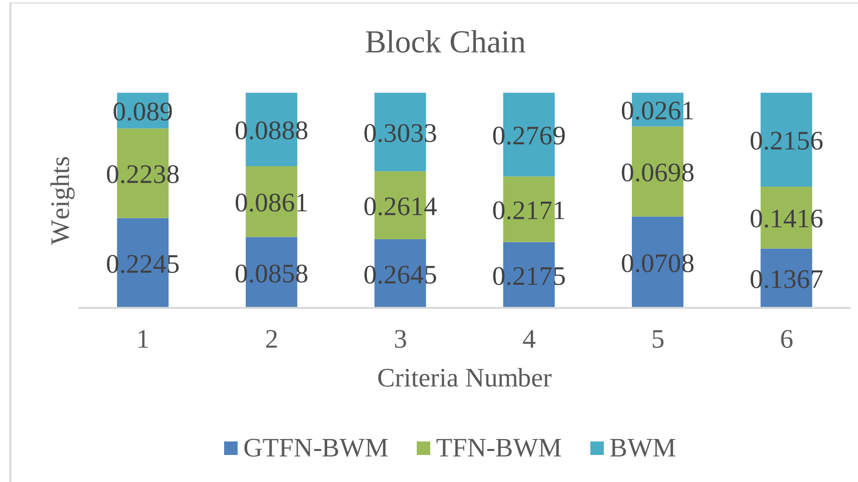

Figure 5.26 Expert 2 Weights for Subcategory Enablers of BCT

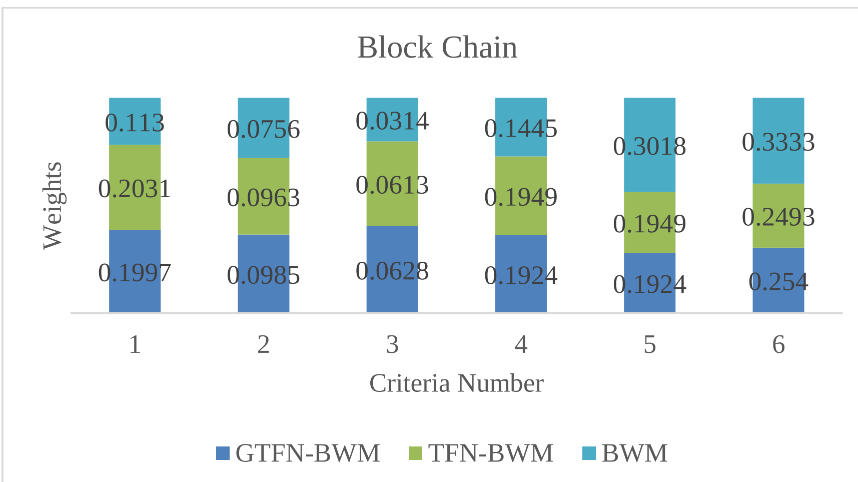

Figure 5.27 Expert 3 Weights for Subcategory Enablers of BCT

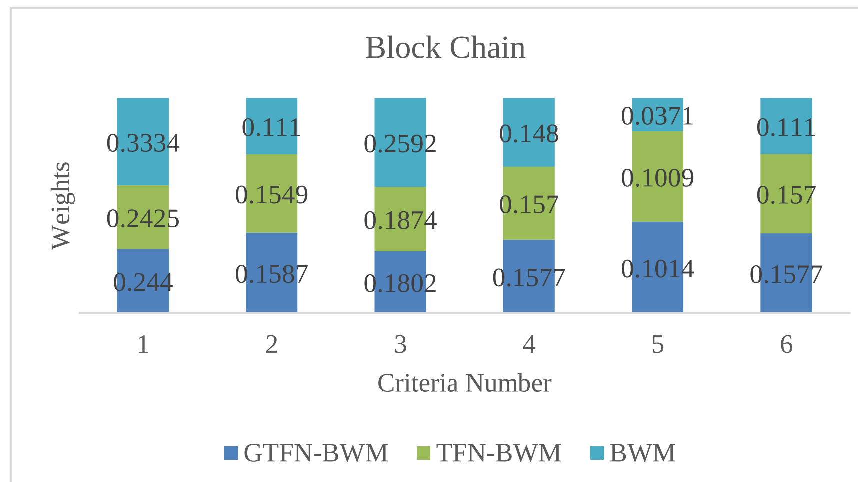

Figure 5.28 Expert 4 Weights for Subcategory Enablers of BCT

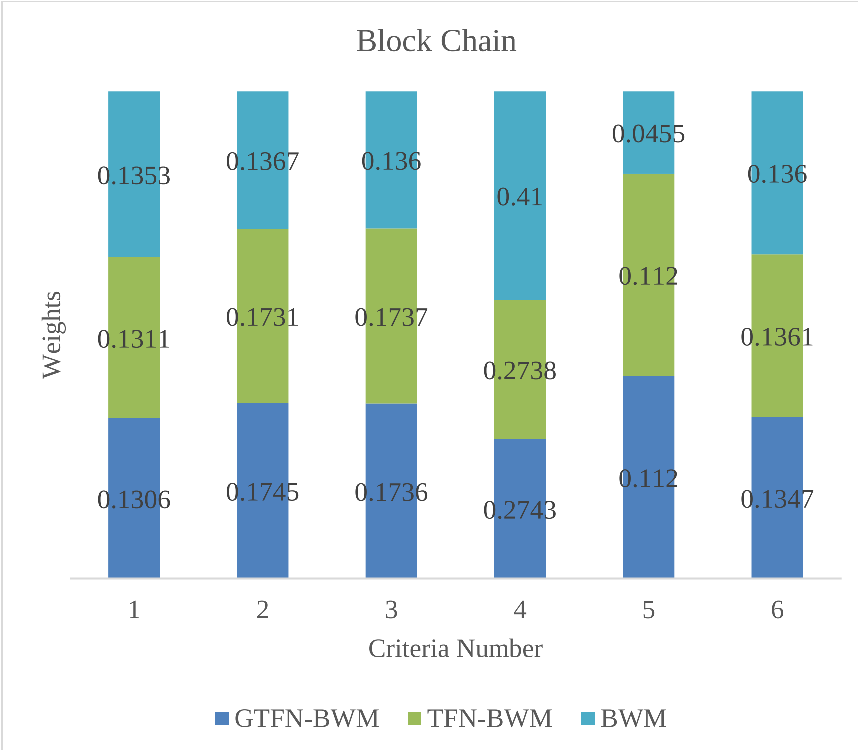

Figure 5.29 Expert 5 Weights for Subcategory Enablers of BCT

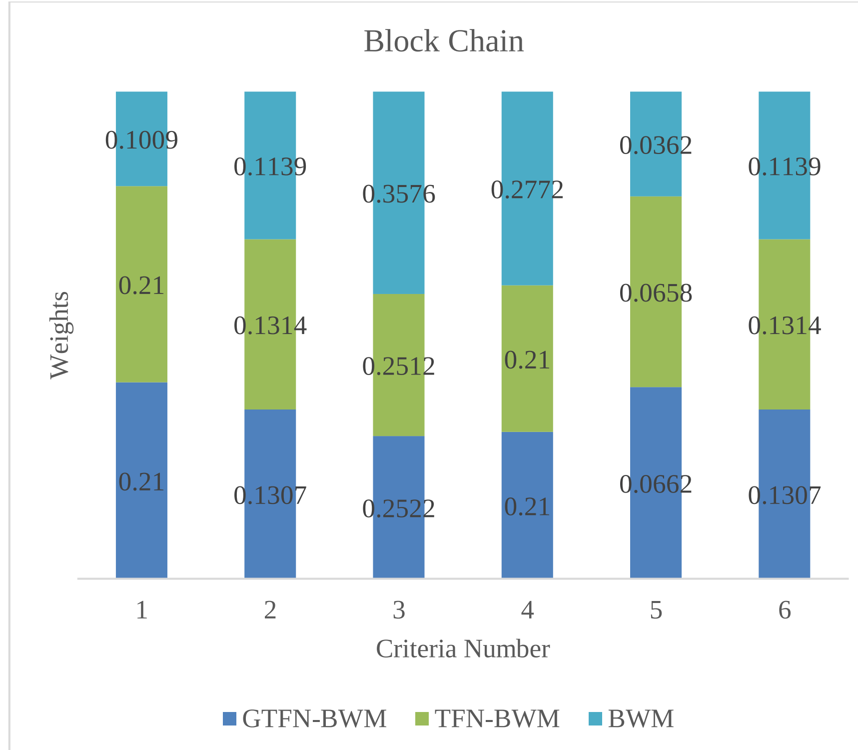

Figure 5.30 Expert 6 Weights for Subcategory Enablers of BCT

Table 5.9 Weights and Ranks for Subcategory Enablers of BCT using BWM and TFN-BWM

Values	Expert 1		Expert 2		Expert 3		Expert 4		Expert 5		Expert 6	
	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM	BWM	TFN-BWM
Criteria 1	0.3269 1^{st}	0.2961 1^{st}	0.0890 4^{th}	0.2238 2^{nd}	0.1130 4^{th}	0.2031 2^{nd}	0.3334 1^{st}	0.2425 1^{st}	0.1353 5^{th}	0.1311 5^{th}	0.1009 5^{th}	0.2100 2^{nd} /3^{rd}
Criteria 2	0.1359 3^{rd} /4^{th}	0.1506 3^{rd}	0.0888 5^{th}	0.0861 5^{th}	0.0756 5^{th}	0.0963 5^{th}	0.111 4^{th} / 5^{th}	0.1549 5^{th}	0.1367 2^{nd}	0.1731 3^{rd}	0.1139 3^{rd} /4^{th}	0.1314 4^{th} /5^{th}
Criteria 3	0.2960 2^{nd}	0.2342 2^{nd}	0.3033 1^{st}	0.2614 1^{st}	0.0314 6^{th}	0.0613 6^{th}	0.2592 2^{nd}	0.1874 2^{nd}	0.1360 3^{rd} /4^{th}	0.1737 2^{nd}	0.3576 1^{st}	0.2512 1^{st}
Criteria 4	0.0742 5^{th}	0.1190 5^{th}	0.2769 2^{nd}	0.2171 3^{rd}	0.1445 3^{rd}	0.1949 3^{rd} /4^{th}	0.1480 3^{rd}	0.1570 3^{rd} /4^{th}	0.4100 1^{st}	0.2738 1^{st}	0.2772 2^{nd}	0.2100 2^{nd} /3^{rd}
Criteria 5	0.0308 6^{th}	0.0798 6^{th}	0.0261 6^{th}	0.0698 6^{th}	0.3018 2^{nd}	0.1949 3^{rd} /4^{th}	0.0371 6^{th}	0.1009 6^{th}	0.0455 6^{th}	0.1120 6^{th}	0.0362 6^{th}	0.0658 6^{th}
Criteria 6	0.1359 3^{rd} /4^{th}	0.1202 4^{th}	0.2156 3^{rd}	0.1416 4^{th}	0.3333 1^{st}	0.2493 1^{st}	0.1110 4^{th} /5^{th}	0.1570 3^{rd} /4^{th}	0.1360 3^{rd} /4^{th}	0.1361 4^{th}	0.1139 3^{rd} /4^{th}	0.1314 4^{th} /5^{th}
Zeta	2.594	0.5000	3.594	0.3005	2.594	0.4258	1.999	0.5655	1.99	0.5655	1.859	0.2145
CI	4.47	8.04	4.47	8.04	4.47	8.04	3.73	6.69	3.73	6.69	4.47	8.04
CR	0.5803	0.0621	0.8040	0.0373	0.5803	0.0529	0.5359	0.0845	0.5359	0.0845	0.4158	0.0266
GMIR Difference	---	0.2163	---	0.1916	---	0.1880	---	0.1416	---	0.1618	---	0.1854

Table 5.10 Weights and Ranks for Subcategory Enablers of BCT using GTFN-BWM

Values	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Criteria 1	0.2762 1st	0.2245 2nd	0.1997 2nd	0.2440 1st	0.1306 5th	0.2100 2nd / 3rd
Criteria 2	0.1761 3rd	0.0858 5th	0.0985 5th	0.1587 3rd	0.1745 2nd	0.1307 4th /5th
Criteria 3	0.2506 2nd	0.2645 1st	0.0628 6th	0.1802 2nd	0.1736 3rd	0.2522 1st
Criteria 4	0.1110 5th	0.2175 3rd	0.1924 3rd / 4th	0.1577 4th /5th	0.2743 1st	0.2100 2nd / 3rd
Criteria 5	0.0741 6th	0.0708 6th	0.1924 3rd / 4th	0.1014 6th	0.1120 6th	0.0662 6th
Criteria 6	0.1117 4th	0.1367 4th	0.2540 1st	0.1577 4th / 5th	0.1347 4th	0.1307 4th / 5th
Zeta	0.5000	0.3005	0.4258	0.5655	0.5655	0.2145
CI	8.04	8.04	8.04	6.69	6.69	8.04
CR	0.0621	0.0373	0.0529	0.0845	0.0845	0.0266
GMIR Difference	0.2021	0.1937	0.1912	0.1426	0.1623	0.1860

The Table 5.9 and 5.10 show that for expert 1 the ranks obtained using GTFN BWM, TFN BW are the same whereas those obtained using BWM are different. Similarly, the ranks obtained using GTFN-BWM and TFN-BWM for expert 2 are the same whereas different weights are obtained using these two methodologies, whereas the ranks and weights obtained by the use of BWM for expert 2 are different from the previous two methodologies. For expert 3 the ranks obtained using GTFN-BWM and TFN-BWM are the same whereas different weights are obtained using these two methodologies, whereas the ranks and weights obtained using BWM for expert 3 are different from the previous two methodologies. The Table 5.9 and 5.10 show that for expert 4 the weights and ranks obtained using all three methodologies i.e., BWM, TFN-BWM and GTFN-BWM are different. The same trend is observed for expert 6 where the ranks obtained using all three methodologies are different as listed down in Table 5.9 and 5.10. Lastly for expert 6 the ranks obtained using TFN-BWM and GTFN-BWM are same whereas different ranks are obtained using BWM.

The CR obtained using GTFN-BWM is much lower as obtained using BWM which develops that the methodology developed in this research provides much better results as compared to BWM. The comparison with fuzzy BWM cannot be conducted based on CR as it is based on the defuzzification method used, the shortcomings of which are explained in detail in chapter 6, however the GMIR difference value obtained by the comparison of the best and the worst ranked criteria is used to compare GTNF-BWM with TFN-BWM. In each case, the GMIR difference values obtained by both methodologies are enlisted in the Table 5.9 and 5.10.

This chapter has enlisted the individual results obtained for each expert for main and sub-category enablers. The main enablers and sub-category enablers were ranked using GTFN-BWM (proposed methodology), TFN-BWM, and BWM. Also, ξ value for every model developed has been enlisted in the Tables 5.1 to 5.10. Based on the linguistic scale the value of a_{bw} was used to determine the value of the consistency index. For BWM a 9-point linguistic scale was used to determine the value of CI. For TFN-BWM a five-point normalized linguistic scale was used to determine the value of CI. For GTFN-BWM a five-point generalized linguistic scale was used to determine the value of CI as listed in Table 3.2. The comparison to determine which method provided better results based on the consistency ratio and GMIR difference between the best and the worst ranked criteria is explained in chapter 6.

5.6 Global Weights and Ranks of Main and Subcategory Enablers:

The ranks and weights of the main category enabler obtained from GTFN-BWM, BWM and TFN-BWM are listed in the Table 5.11. The Table shows that the same ranks are obtained from GTFN-BWM, BWM and TFN-BWM for main category enablers i.e., $C_1 > C_4 > C_2 > C_3$. However, the respective weight obtained for these enablers is different as shown in the Table.

Table 5.11 Consolidated Weights and Ranks of Main Enablers

Criteria Name	**GTFN-BWM Global Weight**	**GTFN Rank**	**BWM Global Weight**	**BWM Rank**	**TFN-BWM Global Weights**	**TFN-BWM Ranks**
Big Data Analytics	0.29	1st	0.3202	1st	0.2891	1st
Internet of Things	0.2307	3rd	0.2232	3rd	0.2297	3rd
Industry 4.0	0.2263	4th	0.1863	4th	0.2251	4th
Block Chain Technology	0.2528	2nd	0.2699	2nd	0.2559	2nd

The ranks and weight of sub-category enablers obtained from GTFN-BWM, BWM and TFN-BWM are listed in the Table 5.12, 5.13 and 5.14 respectively. The Table shows that the ranks and global weights obtained for all 26 sub-criteria using GTFN-BWM, BWM and TFN-BWM are different. The ranks obtained from GTFN-BWM are as follows:

$$C_{21} > C_{20} > C_{23} > C_{24} > C_{17} > C_{16} > C_{18} > C_1 > C_{12} > C_2 > C_{11} > C_3 > C_{26} > C_8 > C_{22} > C_6 > C_{19} > C_9 > C_4 > C_5 > C_{15} > C_7 > C_{10} > C_{13} > C_{25} > C_{14}$$

The ranks obtained using BWM are as follows:

$$C_{23} > C_{24} > C_{11} > C_3 > C_2 > C_{21} > C_{17} > C_1 > C_{26} > C_{16} > C_{20} > C_8 > C_{12} > C_6 > C_4 > C_5 > C_{13} = C_{18} > C_9 > C_{22} > C_{10} > C_{15} > C_7 > C_{25} > C_{19} > C_{14}$$

The ranks obtained using TFN-BWM are as follows:

$$C_{21} > C_{20} > C_{24} > C_{23} > C_{17} > C_{16} > C_{11} > C_{18} > C_{2} > C_{1} > C_{3} > C_{12} > C_{26} > C_{8} > C_{19} > C_{22} > C_{6} > C_{9} > C_{4} > C_{5} > C_{7} > C_{10} > C_{13} > C_{15} > C_{25} > C_{14}$$

This provides that using GTFN-BWM the best ranked criteria is criteria 21 i.e., transparency and visibility followed by effective management of technologies and automation using smart contract as the second and third important subcategory enabler to improve the performance of a supply chain. The Table 5.-13 provides that by using BWM the best ranked criteria obtained is criteria 23 i.e., automation using smart contracts. The second and the third important criteria obtained using BWM are integrity of products and radio frequency identification respectively. Using TFN-BWM the most important ranked sub criteria is criteria 21 i.e., transparency and visibility followed by effective management of technologies as the second most important subcategory enabler as enlisted in Table 5.14. The third most important enabler obtained using TFN-BWM is integrity of product whereas it is the fourth most important criteria according to GTFN-BWM. For all these methodologies the least important criterion is criterion 14 i.e., software defined networking.

Table 5.12 GTFN-BWM Global Weights for Subcategory Enablers

S. No.	Main Technology Name	Weight	Sub Criteria Names	Weight	Global Weight	Rank
1	Big Data Analytics	0.29	Data Capturing and Storage	0.148	0.0429	8th
			Data Security and Privacy	0.1469	0.04258	10th
			Data and Information Technology Integration	0.1441	0.0418	12th
			Change Management	0.1117	0.0324	19th
			Feasibility Study on BDA	0.1064	0.0309	20th
			Organizational Openness	0.1176	0.03410	16th
			Synchronization of Processes	0.1006	0.0292	22nd
			Adequate System Capabilities	0.1244	0.0361	14th
2	Internet of Things	0.2307	Cloud-Centric IoT for Logistics and Manufacturing	0.1419	0.0327	18th
			Enterprise Modelling/manufacturing	0.1259	0.02904	23rd
			Radio Frequency Identification	0.1829	0.0422	11th
			Sensor Networks	0.1848	0.0426	9th
			NFC, QR Codes, Structured Data, Beacons & Bluetooth	0.1257	0.02900	24th
			Software Defined Networking	0.1061	0.0245	26th
			Big Data Supported Manufacturing	0.1291	0.0298	21st

Continued on Next Page

3	Industry 4.0	0.2263	E-Supply Chain Management	0.2098	0.0475	6th
			Tracking and Localization of Products	0.2142	0.0485	5th
			Additive Manufacturing and 3D Printing	0.1955	0.0442	7th
			Innovative Business Models	0.1505	0.03407	17th
			Effective Management of Technologies	0.2264	0.0512	2nd
4	Block Chain Technology	0.2528	Transparency and Visibility	0.2142	0.0542	1st
			Validation of Data and Transactions	0.1374	0.0347	15th
			Automation using Smart Contracts	0.1973	0.0499	3rd
			Integrity of Products	0.1938	0.0490	4th
			Standardization and Automation of Processes	0.1028	0.0260	25th
			Real-Time Information	0.1542	0.0390	13th

Table 5.13 BWM Global Weights for Subcategory Enablers

S. No.	Main Technology Name	Weight	Sub Criteria Names	Weight	Global Weight	Rank
1	Big Data Analytics	0.3202	Data Capturing and Storage	0.1476	0.0473	8th
			Data Security and Privacy	0.1625	0.0520	5th
			Data and Information Technology Integration	0.1649	0.0528	4th
			Change Management	0.1070	0.0343	15th
			Feasibility Study on BDA	0.1008	0.0323	16th
			Organizational Openness	0.1083	0.0347	14th
			Synchronization of Processes	0.0712	0.0228	23rd
			Adequate System Capabilities	0.1374	0.0440	12th
2	Internet of Things	0.2232	Cloud-Centric IoT for Logistics and Manufacturing	0.1390	0.0310	19th
			Enterprise Modelling/manufacturing	0.1204	0.0269	21st
			Radio Frequency Identification	0.2425	0.0541	3rd
			Sensor Networks	0.1848	0.0413	13th
			NFC, QR Codes, Structured Data, Beacons & Bluetooth	0.1392	0.0311	17th/18th
			Software Defined Networking	0.0707	0.0158	26th
			Big Data Supported Manufacturing	0.1031	0.0230	22nd

Continued on Next Page

3	Industry 4.0	0.1863	E-Supply Chain Management	0.2455	0.0457	10th
			Tracking and Localization of Products	0.2562	0.0477	7th
			Additive Manufacturing and 3D Printing	0.1671	0.0311	17th/18th
			Innovative Business Models	0.0914	0.0170	25th
			Effective Management of Technologies	0.2396	0.0446	11th
4	Block Chain Technology	0.2699	Transparency and Visibility	0.1831	0.0494	6th
			Validation of Data and Transactions	0.1103	0.0298	20th
			Automation using Smart Contracts	0.2306	0.0622	1st
			Integrity of Products	0.2218	0.0599	2nd
			Standardization and Automation of Processes	0.0796	0.0215	24th
			Real-Time Information	0.1743	0.0470	9th

Table 5.14 TFN-BWM Global Weights for Subcategory Enablers

S. No.	Main Technology Name	Weight	Sub Criteria Names	Weight	Global Weight	Rank
1	Big Data Analytics	0.2891	Data Capturing and Storage	0.1462	0.0423	10th
			Data Security and Privacy	0.1494	0.0432	9th
			Data and Information Technology Integration	0.1432	0.0414	11th
			Change Management	0.1102	0.0319	19th
			Feasibility Study on BDA	0.1050	0.0304	20th
			Organizational Openness	0.1157	0.0335	17th
			Synchronization of Processes	0.1032	0.0298	21st
			Adequate System Capabilities	0.1266	0.0366	14th
2	Internet of Things	0.2297	Cloud-Centric IoT for Logistics and Manufacturing	0.141566667	0.0325	18th
			Enterprise Modelling/manufacturing	0.12755	0.0293	22nd
			Radio Frequency Identification	0.195408333	0.0449	7th
			Sensor Networks	0.178483333	0.0410	12th
			NFC, QR Codes, Structured Data, Beacons & Bluetooth	0.126230556	0.0290	23rd
			Software Defined Networking	0.107116667	0.0246	26th
			Big Data Supported Manufacturing	0.123291667	0.0283	24th

Continued on Next Page

3	Industry 4.0	0.2251	E-Supply Chain Management	0.209988889	0.0473	6th
			Tracking and Localization of Products	0.214025	0.0482	5th
			Additive Manufacturing and 3D Printing	0.195322222	0.0440	8th
			Innovative Business Models	0.150433611	0.0339	15th
			Effective Management of Technologies	0.229980556	0.0518	2nd
4	Block Chain	0.2559	Transparency and Visibility	0.217747222	0.0557	1st
			Validation of Data and Transactions	0.132058333	0.0338	16th
			Automation using Smart Contracts	0.194850556	0.0499	4th
			Integrity of Products	0.195291667	0.0500	3rd
			Standardization and Automation of Processes	0.103852778	0.0266	25th
			Real-Time Information	0.155922222	0.0399	13th

6 Discussion:

The methodology used in this research to rank the main enablers and subcategory enablers is Generalized Triangular Fuzzy Number (GTFN) with Best Worst Method (BWM). The results obtained from this methodology were compared with Best Worst Method (BWM) and with Triangular Fuzzy Number Best Worst Method (TFN-BWM). This Section compares the results of all three methodologies the results of which are mentioned in Section 5 using the data listed in Appendix B and determines whether the methodology developed in this study provides better results or not.

6.1 GTFN-BWM Results Comparison with BWM:

To compare the results obtained and mentioned in chapter 5 consistency Index (CI) and consistency ratio (CR) of BWM is used. Similarly, on the same parameters, the consistency index and consistency ratio of GTFN-BWM mentioned in Section 3.7 are used. Lower the value of CR better results/ranks are obtained from the model. The value of CR closer to zero (0) is the better value (Rezaei, 2015). The consistency ratio (CR) is used to determine which method i.e., GTFN-BWM or BWM provides better results. The Table 6.1 shows the CR value for both main enablers and subcategory enablers for all six experts.

Table 6.1 CR Values of Main and Subcategory Enablers

Main Enablers			
S. NO.	Expert	GTFN CR	BWM CR
1	Expert 1	0.0429	0.1057
2	Expert 2	0.0529	0.5803
3	Expert 3	0.0984	0.5803
4	Expert 4	0.0839	0.5359
5	Expert 5	0.0529	0.5803
6	Expert 6	0.0621	0.5803

Big Data Analytics			
S. NO.	Expert	GTFN CR	BWM CR
1	Expert 1	0.0549	0.5803
2	Expert 2	0.0517	0.5361
3	Expert 3	0.1015	0.5359
4	Expert 4	0.0696	0.5794
5	Expert 5	0.0696	0.8031
6	Expert 6	0.0621	0.5803

Internet of Things			
S. NO.	Expert	GTFN CR	BWM CR
1	Expert 1	0.0559	0.416
2	Expert 2	0.0432	0.5361
3	Expert 3	0.061	0.804
4	Expert 4	0.0787	0.804
5	Expert 5	0.0621	0.5803
6	Expert 6	0.0839	0.5359

Industry 4.0			
S. NO.	Expert	GTFN CR	BWM CR
1	Expert 1	0.0267	0.416
2	Expert 2	0.02667	0.416
3	Expert 3	0.0696	0.5803
4	Expert 4	0.0266	0.416
5	Expert 5	0.0548	0.5803
6	Expert 6	0.0845	0.5361

Block Chain Technology			
S. NO.	Expert	GTFN CR	BWM CR
1	Expert 1	0.0621	0.5803
2	Expert 2	0.0373	0.804
3	Expert 3	0.0529	0.5803
4	Expert 4	0.0845	0.5361
5	Expert 5	0.0845	0.5359
6	Expert 6	0.0266	0.416

This Table shows that for each model developed the CR value obtained using GTFN-BWM is much lower than that obtained using BWM, which shows that the results obtained from the methodology developed in this research are more consistent. The Figure 6.1 shows the same comparison for the subcategory enablers and Figure 6.2 shows the CR values obtained for the main category enablers and both figures illustrate the effectiveness of GTFN-BWM over BWM for developing weights and ranks of criteria.

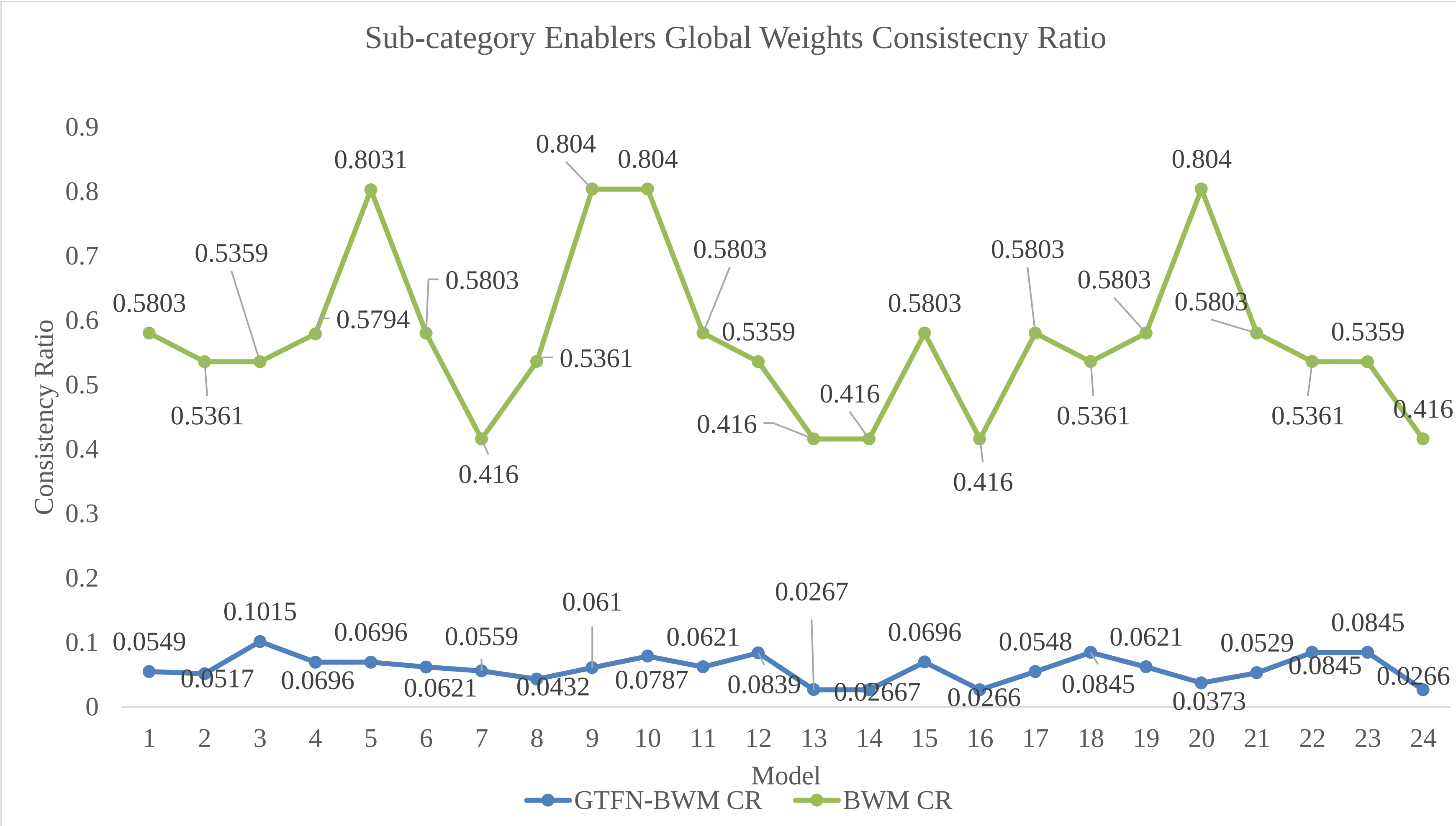

Figure 6.1 CR Values of BWM and GTFN-BWM for Subcategory Enablers

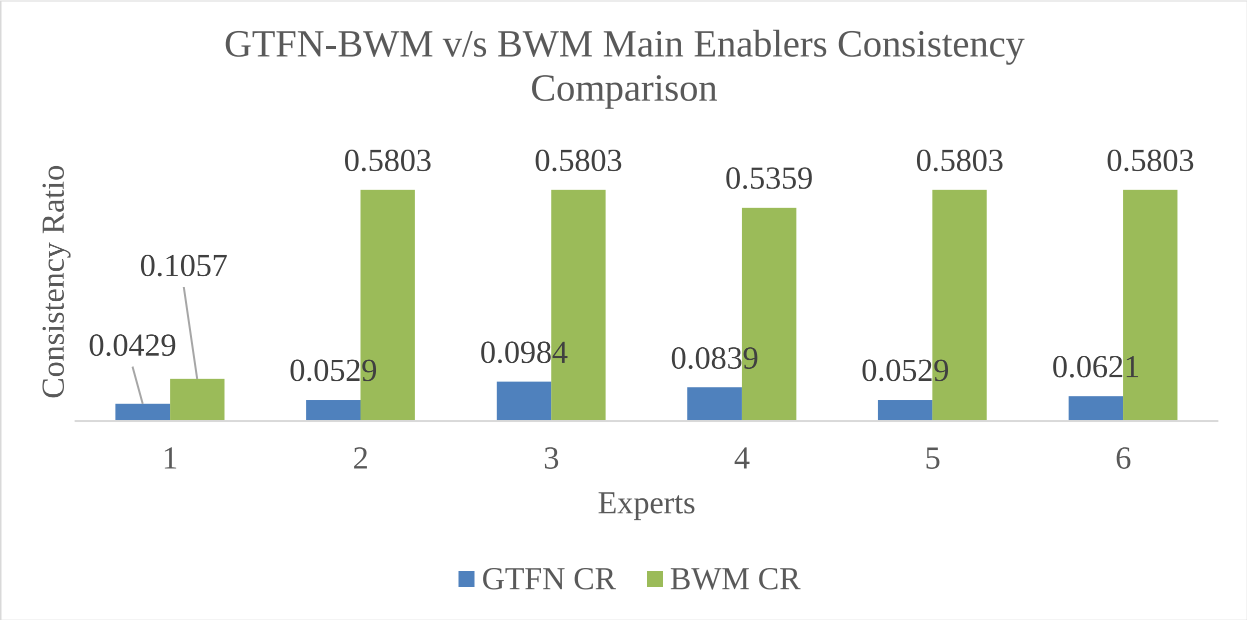

Figure 6.2 CR Values of BWM and GTFN-BWM for Main Enablers

6.2 GTFN-BWM Results Comparison with TFN-BWM:

In each case the Consistency Ratio obtained using GTFN-BWM and TFN-BWM is the same which is owing to the defuzzification procedure used in both this method. Graded Mean Integration (GMIR) is used in both for the defuzzification of values (Chen & Wang, 2006) GMIR although provides better results for defuzzification it, however, uses the same formula for both normalized and generalized triangular fuzzy numbers. This means that it does not take into consideration the height of the membership function of a fuzzy number when de-fuzzifying generalized triangular fuzzy numbers. This means that for different values of *w* (height of the membership function) same values of *R(A)* are obtained which is unreasonable. Therefore, using GMIR for defuzzification the comparison cannot be conducted based on the consistency ratio and consistency index to determine which method provides better results. For this purpose, the difference between the highest ranked value and the lowest ranked value is determined. The method providing the overall greater value of the difference is determined as the better method as it provides greater distinguishing power (Wan et al., 2021).

6.2.1 GMIR Difference of Best and Worst Criteria for GTFN-BWM and TFN-BWM:

The Table 6.2 shows that in 58 % of cases GTFN-BWM provides a greater GMIR difference between the best and the worst criteria, which shows that GTFN-BWM provides more detailed and precise results as compared to TFN-BWM and has better distinguishing power as compared to TFN-BWM (Dutta & Dash, 2018; Wan et al., 2021).

Table 6.2 GMIR Difference of GTFN-BWM and TFN-BWM Main and Subcategory Enablers

Main Enablers		
Model	GTFN Difference	TFN Difference
1	0.2407	0.2422
2	0.3089	0.3168
3	0.3013	0.2972
4	0.2187	0.2178
5	0.3475	0.3462
6	0.2811	0.281

Big Data Analytics		
Model	GTFN Difference	TFN Difference
1	0.1854	0.1853
2	0.1194	0.1196
3	0.1031	0.1037
4	0.1479	0.136
5	0.1431	0.1434
6	0.146	0.1398

Internet of Things		
Model	GTFN Difference	TFN Difference
1	0.2069	0.1894
2	0.1484	0.1257
3	0.1759	0.1788
4	0.1468	0.1519
5	0.1968	0.1972
6	0.122	0.1295

Industry 4.0		
Model	GTFN Difference	TFN Difference
1	0.2142	0.2143
2	0.2357	0.2365
3	0.273	0.267
4	0.256	0.2522
5	0.2198	0.1593
6	0.1746	0.1741

Block Chain Technology		
Model	GTFN Difference	TFN Difference
1	0.2024	0.2163
2	0.1936	0.1916
3	0.1912	0.188
4	0.1426	0.1417
5	0.1623	0.1618
6	0.186	0.1854

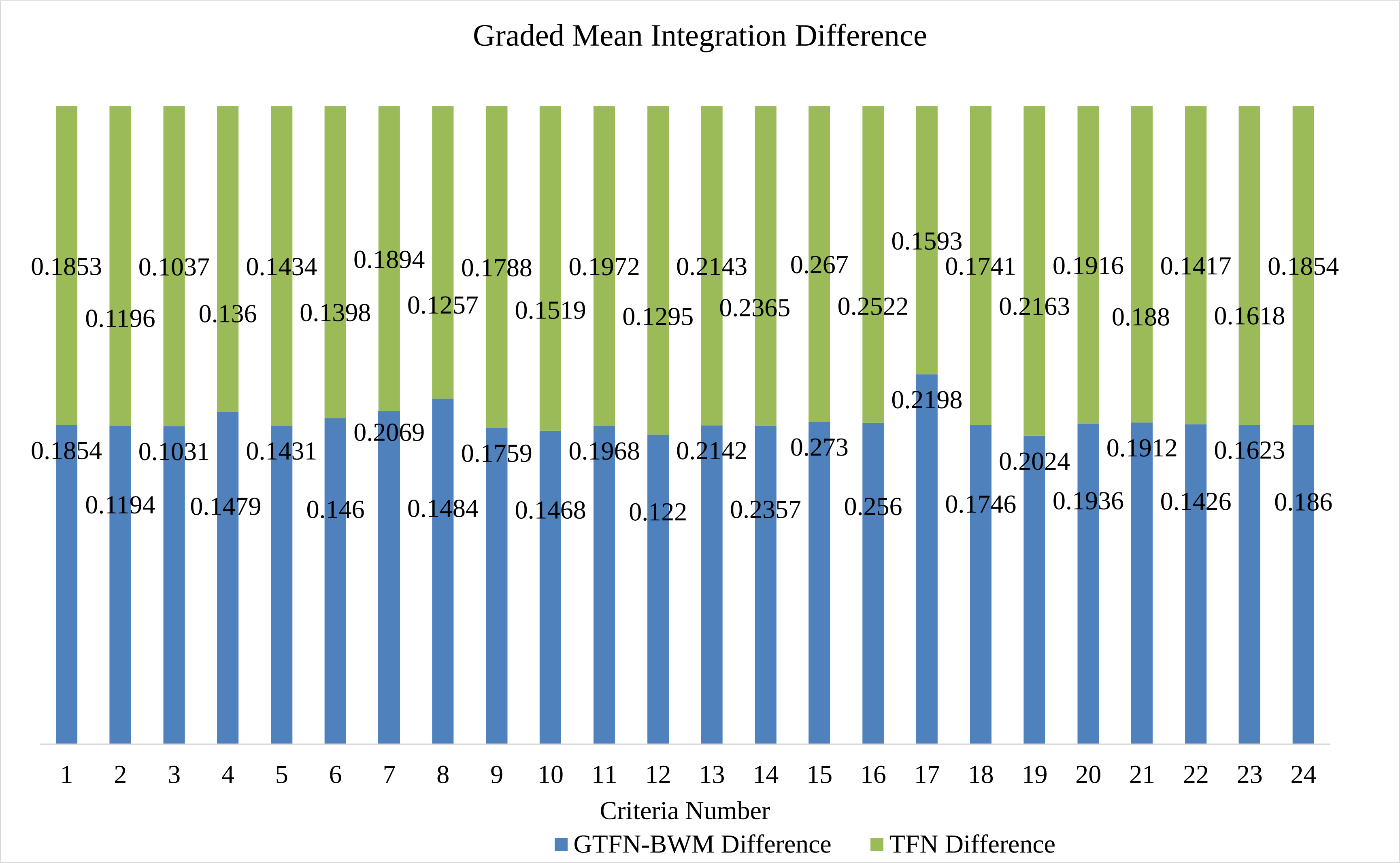

Figure 6.3 GMIR Difference for TFN-BWM and GTFN-BWM

7 Case Studies for Data Validation:

In this Chapter, three practical case studies have been selected and the model developed in chapter 3 is implemented on it. The results of the problems obtained are also compared with the results obtained by best worst method and triangular fuzzy number best worst method. Comparison with BWM is conducted based on the consistency ratio, and the method which provides a lower value of consistency ratio is considered the better method for ranking criteria. In the case of TFN-BWM, the comparison is conducted based on the GMIR difference value between the best and the worst criteria. Case 1 is of selection of an optimal transportation mode for product delivery to market. Case 2 is the selection parameters of a high-performance high-cost car. Case 3 is to determine the importance of supplier willingness for supplier development.

7.1 Selection of Optimal Transportation Mode:

Case study 1 is for the selection of a transportation mode for a company to deliver products to the market. 3 criteria are to be considered for this. The criteria names are: Load Flexibility (C1), Accessibility (C2) and Cost (C3). Among these criteria, the best criterion selected by the decision maker is cost (C3) and the worst criterion selected by the decision maker is load flexibility (C1). Using the best criteria, the best to other vector values using a BWM linguistic scale (1-9 scale) are listed in the Table 7.1. Using the worst criteria, the other to worst vector values using BWM linguistic scale are listed in Table 7.2 (Rezaei, 2015).

Table 7.1 Case Study 1 Best to Other Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**
Best Criteria: C3	Absolutely Important	Weakly Important	Equally Important
Comparison Value	8	2	1

Table 7.2 Case Study 1 Other to Worst Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**
Worst Criteria: C1	Equally Important	Fairly Important	Absolutely Important
Comparison Value	1	5	8

For the same 3 criteria, a fuzzy reference comparison was performed and the following values and linguistic terms were obtained for best to other vector (Guo & Zhao, 2017).

Table 7.3 Case Study 1 Best to Other Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**
Best Criteria: C3	Absolutely Important	Weakly Important	Equally Important
Comparison Value	(7/2,4,9/2)	(2/3,1,3/2)	(1,1,1)

On the same scale, a fuzzy comparison was carried out and the following values for the other to worst vector were obtained (Guo & Zhao, 2017).

Table 7.4 Case Study 1 Other to Worst Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**
Worst Criteria: C1	Equally Important	Fairly Important	Absolutely Important
Comparison Value	(1,1,1)	(3/2,2,5/2)	(7/2,4,9/2)

For GTFN-BWM, the value of *w* is required as per the linguistic scale listed in chapter 3, however the same is not available in both the data sets mentioned in Tables 7.1 – 7.4 therefore sensitivity analysis is conducted based on the value of *w*, where *w* ranges between 0 to 1. Based on the above analysis for getting the optimal weights for the criteria the following model is created using the methodology listed in chapter 3. Using TFN-BWM and BWM the weights, zeta, CI, CR and GMIR difference value for best and worst criteria rank are obtained and listed in Table 7.5 (Guo & Zhao, 2017; Rezaei, 2015). The value of the same parameters using GTFN-BWM are listed in Table 7.6. The comparison of the GMIR difference value for GTFN-BWM and TFN-BWM are listed in Table 7.7.

Table 7.5 Weights and Ranks for BWM and TFN-BWM for Case Study 1

Value	Criteria 1	Criteria 2	Criteria 3	Zeta	CI	CR	GMIR Difference
BWM	0.0714 3rd	0.3387 2nd	0.5899 1st	0.26	4.47	0.058	---
TFN-BWM	0.1431 3rd	0.3496 2nd	0.5073 1st	0.4495	8.04	0.0559	0.3642

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_1, m_1, u_1; w_1)} - (l_{31}, m_{31}, u_{31}; w_{31}) \right| \le (k, k, k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_2, m_2, u_2; w_2)} - (l_{32}, m_{32}, u_{32}; w_{32}) \right| \le (k, k, k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_3, m_3, u_3; w_3)} - (l_{33}, m_{33}, u_{33}; w_{33}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_1, m_1, u_1; w_1)} - (l_{11}, m_{11}, u_{11}; w_{11}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_1, m_1, u_1; w_1)} - (l_{21}, m_{21}, u_{21}; w_{21}) \right| \le (k, k, k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_1, m_1, u_1; w_1)} - (l_{31}, m_{31}, u_{31}; w_{31}) \right| \le (k, k, k) \\
&\sum_{j=1}^{3} R(\tilde{w}_j) = 1 \\
&l_1 \le m_1 \le u_1;\ l_2 \le m_2 \le u_2;\ l_3 \le m_3 \le u_3 \\
&l_1 \ge 0;\ l_2 \ge 0;\ l_3 \ge 0;\ k \ge 0 \\
&0 \le w_1 \le 1;\ 0 \le w_2 \le 1;\ 0 \le w_3 \le 1
\end{aligned}
\tag{7.1}
$$

The Table 7.5 and 7.6 shows that the ranks obtained by BWM, TFN-BWM, and GTFN-BWM are the same i.e.C_3 > C_2 >C_1. This is in line with the decision of the decision makers where criteria number 3 i.e., the cost is the most important criterion for the selection of transportation mode, and criteria 1 i.e., load flexibility is the least important criterion and the same has been selected as the worst criteria by the decision-makers. By using BWM consistency ratio obtained is 0.058 whereas the consistency ratio obtained for GTFN-BWM is 0.0559 which is lower than that obtained by BWM, therefore the results and the weights obtained by GTFN-BWM are more consistent than those obtained by BWM. Hence, it can be concluded that GTFN-BWM deals with uncertainty associated with the use of human judgment in a better way as it provides a much lower value of consistency ratio.

Table 7.6 Case Study 1 Weights using GTFN-BWM

S.No.	Crisp Weights	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
1	W1	0.1431	0.1431	0.1430	0.1430	0.1430	0.1430	0.1430	0.1430	0.1430
2	W2	0.3493	0.3492	0.3492	0.3491	0.3493	0.3493	0.3491	0.3493	0.3492
3	W3	0.5076	0.5077	0.5076	0.5078	0.5076	0.5076	0.5077	0.5076	0.5076
4	Zeta	0.4494								
5	CI	8.04								
6	CR	0.0559								
7	GMIR Difference	0.3645	0.3646	0.3647	0.3648	0.3645	0.3645	0.3647	0.3646	0.3646

Table 7.7 Case Study 1 GMIR Difference Different Values of *w*

Attribute	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
TFN-BWM.	0.3642								
GTFN-BWM.	0.3645	0.3646	0.3647	0.3648	0.3645	0.3645	0.3647	0.3646	0.3646

Table 7.7 shows the comparison of GMIR difference between the best and the worst criteria for different values of *w*. For each value of *w*, the GMIR difference obtained using GTFN-BWM is higher as compared to TFN-BWM which is also in line with the past studies that the use of generalized triangular fuzzy number provides much better and detailed results. This provides that GTFN-BWM provides better results than TFN-BWM. The consistency ratio value can be improved by using a better defuzzification method which accounts for the changes in the values of *w*, as the same is not accounted for by GMIR. The same results are displayed in the Figure 7.1:

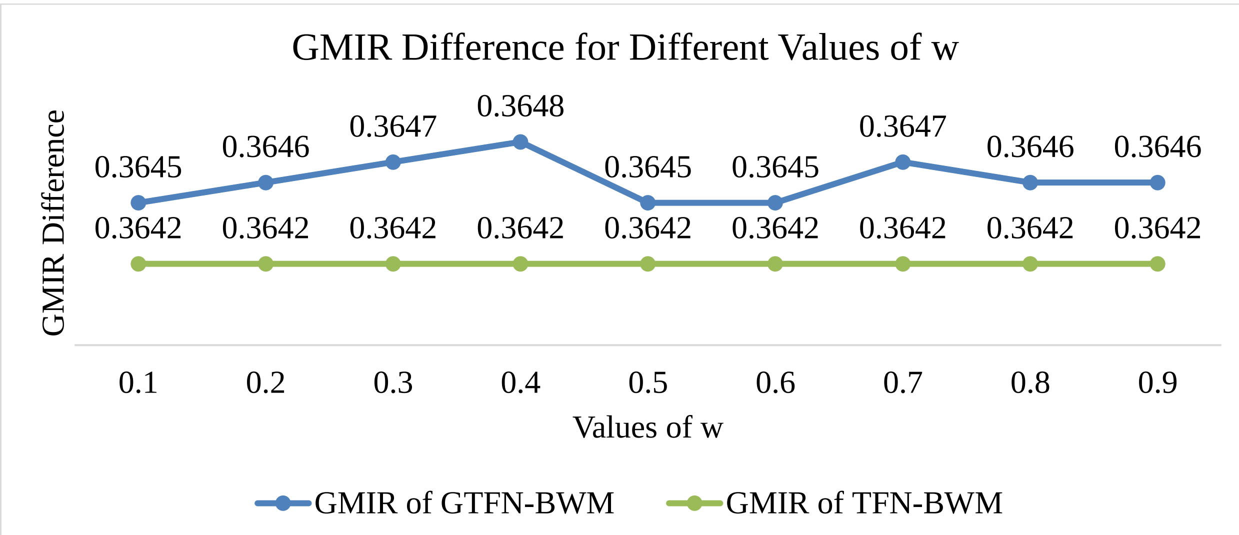

Figure 7.1 GMIR Difference of Best and Worst Ranked Criteria for Case Study 1

7.2 Selection of a High-Performance High-Cost Car:

Case study 2 is for the selection of a high-performance high-cost car. 5 criteria are to be considered for this. The criteria names are:

1. Quality (C1)
2. Price (C2)
3. Comfort (C3)
4. Safety (C4)
5. Style (C5)

Among these criteria, the best criterion selected by the decision maker is the price (C2) and the worst criterion selected by the decision maker is style (C5). Using the best criteria, the best to other vector values using a BWM linguistic scale (1-9 scale) are listed in the Table 7.8. Using the worst criteria, the other to worst vector values using BWM linguistic scale are listed in Table 7.9 (Rezaei, 2016).

Table 7.8 Case Study 2 Best to Other Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**
Best Criteria: C2	Weakly Important	Equally Important	Fairly Important	Weakly Important	Absolutely Important
Comparison Value	2	1	4	3	8

Table 7.9 Case Study 2 Other to Worst Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**
Worst Criteria: C5	Fairly Important	Absolutely Important	Fairly Important	Weakly Important	Equally Important
Comparison Value	4	8	4	2	1

For the same 5 criteria, a fuzzy reference comparison was performed and the following values and linguistic terms were obtained for best to other vector (Guo & Zhao, 2017).

Table 7.10 Case Study 2 Best to Other Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**
Best Criteria: C2	Weakly Important	Equally Important	Fairly Important	Weakly Important	Absolutely Important
Comparison Value	(2/3,1,3/2)	(1,1,1)	(3/2,2,5/2)	(2/3,1,3/2)	(7/2,4,9/2)

On the same scale, a fuzzy comparison was carried out and the following values for the other to worst vector were obtained (Guo & Zhao, 2017).

Table 7.11 Case Study 2 Other to Worst Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**
Worst Criteria: C5	Fairly Important	Absolutely Important	Fairly Important	Weakly Important	Equally Important
Comparison Value	(3/2,2,5/2)	(7/2,4,9/2)	(3/2,2,5/2)	(2/3,1,3/2)	(1,1,1)

For GTFN-BWM, the value of *w* is required as per the linguistic scale listed in section 3.6.2, however the same is not available in both the data sets mentioned in Tables 7.8 – 7.11 therefore sensitivity analysis is conducted based on the value of *w*, where *w* ranges between 0 to 1. Based on the above analysis for getting the optimal weights for the criteria the following model is created using the methodology listed in chapter 4. Solving using TFN-BWM and BWM the weights, zeta, consistency index, consistency ratio, and GMIR difference value for best and worst criteria rank obtained are mentioned in Table 7.12 (Guo & Zhao, 2017; Rezaei, 2016).

Table 7.12 Weights and Ranks for BWM and TFN-BWM for Case Study 2

Value	**BWM**	**TFN-BWM**
Criteria 1	0.1919 2nd	0.2470 2nd
Criteria 2	0.4634 1st	0.2842 1st
Criteria 3	0.1544 3rd	0.2189 3rd
Criteria 4	0.1385 4th	0.1608 4th
Criteria 5	0.0514 5th	0.0891 5th
Zeta	1	0.7913
CI	4.47	8.04
CR	0.2237	0.0984
GMIR Difference	---	0.1952

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_1, m_1, u_1; w_1)} - (l_{21}, m_{21}, u_{21}; w_{21}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_2, m_2, u_2; w_2)} - (l_{22}, m_{22}, u_{22}; w_{22}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_3, m_3, u_3; w_3)} - (l_{23}, m_{23}, u_{23}; w_{23}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_4, m_4, u_4; w_4)} - (l_{24}, m_{24}, u_{24}; w_{24}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_5, m_5, u_5; w_5)} - (l_{25}, m_{25}, u_{25}; w_{25}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_5, m_5, u_5; w_5)} - (l_{15}, m_{15}, u_{15}; w_{15}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_5, m_5, u_5; w_5)} - (l_{25}, m_{25}, u_{25}; w_{25}) \right| \le (k, k, k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_5, m_5, u_5; w_5)} - (l_{35}, m_{35}, u_{35}; w_{35}) \right| \le (k, k, k) \\
&\left| \frac{(l_4, m_4, u_4; w_4)}{(l_5, m_5, u_5; w_5)} - (l_{45}, m_{45}, u_{45}; w_{45}) \right| \le (k, k, k) \\
&\left| \frac{(l_5, m_5, u_5; w_5)}{(l_5, m_5, u_5; w_5)} - (l_{55}, m_{55}, u_{55}; w_{55}) \right| \le (k, k, k) \\
&\sum_{j=1}^{5} R(\tilde{w}_j) = 1 \\
&l_1 \le m_1 \le u_1;\ l_2 \le m_2 \le u_2;\ l_3 \le m_3 \le u_3;\ l_4 \le m_4 \le u_4;\ l_5 \le m_5 \le u_5 \\
&l_1 \ge 0;\ l_2 \ge 0;\ l_3 \ge 0;\ l_4 \ge 0;\ \ l_5 \ge 0; k \ge 0 \\
&0 \le w_1 \le 1;\ 0 \le w_2 \le 1;\ 0 \le w_3 \le 1;\ 0 \le w_4 \le 1;\ 0 \le w_5 \le 1
\end{aligned}
\tag{7.2}
$$

The results for GTFN-BWM are listed in Table 7.13 and the GMIR Difference comparison for GTFN-BWM and TFN-BWM is listed in Table 7.14.

Table 7.13 Case Study 2 Weights using GTFN-BWM

S.No.	Crisp Weights	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
1	W1	0.2178	0.2414	0.2112	0.2254	0.2252	0.2414	0.2172	0.2315	0.2367
2	W2	0.3267	0.2842	0.3250	0.3177	0.3175	0.2842	0.3244	0.3011	0.2893
3	W3	0.1703	0.2273	0.1802	0.1803	0.1800	0.2274	0.1755	0.2051	0.2237
4	W4	0.1831	0.1588	0.1822	0.1776	0.1782	0.1588	0.1816	0.1684	0.1608
5	W5	0.1018	0.0881	0.1012	0.0988	0.0990	0.0881	0.1011	0.0937	0.0893
4	Zeta	0.7912								
5	CI	8.04								
6	CR	0.0984								
7	GMIR Difference	0.2250	0.1961	0.2237	0.2189	0.2185	0.1962	0.2233	0.2074	0.1999

Table 7.14 Case Study 2 GMIR Difference for Different Values of *w*

Attribute	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
TFN-BWM.	0.1952								
GTFN-BWM.	0.2250	0.1961	0.2237	0.2189	0.2185	0.1962	0.2233	0.2074	0.1999

The Table 7.12 and 7.13 show that the ranks obtained by BWM, TFN-BWM and GTFN-BWM are the same i.e., $C_2 > C_1 > C_3 > C_4 > C_5$. This is in line with the decision of the decision makers where criteria number 2 i.e., price is the most important criterion for the selection of a high-cost and high-performance car and criteria 5 i.e., style is the least important criterion and the same has been selected as the worst criteria by the decision-makers. By using BWM consistency ratio obtained is 0.2237 whereas the consistency ratio obtained for GTFN-BWM is 0.0984 which is lower than that obtained by BWM, therefore the results and the weights obtained by GTFN-BWM are more consistent than those obtained by BWM. Hence, it can be concluded that GTFN-BWM deals with uncertainty associated with the use of human judgment in a better way as it provides a much lower value of consistency ratio.

Table 7.14 shows the comparison of GMIR difference between the best and the worst criteria for different values of *w*. For each value of *w*, the GMIR difference obtained using GTFN-BWM is higher as compared to TFN-BWM which is also in line with the past studies, that the use of generalized triangular fuzzy number provides much better and detailed results. This provides that GTFN-BWM provides better results than TFN-BWM. The consistency ratio value can be improved by using a better defuzzification method which accounts for the changes in the values of *w*, as the same is not accounted for by GMIR. The same results are displayed in the Figure 7.2:

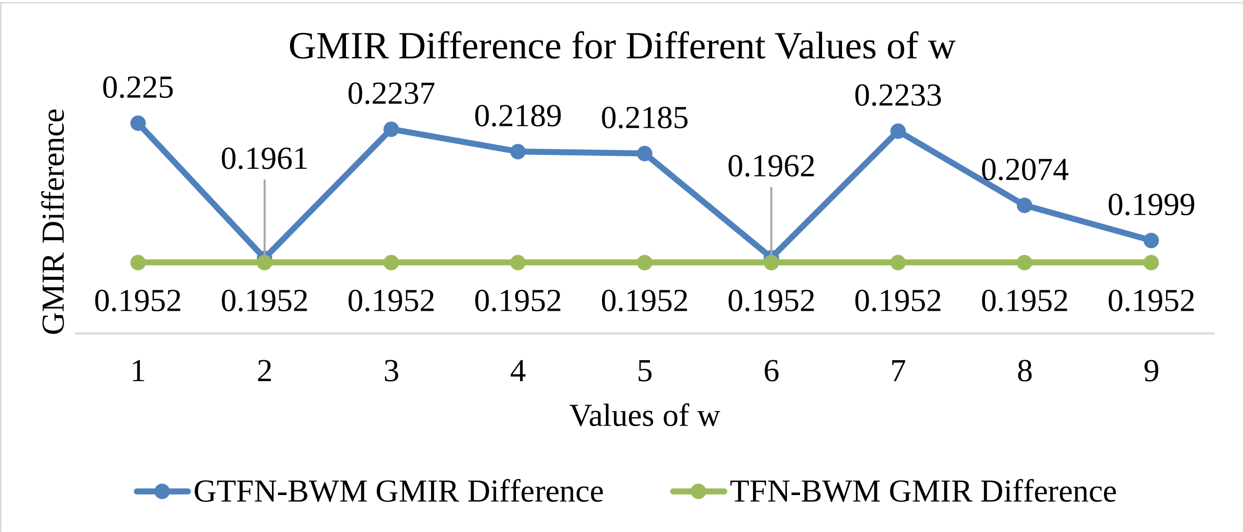

Figure 7.2 GMIR Difference of Best and Worst Ranked Criteria for Case Study 2

7.3 Importance of Supplier Willingness Towards Supplier Development:

Case study 3 is for supplier willingness towards supplier development. 4 criteria are to be considered for this. The criteria names are:

1. Willingness to improve performance (C1)
2. Willingness to share information (C2)
3. Willingness to rely on each other (C3)
4. Willingness to become involved in a long-term relationship (C4)

From among these criteria, the best criterion selected by the decision maker is the willingness to improve performance (C1) and the worst criterion selected by the decision maker is the willingness to share information (C2). Using the best criteria, the best to other vector values using a BWM linguistic scale (1-9 scale) are listed in the Table 7.15. Using the worst criteria, the other to worst vector values using BWM linguistic scale are listed in Table 7.16 (Rezaei et al., 2015).

Table 7.15 Case Study 3 Best to Other Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**
Best Criteria: C1	Equally Important	Very Important	Weakly Important	Weakly Important
Comparison Value	1	6	3	2

Table 7.16 Case Study 3 Other to Worst Vector using BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**
Worst Criteria: C2	Very Important	Equally Important	Fairly Important	Fairly Important
Comparison Value	6	1	5	4

For the same 4 criteria, a fuzzy reference comparison was performed and the following values and linguistic terms were obtained for best to other vector (Guo & Zhao, 2017).

Table 7.17 Case Study 3 Best to Other Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**
Best Criteria: C1	Equally Important	Very Important	Weakly Important	Weakly Important
Comparison Value	(1,1,1)	(5/2,3,7/2)	(2/3,1,3/2)	(2/3,1,3/2)

On the same scale, a fuzzy comparison was carried out and the following values for the other to worst vector were obtained (Guo & Zhao, 2017).

Table 7.18 Case Study 3 Other to Worst Vector using Fuzzy BWM Linguistic Scale

Criteria	**C1**	**C2**	**C3**	**C4**
Worst Criteria: C2	Very Important	Equally Important	Fairly Important	Fairly Important
Comparison Value	(5/2,3,7/2)	(1,1,1)	(3/2,2,5/2)	(3/2,2,5/2)

For GTFN-BWM, the value of *w* is required as per the linguistic scale listed in section 3.6.2, however the same is not available in both the data sets mentioned in Tables 7.15 – 7.18 therefore sensitivity analysis is conducted based on the value of *w*, where *w* ranges between 0 to 1. Based on the above analysis for getting the optimal weights for the criteria the model created is listed in equation 7.3.

Using TFN-BWM and BWM the weights, zeta, consistency index, consistency ratio, and GMIR difference value for best and worst ranked criteria obtained is enlisted in Table 7.19 (Guo & Zhao, 2017; Rezaei et al., 2015).

Table 7.19 Case Study 3 Weights and Ranks for BWM and TFN-BWM

Value	**Criteria 1**	**Criteria 2**	**Criteria 3**	**Criteria 4**	**Zeta**	**CI**	**CR**	**GMIR Difference**
BWM	0.4490 1st	0.0630 4th	0.2420 3rd	0.2460 2nd	1.145	3	0.382	---
TFN-BWM	0.3359 1st	0.1218 4th	0.2712 2nd / 3rd	0.2712 2nd / 3rd	0.2361	6.69	0.0353	0.2141

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_1, m_1, u_1; w_1)} - (l_{11}, m_{11}, u_{11}; w_{11}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_2, m_2, u_2; w_2)} - (l_{12}, m_{12}, u_{12}; w_{12}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_3, m_3, u_3; w_3)} - (l_{13}, m_{13}, u_{13}; w_{13}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_4, m_4, u_4; w_4)} - (l_{14}, m_{14}, u_{14}; w_{14}) \right| \le (k, k, k) \\
&\left| \frac{(l_1, m_1, u_1; w_1)}{(l_2, m_2, u_2; w_2)} - (l_{12}, m_{12}, u_{12}; w_{12}) \right| \le (k, k, k) \\
&\left| \frac{(l_2, m_2, u_2; w_2)}{(l_2, m_2, u_2; w_2)} - (l_{22}, m_{22}, u_{22}; w_{22}) \right| \le (k, k, k) \\
&\left| \frac{(l_3, m_3, u_3; w_3)}{(l_2, m_2, u_2; w_2)} - (l_{32}, m_{32}, u_{32}; w_{32}) \right| \le (k, k, k) \\
&\left| \frac{(l_4, m_4, u_4; w_4)}{(l_2, m_2, u_2; w_2)} - (l_{42}, m_{42}, u_{42}; w_{42}) \right| \le (k, k, k) \\
&\sum_{j=1}^{4} R(\tilde{w}_j) = 1 \\
&l_1 \le m_1 \le u_1;\ l_2 \le m_2 \le u_2;\ l_3 \le m_3 \le u_3;\ l_4 \le m_4 \le u_4 \\
&l_1 \ge 0;\ l_2 \ge 0;\ l_3 \ge 0;\ l_4 \ge 0;\ k \ge 0 \\
&0 \le w_1 \le 1;\ 0 \le w_2 \le 1;\ 0 \le w_3 \le 1;\ 0 \le w_4 \le 1
\end{aligned}
\tag{7.3}
$$

For different values of w (the confidence of the decision-maker) the weights, ranks, consistency index, consistency ratio, and GMIR difference for the best and the worst criteria are listed in the Tables 7.20. The GMIR difference value for GTFN-BWM and TFN-BWM are listed in Table 7.21.

Table 7.20 Case Study 3 Weights using GTFN-BWM

S.No.	Crisp Weights	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
1	W1	0.3358	0.3358	0.3358	0.3358	0.3358	0.3358	0.3358	0.3358	0.3358
2	W2	0.1217	0.1217	0.1218	0.1217	0.1217	0.1217	0.1218	0.1218	0.1217
3	W3	0.2712	0.2712	0.2711	0.2711	0.2712	0.2711	0.2711	0.2712	0.2712
4	W4	0.2712	0.2712	0.2711	0.2711	0.2712	0.2711	0.2711	0.2712	0.2712
5	Zeta	0.236								
6	CI	6.69								
7	CR	0.0353								
8	GMIR Difference	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2140	0.2140	0.2140

Table 7.21 Case Study 3 GMIR Difference for Different Values of *w*

Attribute	W=0.1	W=0.2	W=0.3	W=0.4	W=0.5	W=0.6	W=0.7	W=0.8	W=0.9
TFN-BWM.	0.2140								
GTFN-BWM.	0.2141	0.2141	0.2141	0.2141	0.2141	0.2141	0.2140	0.2140	0.2140

The Table 7.19 and 7.20 show that the ranks obtained by BWM are $C_1 > C_4 > C_3 > C_2$, whereas the results obtained by TFN-BWM and GTFN-BWM are $C_1 > C_3 = C_4 > C_2$. This is in line with the decision of the decision makers where criteria number 1 i.e., willingness to improve performance is the most important criterion for supplier development, and criterion 2 i.e., willingness to share information is the least important criterion and the same has been selected as the worst criteria by the decision-makers. By using BWM consistency ratio obtained is 0.382 whereas the consistency ratio obtained for GTFN-BWM is 0.0353 which is lower than that obtained by BWM, therefore the results and the weights obtained by GTFN-BWM are more consistent than those obtained by BWM. Hence, it can be concluded that GTFN-BWM deals with uncertainty associated with the use of human judgment in a better way as it provides a much lower value of consistency ratio.

Table 7.21 shows the comparison of GMIR difference between the best and the worst criteria for different values of *w*. For each value of *w*, the GMIR difference obtained using GTFN-BWM is either higher or the same as compared to TFN-BWM which is also in line with the past studies, that the use of generalized triangular fuzzy number provides much better and detailed results. This provides that GTFN-BWM provides better results than TFN-BWM. The consistency ratio value can be improved by using a better defuzzification method which accounts for the changes in the values of *w*, as the same is not accounted for by GMIR. The same results are displayed in the Figure 7.3:

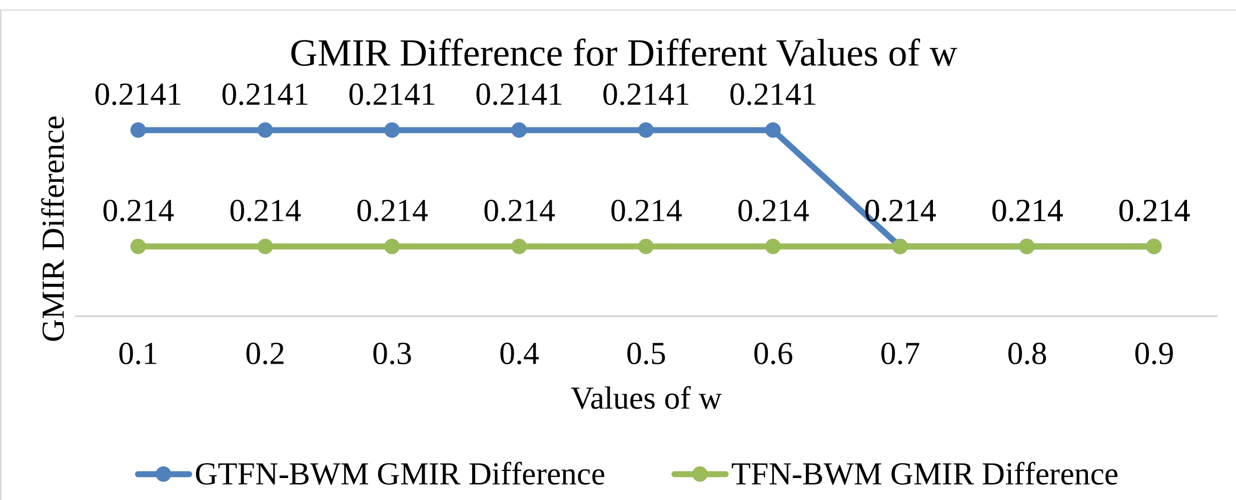

Figure 7.3 GMIR Difference of Best and Worst Ranked Criteria for Case Study 3

8 Findings and Conclusion:

The global ranks and weights obtained using GTFN-BWM are listed in section 5.6. which shows that in the case of Main Enablers, Big Data Analytics is the most important enabler among the four main enablers i.e., Big Data Analytics, Internet of Things, Industry 4.0, and Block Chain Technology. Block Chain Technology is the second most important enabler after Big Data Analytics and is followed by the Internet of Things and Industry 4.0. In the case of Global Weights for subcategory enablers, Transparency and Visibility is the most important subcategory enabler followed by Effective Management of Technologies.

Big Data Analytics has been determined as the most important enabler for improving the supply chain performance of an organization. Different past studies have also highlighted the importance and role of Big Data Analytics in improving the supply chain performance of organizations. The biggest problem facing the organization in the use of Big Data is the large volume of data being generated in different varieties and veracities and how to use it to perform analysis for improving Supply chain performance (Waller & Fawcett, 2013). A fundamental problem in SCM is determining the design of the distribution network. By the use of large data generated (Big Data) by the distribution operations, Wang determined the optimal number of distribution centers and assigned customers to these centers which improved SCM performance (Wang et al., 2018). Big Data Analytics has found its applications in all fields of SCM including but not limited to procurement, inventory management, network design, logistics and distribution, the agility of a supply chain, and sustainability in a supply chain and production, etc. (Ayed et al., 2015; Brouer et al., 2016; Wang et al., 2018; Wang et al., 2016; Zhao et al., 2017).

The second rank among the main category enablers is of Blockchain Technology which is defined as a distributed shared ledger of transactions being carried out in the supply chain. The performance of the supply chain can be enhanced a great deal by the adoption of blockchain technology as it helps in data sharing and tracking of products and prevents loss of product due to non-sharing of data among supply chain partners and lack of tracing (Babich & Hilary, 2020; Kshetri, 2018). Kim and Shin showed in their research that blockchain technology and its subcategory enablers of information transparency and immutability and smart contracts help in providing partnership growth which resultantly improves the Supply chain performance and organization’s performance (Shin et al., 2018). Blockchain technology finds its application in platforms like Blockverify which help provide transparency in supply chain processes. IBM and Maersk are launching a joint venture which helps in providing efficiency and security among supply chain partners by providing product location tracking and specification of transportation activities blockchain help in reducing the processing time of transactions as compared to traditional systems (Golosova & Romanovs, 2018).

Among sub-criteria enablers “Transparency and Visibility” achieved using blockchain technology has the first rank. Chod found out in his research that the biggest advantage of the adoption of blockchain technology is that it makes the supply chain transparent and increases visibility across the supply chain. It helps in reducing financing terms at lower signaling costs (Chod et al., 2020). Sodhi found in his research that transparency in a supply chain means disclosing information downstream of the supply chain to customers, investors, and other stakeholders whereas visibility refer to increased information sharing upstream of the supply chain with suppliers. Visibility and transparency in the supply chain help in reducing exposure to risk, reducing reputational damages and improving supply chain efficiency, and increasing consumers’ and investors’ trust (Sodhi & Tang, 2019). Sunny found in his research that blockchain technology helps in improving transparency across the supply chain through tracking and tracing and therefore helps in overcoming the shortcoming of centralized traceability solutions such as single points of failure and data manipulations (Sunny et al., 2020).

The second rank among sub-criteria enablers is “Effective Management of Technologies” for industry 4.0. Industry 4.0 technologies include advanced robotics, augmented virtual and mixed reality, and cloud computing all of which improve the supply chain performance by helping in manufacturing, self-reporting, etc. Effective management of these technologies is essential to reap the benefits of industry 4.0 including but not limited to increased profitability, higher return on investments, competitive advantage, and consumer satisfaction among others (Ammar et al., 2021). Lack of management support and lack of coordination and collaboration are identified as the top barriers that reduce the impact of Industry 4.0 technologies, addressing these issues through effective management of technologies will improve supply chain performance (Ghadge et al., 2020).

The main and subcategory enablers of digitization that improve supply chain performance were ranked using the GTFN-BWM model that was proposed in this study. Three cases—optimal transportation mode selection, car purchase decision, and supplier performance evaluation—were also used to test the applicability of the proposed fuzzy BWM. The findings indicate that the fuzzy BWM outperforms both the BWM and the normalized triangular fuzzy BWM because it can achieve a better comparison consistency than the BWM and a larger GMIR difference between the best and worst rated criterion than the latter. The results of this study may be summed up as follows:

1. In all 3 case studies and among the digital supply chain performance enablers, a higher consistency ratio was attained compared to BWM.
2. All three case studies obtained better GMIR Difference for Best to Worst rated criteria as compared to TFN-BWM, and in over 58% of cases when rating supply chain performance-improving digitization enablers.
3. Big data analytics is the best criterion among the key enablers, whereas Industry 4.0 is the least significant criterion.
4. Transparency and visibility are the best criteria among the subcategory enablers, while software-defined networking is the least significant one.

The intrinsic flaws of Graded Mean Integration (GMIR), which is used to de-fuzzify generalized triangular fuzzy numbers, have also been brought to light by this study since it neglects to take into consideration the changing height of the fuzzy membership function.

Additionally, the proposed fuzzy BWM may be used in conjunction with other MCDM techniques such as TOPSIS and VIKOR. The nonlinearly constrained optimization problem (Section 3.5) can also be solved in the future study by combining it with bionic intelligence algorithms such as the monarch butterfly optimization (MBO), earthworm optimization (EWA), elephant herding optimization (EHO), and moth search (MS) method. Future studies might be conducted in this area by combining this strategy with additional defuzzification techniques, such as the center of gravity, etc. (Chen & Chen, 2003b). This approach might potentially be strengthened by creating a new GMIR formula that takes the changing height of the membership function into consideration.

References:

Ageron, B., Bentahar, O., & Gunasekaran, A. (2020, July). Digital supply chain: challenges and future directions. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 3, pp. 133-138). Taylor & Francis.

Agrawal, P., & Narain, R. (2018, December). Digital supply chain management: An Overview. In *IOP Conference Series: Materials Science and Engineerin* (Vol. 455, No. 1, p. 012074). IOP Publishing.

S. Aich, S. Chakraborty, M. Sain, H. -i. Lee and H. -C. Kim, "A Review on Benefits of IoT Integrated Blockchain based Supply Chain Management Implementations across Different Sectors with Case Study, ”*2019 21st International Conference on Advanced Communication Technology (ICACT)*, PyeongChang, Korea (South), 2019, pp. 138-141.

Aikhuele, D., & Odofin, S. (2017). A Generalized Triangular Intuitionistic Fuzzy Geometric Averaging Operator for Decision-Making in Engineering and Management. *Information*, *8*(3), 78. MDPI AG.

A. A. Hadwer, D. Gillis and D. Rezania, "Big Data Analytics for Higher Education in The Cloud Era,"*2019 IEEE 4th International Conference on Big Data Analytics (ICBDA)*, Suzhou, China, 2019, pp. 203-207.

Ali, A., & Rashid, T. (2020). Generalized interval-valued trapezoidal fuzzy best-worst multiple criteria decision-making method with applications. *Journal of Intelligent & Fuzzy Systems, 38*(2), 1705-1719.

Ali, Z., Gongbing, B., & Mehreen, A. (2019). Predicting supply chain effectiveness through supply chain finance: evidence from small and medium enterprises. *The International Journal of Logistics Management, 30*(2), 488-505.

Alicke, K., Rexhausen, D., & Seyfert, A. (2017). Supply Chain 4.0 in consumer goods. *McKinsey & Company*, *1*(11).

Alotaibi, S., Mehmood, R., & Katib, I. (2020). The role of big data and twitter data analytics in healthcare supply chain management. *Smart Infrastructure and Applications: Foundations for Smarter Cities and Societies*, 267-279.

Amiri, M., Hashemi-Tabatabaei, M., Ghahremanloo, M., Keshavarz-Ghorabaee, M., Zavadskas, E. K., & Banaitis, A. (2021). A new fuzzy BWM approach for evaluating and selecting a sustainable supplier in supply chain management. *International Journal of Sustainable Development & World Ecology*, *28*(2), 125-142.

Ammar, M., Haleem, A., Javaid, M., Walia, R., & Bahl, S. (2021). Improving material quality management and manufacturing organizations system through Industry 4.0 technologies. *Materials Today: Proceedings*, *45*, 5089-5096.

Appelbaum, D., & Smith, S. S. (2018). Blockchain basics and hands-on guidance: taking the next step toward implementation and adoption. *The CPA Journal*, *88*(6), 28-37.

Aruldoss, M., Lakshmi, T. M., & Venkatesan, V. P. (2013). A survey on multi criteria decision making methods and its applications. *American Journal of Information Systems*, *1*(1), 31-43.

Aryal, A., Liao, Y., Nattuthurai, P., & Li, B. (2020). The emerging big data analytics and IoT in supply chain management: a systematic review. *Supply Chain Management: An International Journal*, *25*(2), 141-156.

H. Asri, H. Mousannif, H. Al Moatassime and T. Noel, "Big data in healthcare: Challenges and opportunities,"*2015 International Conference on Cloud Technologies and Applications (CloudTech)*, Marrakech, Morocco, 2015, pp. 1-7.

Atlam, H. F., Alenezi, A., Alharthi, A., Walters, R. J., & Wills, G. B. (2017, June). Integration of cloud computing with internet of things: challenges and open issues. In *2017 IEEE international conference on internet of things (iThings) and IEEE green computing and communications (GreenCom) and IEEE cyber, physical and social computing (CPSCom) and IEEE smart data (SmartData)* (pp. 670-675). IEEE.

Attaran, M. (2020, July). Digital technology enablers and their implications for supply chain management. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 3, pp. 158-172). Taylor & Francis.

Ayed, A. B., Halima, M. B., & Alimi, A. M. (2015, May). Big data analytics for logistics and transportation. In *2015 4th international conference on advanced logistics and transport (ICALT)* (pp. 311-316). IEEE.

Babich, V., & Hilary, G. (2020). OM Forum—Distributed ledgers and operations: What operations management researchers should know about blockchain technology. *Manufacturing & Service Operations Management, 22*(2), 223-240.

Bag, S., Telukdarie, A., Pretorius, J. C., & Gupta, S. (2021). Industry 4.0 and supply chain sustainability: framework and future research directions. *Benchmarking: An International Journal, 28*(5), 1410-1450.

Ben-Daya, M., Hassini, E., & Bahroun, Z. (2019). Internet of things and supply chain management: a literature review. *International Journal of Production Research, 57*(15-16), 4719-4742.

Ben-Daya, M., Hassini, E., Bahroun, Z., & Banimfreg, B. H. (2020). The role of internet of things in food supply chain quality management: A review. *Quality Management Journal, 28*(1), 17-40.

Benias, N., & Markopoulos, A. P. (2017, September). A review on the readiness level and cyber-security challenges in Industry 4.0. In *2017 South Eastern European Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)* (pp. 1-5). IEEE.

Bigini, G., Freschi, V., & Lattanzi, E. (2020). A review on blockchain for the internet of medical things: Definitions, challenges, applications, and vision. *Future Internet, 12*(12), 208.

Blankenberg, S. (2016). *The Difference Between IoT & Industry 4.0?* EBV Blog News. Retrieved 15th March 2022 from https://blog.ebv.com/vision-do-you-know-the-difference-between-iot-and-industry-4-0-part-i/

Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. *Computers in Industry, 101*, 1-12.

Brouer, B. D., Karsten, C. V., & Pisinger, D. (2016). Big data optimization in maritime logistics. *Big data optimization: Recent developments and challenges*, 319-344.

Büyüközkan, G., & Göçer, F. (2018). Digital Supply Chain: Literature review and a proposed framework for future research. *Computers in Industry, 97,* 157-177.

Chehbi-Gamoura, S., Derrouiche, R., Damand, D., & Barth, M. (2020). Insights from big Data Analytics in supply chain management: an all-inclusive literature review using the SCOR model. *Production Planning & Control, 31*(5), 355-382.

Chen, S.-H. (1985). Ranking fuzzy numbers with maximizing set and minimizing set. *Fuzzy Sets and Systems*, *17*(2), 113-129.

Chen, S.-J., & Chen, S.-M. (2003a). Fuzzy risk analysis based on similarity measures of generalized fuzzy numbers. *IEEE Transactions on Fuzzy Systems*, *11*(1), 45-56.

Chen, S.-J., & Chen, S.-M. (2003b). A new method for handling multicriteria fuzzy decision-making problems using FN-IOWA operators. *Cybernetics &Systems, 34*(2), 109-137.

Chen, S. H., & Hsieh, C. H. (2000). Representation, ranking, distance, and similarity of LR type fuzzy number and application. *Australian Journal of Intelligent Processing Systems, 6*(4), 217-229.

Chen, S. H., & Wang, C. C. (2006, October). Fuzzy distance of trapezoidal fuzzy numbers. In *9th Joint International Conference on Information Sciences (JCIS-06)*. Atlantis Press.

Chen, Y. (2018). Blockchain tokens and the potential democratization of entrepreneurship and innovation. *Business Horizons, 61*(4), 567-575.

Cheng, J. C., Law, K. H., Bjornsson, H., Jones, A., & Sriram, R. (2010). A service oriented framework for construction supply chain integration. *Automation in Construction, 19*(2), 245-260.

Chod, J., Trichakis, N., Tsoukalas, G., Aspegren, H., & Weber, M. (2020). On the financing benefits of supply chain transparency and blockchain adoption. *Management Science, 66*(10), 4378-4396.

Christidis, K., & Devetsikiotis, M. (2016). Blockchains and smart contracts for the internet of things. *IEEE Access, 4*, 2292-2303.

Chutia, R., Mahanta, S., & Datta, D. (2013). Linear equations of generalized triangular fuzzy numbers. *Annals of Fuzzy Mathematics and Informatics, 6*(2), 371-376.

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2020). Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information & Management, 57*(1), 103141.

Costa, F., Genovesi, S., Borgese, M., Michel, A., Dicandia, F. A., & Manara, G. (2021). A review of RFID sensors, the new frontier of internet of things. *Sensors, 21*(9), 3138.

Crosby, M., Pattanayak, N., Verma, S., & Kalyanaraman, V. (2015). BlockChain Technology: Beyond Bitcoin, Sutardja Centre for Entrepreneurship & Technology Technical Report. *October*(16), 35.

Culot, G., Nassimbeni, G., Orzes, G., & Sartor, M. (2020). Behind the definition of Industry 4.0: Analysis and open questions. *International Journal of Production Economics, 226*, 107617.

Dallasega, P., Rauch, E., & Linder, C. (2018). Industry 4.0 as an enabler of proximity for construction supply chains: A systematic literature review. *Computers in Industry, 99*, 205-225.

Danys, L., Zolotova, I., Romero, D., Papcun, P., Kajati, E., Jaros, R., Koudelka, P., Koziorek, J., & Martinek, R. (2022). Visible Light Communication and localization: A study on tracking solutions for Industry 4.0 and the Operator 4.0. *Journal of Manufacturing Systems, 64*, 535-545.

Davenport, T. H., & Patil, D. (2012). Data scientist. *Harvard Business Review, 90*(5), 70-76.

de Assis Santos, L., & Marques, L. (2022). Big data analytics for supply chain risk management: research opportunities at process crossroads. *Business Process Management Journal, 28*(4), 1117-1145.

Di Vaio, A., & Varriale, L. (2020). Blockchain technology in supply chain management for sustainable performance: Evidence from the airport industry. *International Journal of Information Management, 52*, 102014.

Dubois, D., & Prade, H. (2012). *Fundamentals of fuzzy sets* (Vol. 7). Springer Science & Business Media.

Dutta, P., & Dash, S. R. (2018). Medical decision making via the arithmetic of generalized triangular fuzzy numbers. *The Open Cybernetics & Systemics Journal, 12*(1).

Ecer, F., & Pamucar, D. (2020). Sustainable supplier selection: A novel integrated fuzzy best worst method (F-BWM) and fuzzy CoCoSo with Bonferroni (CoCoSo'B) multi-criteria model. *Journal of Cleaner Production, 266*, 121981.

Er Kara, M., & Oktay Fırat, S. Ü. (2018). Supplier risk assessment based on best-worst method and K-means clustering: a case study. *Sustainability, 10*(4), 1066.

Evtodieva, T., Chernova, D., Ivanova, N., & Wirth, J. (2019). The internet of things: possibilities of application in intelligent supply chain management. *Digital transformation of the economy: Challenges, trends and new opportunities*, 395-403.

Fang, H., Fang, F., Hu, Q., & Wan, Y. (2022). Supply Chain Management: A Review and Bibliometric Analysis. *Processes, 10*(9), 1681.

Farajpour, F., Hassanzadeh, A., Elahi, S., & Ghazanfari, M. (2022). Digital supply chain blueprint via a systematic literature review. *Technological Forecasting and Social Change, 184*, 121976.

Favaretto, M., De Clercq, E., Schneble, C. O., & Elger, B. S. (2020). What is your definition of Big Data? Researchers' understanding of the phenomenon of the decade. *PLOS ONE, 15*(2), e0228987.

Fawcett, S. E., Magnan, G. M., & McCarter, M. W. (2008). Benefits, barriers, and bridges to effective supply chain management. *Supply Chain Management: An International Journal*, Vol. 13 No. 1, pp. 35-48.

Ganbold, O., Matsui, Y., & Rotaru, K. (2021). Effect of information technology-enabled supply chain integration on firm's operational performance. *Journal of Enterprise Information Management, 34*(3), 948-989.

Garengo, P., & Sardi, A. (2021). Performance measurement and management in the public sector: state of the art and research opportunities. *International Journal of Productivity and Performance Management, 70*(7), 1629-1654.

Gass, S. I., & Assad, A. A. (2005). *An annotated timeline of operations research: An informal history* (Vol. 75). Springer Science & Business Media.

Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management, 31*(4), 669-686.

Navakauskas, D., Romanovs, A., & Plonis, D. (2018). *2018 IEEE. 6th workshop on Advances in Information, Electronic and Electrical Engineering (AIEEE), November 8-10, 2018 Vilnius, Lithuania: proceedings*. IEEE.

Gottge, S., Menzel, T., & Forslund, H. (2020). Industry 4.0 technologies in the purchasing process. *Industrial Management & Data Systems, 120*(4), 730-748.

Goumagias, N., Whalley, J., Dilaver, O., & Cunningham, J. (2021). Making sense of the internet of things: a critical review of internet of things definitions between 2005 and 2019. *Internet Research, 31*(5), 1583-1610.

Guan, Z., Zhang, X., Zhou, M., & Dan, Y. (2020). Demand information sharing in competing supply chains with manufacturer-provided service. *International Journal of Production Economics, 220*, 107450.

Guo, S., & Zhao, H. (2017). Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowledge-Based Systems, 121*, 23-31.

Gupta, H., & Barua, M. K. (2016). Identifying enablers of technological innovation for Indian MSMEs using best–worst multi criteria decision making method. *Technological Forecasting and Social Change, 107*, 69-79.

Gupta, H., Kumar, S., Kusi-Sarpong, S., Jabbour, C. J. C., & Agyemang, M. (2021). Enablers to supply chain performance on the basis of digitization technologies. *Industrial Management & Data Systems, 121*(9), 1915-1938.

Gurtu, A., & Johny, J. (2019). Potential of blockchain technology in supply chain management: a literature review. *International Journal of Physical Distribution & Logistics Management*, Vol. 49 No. 9, pp. 881-900.

Haddud, A., & Khare, A. (2020). Digitalizing supply chains potential benefits and impact on lean operations. *International Journal of Lean Six Sigma, 11*(4), 731-765.

Hafezalkotob, A., Hafezalkotob, A., Liao, H., & Herrera, F. (2019). Interval MULTIMOORA method integrating interval Borda rule and interval best–worst-method-based weighting model: case study on hybrid vehicle engine selection. *IEEE Transactions on Cybernetics, 50*(3), 1157-1169.

Helo, P., & Shamsuzzoha, A. (2020). Real-time supply chain—A blockchain architecture for project deliveries. *Robotics and Computer-Integrated Manufacturing*, *63*, 101909.

Hennelly, P. A., Srai, J. S., Graham, G., & Fosso Wamba, S. (2020). Rethinking supply chains in the age of digitalization. *Production Planning & Control, 31*(2-3), 93-95.

Huang, B., Zhang, L., Ma, L., Bai, W., & Ren, J. (2021). Multi-criteria decision analysis of China's energy security from 2008 to 2017 based on Fuzzy BWM-DEA-AR model and Malmquist Productivity Index. *Energy, 228*, 120481.

Huo, B., Haq, M. Z. U., & Gu, M. (2021). The impact of information sharing on supply chain learning and flexibility performance. *International Journal of Production Research, 59*(5), 1411-1434.

Irfan, I., Sumbal, M. S. U. K., Khurshid, F., & Chan, F. T. (2022). Toward a resilient supply chain model: critical role of knowledge management and dynamic capabilities. *Industrial Management & Data Systems*(ahead-of-print), Vol. 122 No. 5, pp. 1153-1182.

Isnaini, D. B. Y., Nurhaida, T., & Pratama, I. (2020). Moderating effect of supply chain dynamic capabilities on the relationship of sustainable supply chain management practices and organizational sustainable performance: A study on the restaurant industry in Indonesia. *International Journal of Supply Chain Management (IJSCM), 9*(1), 97-105.

Jabbour, C. J. C., Fiorini, P. D. C., Ndubisi, N. O., Queiroz, M. M., & Piato, É. L. (2020). Digitally-enabled sustainable supply chains in the 21st century: A review and a research agenda. *Science of The Total Environment, 725*, 138177.

Jafarzadeh Ghoushchi, S., Khazaeili, M., Amini, A., & Osgooei, E. (2019). Multi-criteria sustainable supplier selection using piecewise linear value function and fuzzy best-worst method. *Journal of Intelligent & Fuzzy Systems, 37*(2), 2309-2325.

Jagtap, S., & Rahimifard, S. (2019). Unlocking the potential of the Internet of Things to improve resource efficiency in food supply chains. In *Innovative Approaches and Applications for Sustainable Rural Development: 8th International Conference, HAICTA 2017, Chania, Crete, Greece, September 21-24, 2017, Selected Papers 8* (pp. 287-301). Springer International Publishing.

Janvier-James, A. M. (2012). A new introduction to supply chains and supply chain management: Definitions and theories perspective. *International Business Research, 5*(1), 194-207.

Jiang, N., Tian, E., Daneshmand Malayeri, F., & Balali, A. (2020). A new model for investigating the impact of urban knowledge, urban intelligent transportation systems and

IT infrastructures on the success of SCM systems in the distributed organizations. *Kybernetes*, *49*(11), 2799-2818.

Kalyar, M. N., Shoukat, A., & Shafique, I. (2020). Enhancing firms' environmental performance and financial performance through green supply chain management practices and institutional pressures. *Sustainability Accounting, Management and Policy Journal*, *11*(2), 451-476.

Kassab, W. a., & Darabkh, K. A. (2020). A–Z survey of Internet of Things: Architectures, protocols, applications, recent advances, future directions and recommendations. *Journal of Network and Computer Applications*, *163*, 102663.

Kayikci, Y. (2018). Sustainability impact of digitization in logistics. *Procedia Manufacturing*, *21*, 782-789.

Khan, S., Haleem, A., & Khan, M. I. (2021, January). Assessment of risk in the management of Halal supply chain using fuzzy BWM method. In *Supply Chain Forum: An International Journal* (Vol. 22, No. 1, pp. 57-73). Taylor & Francis.

Khanmohammadi, E., Zandieh, M., & Tayebi, T. (2019). Drawing a strategy canvas using the fuzzy best–worst method. *Global Journal of Flexible Systems Management, 20*, 57-75.

Khayer, A., Bao, Y., & Nguyen, B. (2020). Understanding cloud computing success and its impact on firm performance: an integrated approach. *Industrial Management & Data Systems*, *120*(5), 963-985.

Khokhar, M., Hou, Y., Rafique, M. A., & Iqbal, W. (2020). Evaluating the social sustainability criteria of supply chain management in manufacturing industries: a role of BWM in MCDM. *Problemy Ekorozwoju, 15*(2).

Kittipanya-Ngam, P., & Tan, K. H. (2020). A framework for food supply chain digitalization: lessons from Thailand. *Production Planning & Control, 31*(2-3), 158-172.

Korherr, P., & Kanbach, D. (2021). Human-related capabilities in big data analytics: A taxonomy of human factors with impact on firm performance. *Review of Managerial Science*, 1-28.

Kothman, I., & Faber, N. (2016). How 3D printing technology changes the rules of the game: Insights from the construction sector. *Journal of Manufacturing Technology Management*, Vol. 27 No. 7, pp. 932-943.

Koul, S. (2018). How-to-achieve-six-figure-benefits-from-digitizing-paper-based-supply-chain-operations. *J Inform Tech Softw Eng, 8*(4), 244.

Kshetri, N. (2018). 1 Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management, 39*, 80-89.

Kumar, A., Singh, R. K., & Modgil, S. (2020). Exploring the relationship between ICT, SCM practices and organizational performance in agri-food supply chain. *Benchmarking: An International Journal*, Vol. 27 No. 3, pp. 1003-1041.

Kumar, G., Goyal, K. K., Batra, N. K., & Rani, D. (2022). Single part reconfigurable flow line design using fuzzy best worst method. *OPSEARCH, 59*(2), 603-631.

Kwon, I. W. G., & Suh, T. (2004). Factors affecting the level of trust and commitment in supply chain relationships. *Journal of Supply Chain Management, 40*(1), 4-14.

Lahri, V., Shaw, K., & Ishizaka, A. (2021). Sustainable supply chain network design problem: Using the integrated BWM, TOPSIS, possibilistic programming, and ε-constrained methods. *Expert Systems with Applications, 168*, 114373.

Lamba, K., & Singh, S. P. (2018). Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management*, Vol. 29 No. 2, pp. 629-658.

Lee, K., Romzi, P., Hanaysha, J., Alzoubi, H., & Alshurideh, M. (2022). Investigating the impact of benefits and challenges of IOT adoption on supply chain performance and organizational performance: An empirical study in Malaysia. *Uncertain Supply Chain Management, 10*(2), 537-550.

Ma, Y., & Fang, R. (2022, May). Blockchain-based power battery traceability system for new energy vehicles. In *2022 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA)* (pp. 248-251). IEEE.

Liang, F., Verhoeven, K., Brunelli, M., & Rezaei, J. (2021). Inland terminal location selection using the multi-stakeholder best-worst method. *International Journal of Logistics Research and Applications*, 1-23.

Lim, M. K., Wang, J., Wang, C., & Tseng, M.-L. (2020). A novel method for green delivery mode considering shared vehicles in the IoT environment. *Industrial Management & Data Systems, 120*(9), 1733-1757.

Lin, M., Lin, C., & Chang, Y.-S. (2021). The impact of using a cloud supply chain on organizational performance. *Journal of Business & Industrial Marketing, 36*(1), 97-110.

Liu, K. P., & Chiu, W. (2021). Supply Chain 4.0: the impact of supply chain digitalization and integration on firm performance. *Asian Journal of Business Ethics, 10*(2), 371-389.

Madhani, P. M. (2019). Building a customer-centric supply chain strategy: Enhancing competitive advantages. *The IUP Journal of Business Strategy, 16*(2), 28-42.

Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research, 59*(6), 1875-1900.

McRae, L., Ellis, K., & Kent, M. (2018). Internet of things (IoT): education and technology. *Relatsh. between Educ. Technol. students with Disabil. Leanne, Res*, 1-37.

Mengke, Y., Xiaoguang, Z., Jianqiu, Z., & Jianjian, X. (2016). Challenges and solutions of information security issues in the age of big data. *China Communications, 13*(3), 193-202.

Min, S., Zacharia, Z. G., & Smith, C. D. (2019). Defining supply chain management: in the past, present, and future. *Journal of Business Logistics, 40*(1), 44-55.

Mostafaeipour, A., Alvandimanesh, M., Najafi, F., & Issakhov, A. (2021). Identifying challenges and barriers for development of solar energy by using fuzzy best-worst method: A case study. *Energy, 226*, 120355.

Muneeb, F. M., Yazdi, A. K., Wanke, P., Yiyin, C., & Chughtai, M. (2020). Critical success factors for sustainable entrepreneurship in Pakistani Telecommunications industry: a hybrid grey systems theory/best-worst method approach. *Management Decision, 58*(11), 2565-2591.

Muravev, D., & Mijic, N. (2020). A novel integrated provider selection multicriteria model: the BWM-MABAC model. *Decision Making: Applications in Management and Engineering, 3*(1), 60-78.

Nowicka, K. (2018). Trust in digital supply chain management. *Logistics and Transport, 39*.

Oh, S., Ryu, Y. U., & Yang, H. (2019). Interaction effects between supply chain capabilities and information technology on firm performance. *Information Technology and Management, 20*, 91-106.

Palattella, M. R., Dohler, M., Grieco, A., Rizzo, G., Torsner, J., Engel, T., & Ladid, L. (2016). Internet of things in the 5G era: Enablers, architecture, and business models. *IEEE Journal on Selected Areas in Communications, 34*(3), 510-527.

Papa, A., Chierici, R., Ballestra, L. V., Meissner, D., & Orhan, M. A. (2021). Harvesting reflective knowledge exchange for inbound open innovation in complex collaborative networks: an empirical verification in Europe. *Journal of Knowledge Management, 25*(4), 669-692.

Pathinathan, T., Ponnivalavan, K., & Dison, E. M. (2015). Different types of fuzzy numbers and certain properties. *Journal of Computer and Mathematical Sciences, 6*(11), 631-651.

Plous, S. (1993). *The psychology of judgment and decision making*. Mcgraw-Hill Book Company.

R. Novais, L., Maqueira, J. M., & Bruque, S. (2019). Supply chain flexibility and mass personalization: a systematic literature review. *Journal of Business & Industrial Marketing, 34*(8), 1791-1812.

Rad, F. F., Oghazi, P., Palmié, M., Chirumalla, K., Pashkevich, N., Patel, P. C., & Sattari, S. (2022). Industry 4.0 and supply chain performance: A systematic literature review of the benefits, challenges, and critical success factors of 11 core technologies. *Industrial Marketing Management*, *105*, 268-293.

Radziwill, N. (2018). Blockchain revolution: How the technology behind Bitcoin is changing money, business, and the world. *The Quality Management Journal, 25*(1), 64-65.

Raju, K. S., Senkerik, R., Lanka, S. P., & Rajagopal, V. (2020). *Data Engineering and Communication Technology: Proceedings of 3rd ICDECT-2K19*. Springer.

Ralston, P., & Blackhurst, J. (2020). Industry 4.0 and resilience in the supply chain: a driver of capability enhancement or capability loss? *International Journal of Production Research, 58*(16), 5006-5019.

Rayes, A., & Salam, S. (2022). The things in iot: Sensors and actuators. In *Internet of Things From Hype to Reality: The Road to Digitization* (pp. 63-82). Springer.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega, 53*, 49-57.

Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega, 64*, 126-130.

Rezaei, J., Wang, J., & Tavasszy, L. (2015). Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems with Applications, 42*(23), 9152-9164.

Rodríguez, R., Svensson, G., & Mehl, E. J. (2020). Digitalization process of complex B2B sales processes–Enablers and obstacles. *Technology in Society, 62*, 101324.

Rosin, F., Forget, P., Lamouri, S., & Pellerin, R. (2020). Impacts of Industry 4.0 technologies on Lean principles. *International Journal of Production Research, 58*(6), 1644-1661.

Sadaghiani, S., Ahmad, K. W., Rezaei, J., & Tavasszy, L. (2015, April). Evaluation of external forces affecting supply chain sustainability in oil and gas industry using Best Worst Method. In *2015 International Mediterranean Gas and Oil Conference (MedGO)* (pp. 1-4). IEEE.

Sakao, T., & Neramballi, A. (2020). A product/service system design schema: Application to big data analytics. *Sustainability, 12*(8), 3484.

Saragih, J., Tarigan, A., Pratama, I., Wardati, J., & Silalahi, E. F. (2020). The impact of total quality management, supply chain management practices and operations capability on firm performance. *Polish Journal of Management Studies*, *21*(2), 384-397.

Schlüter, F., Hetterscheid, E., & Henke, M. (2019). A simulation-based evaluation approach for digitalization scenarios in smart supply chain risk management. *Journal of Industrial Engineering and Management Science*, *2019*(1), 179-206.

Seebacher, S., & Schüritz, R. (2017). Blockchain technology as an enabler of service systems: A structured literature review. In *Exploring Services Science: 8th International Conference, IESS 2017, Rome, Italy, May 24-26, 2017, Proceedings 8* (pp. 12-23). Springer International Publishing.

Sejahtera, F., Wang, W., Indulska, M., & Sadiq, S. (2018). Enablers and inhibitors of effective use of big data: insights from a case study.

Sestino, A., Prete, M. I., Piper, L., & Guido, G. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. *Technovation, 98*, 102173.

Setyono, R. P., & Sarno, R. (2018, September). Vendor track record selection using best worst method. In *2018 International Seminar on Application for Technology of Information and Communication* (pp. 41-48). IEEE.

Shin, J., Kim, H., Sub, J., Kim, C., Sung, W., & Jang, J. W. (2018, June). Modification to dft-based codevectors for beamforming over the scm using circular arrays. In *2018 International Conference on Advances in Computing and Communication Engineering (ICACCE)* (pp. 92-96). IEEE.

Shokouhyar, S., Seddigh, M. R., & Panahifar, F. (2020). Impact of big data analytics capabilities on supply chain sustainability: A case study of Iran. *World Journal of Science, Technology and Sustainable Development*, Vol. 17 No. 1, pp. 33-57.

Sivakumar, V., Ruthramathi, R., & Leelapriyadharsini, S. (2020). Internet of things: Benefits and challenges of logistics service providers in India. *International Journal of Scientific and Technology Research*, *9*(2), 1949-1953.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, *70*, 263-286.

Sodhi, M. S., & Tang, C. S. (2019). Research opportunities in supply chain transparency. *Production and Operations Management*, *28*(12), 2946-2959.

Stackpole, B. (2020). *5 supply chain technologies that deliver competitive advantage*. MIT Management Sloan School. Retrieved 14th February 2022 from https://mitsloan.mit.edu/ideas-made-to-matter/5-supply-chain-technologies-deliver-competitive-advantage

Stock, T., & Seliger, G. (2016). Opportunities of sustainable manufacturing in industry 4.0. *Procedia CIRP*, *40*, 536-541.

Sunny, J., Undralla, N., & Pillai, V. M. (2020). Supply chain transparency through blockchain-based traceability: An overview with demonstration. *Computers & Industrial Engineering*, *150*, 106895.

Taboada, I., & Shee, H. (2021). Understanding 5G technology for future supply chain management. *International Journal of Logistics Research and Applications*, *24*(4), 392-406.

Talib, F., Asjad, M., Attri, R., Siddiquee, A. N., & Khan, Z. A. (2019). Ranking model of total quality management enablers in healthcare establishments using the best-worst method. *The TQM Journal*, Vol. 31 No. 5, pp. 790-814.

Tarofder, A. K., Azam, S. F., & Jalal, A. N. (2017). Operational or strategic benefits: Empirical investigation of internet adoption in supply chain management. *Management Research Review*, *40*(1), 28-52.

Tigga, G. A., Kannabiran, G., & Arumugam, V. (2021). Exploring relationships among IT advancement, IT assimilation, supply chain capabilities and supply chain performance. *Journal of Decision Systems*, *30*(4), 414-438.

Tjahjono, B., Esplugues, C., Ares, E., & Pelaez, G. (2017). What does industry 4.0 mean to supply chain? *Procedia Manufacturing*, *13*, 1175-1182.

Tortorella, G. L., Vergara, A. M. C., Garza-Reyes, J. A., & Sawhney, R. (2020). Organizational learning paths based upon industry 4.0 adoption: An empirical study with Brazilian manufacturers. *International Journal of Production Economics*, *219*, 284-294.

Trappey, A. J., Trappey, C. V., Fan, C.-Y., Hsu, A. P., Li, X.-K., & Lee, I. J. (2017). IoT patent roadmap for smart logistic service provision in the context of Industry 4.0. *Journal of the Chinese Institute of Engineers*, *40*(7), 593-602.

Vahidi, F., Torabi, S. A., & Ramezankhani, M. (2018). Sustainable supplier selection and order allocation under operational and disruption risks. *Journal of Cleaner Production*, *174*, 1351-1365.

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0–a glimpse. *Procedia Manufacturing*, *20*, 233-238.

Voss, S., Sebastian, H.-J., & Pahl, J. (2017). Introduction to intelligent decision support and big data for logistics and supply chain management minitrack.

Wakeel, S., Bingol, S., Bashir, M. N., & Ahmad, S. (2021). Selection of sustainable material for the manufacturing of complex automotive products using a new hybrid Goal Programming Model for Best Worst Method–Proximity Indexed Value method. *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 235*(2), 385-399.

Wan, J., Tang, S., Shu, Z., Li, D., Wang, S., Imran, M., & Vasilakos, A. V. (2016). Software-defined industrial internet of things in the context of industry 4.0. *IEEE Sensors Journal, 16*(20), 7373-7380.

Wan, S., Dong, J., & Chen, S.-M. (2021). Fuzzy best-worst method based on generalized interval-valued trapezoidal fuzzy numbers for multi-criteria decision-making. *Information Sciences, 573*, 493-518.

Wang, G., Gunasekaran, A., & Ngai, E. W. (2018). Distribution network design with big data: Model and analysis. *Annals of Operations Research, 270*, 539-551.

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics, 176,* 98-110.

Wu, P.-J., & Lin, K.-C. (2018). Unstructured big data analytics for retrieving e-commerce logistics knowledge. *Telematics and Informatics, 35*(1), 237-244.

Yalcin, A. S., Kilic, H. S., & Delen, D. (2022). The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review. *Technological Forecasting and Social Change, 174*, 121193.

Zare, A., Malakoutikhah, M., & Alimohammadlou, M. (2020). Selecting lighting system based on workers' cognitive performance using fuzzy best–worst method and QUALIFLEX. *Cognition, Technology & Work, 22,* 641-652.

Zgraggen, R. (2020). Political Risks and Blockchain: Definitions and Possible Case Examples. *International Journal of Security, Privacy and Trust Management (IJSPTM) Vol, 9*.

Zhao, R., Liu, Y., Zhang, N., & Huang, T. (2017). An optimization model for green supply chain management by using a big data analytic approach. *Journal of Cleaner Production, 142*, 1085-1097.

Appendix-**A**

Question 1:

Select the best technology from the following which has the highest impact in improving Supply Chain Performance.

1. Big Data Analytics (BDA)
2. Internet of Things (IOT)
3. Industry 4.0 (IDY)
4. Block Chain Technology (BCT)

Question 2:

Select the worst technology from the following that has the least impact in improving Supply Chain Performance.

1. Big Data Analytics (BDA)
2. Internet of Things (IOT)
3. Industry 4.0 (IDY)
4. Block Chain Technology (BCT)

Question 3:

Based on the best technology selected in Question 1 provide the importance of that best technology over the following technologies. Also provide the degree of confidence for each ranking ranging from 50% to 100% (Best to Best comparison is equally Important).

Best Technology selected as per Question 1: ____________________________________

	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BDA						
2. IOT						
3. IDY						
4. BCT						

Question 4:

Based on the worst technology selected in Question 2 provide the importance of following technologies over the worst technologies. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Worst to Worst comparison is equally Important).

Worst Technology selected as per Question 2: ___________________________________

	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BDA						
2. IOT						
3. IDY						
4. BCT						

Section 2: Subcategory Enablers (Moderators) of Big Data Analytics.

Description: The presence of these enablers in an organization will help in the successful implementation of Big Data Analytics and therefore help in improving the Supply Chain performance. Based on the same parameters as mentioned above answer the following questions.

All questions are mandatory, and the most relevant single entry should be selected.

Question 1:

Select the best criteria from the following criteria, the presence of which will have the most impact in improving the performance of Big Data Analytics.

1. Data Capturing and Storage (BDA 1)
2. Data Security and Privacy (BDA 2)
3. Data and Information Technology Integration (BDA 3)
4. Change Management (BDA 4)
5. Feasibility Study on Big Data Analytics (BDA 5)
6. Organizational Openness (BDA 6)
7. Synchronization of Processes (BDA 7)
8. Adequate System Capabilities (BDA 8)

Question 2:

Select the worst criteria from the following criteria, the presence of which will have the least impact in improving the performance of Big Data Analytics.

1. Data Capturing and Storage (BDA 1)
2. Data Security and Privacy (BDA 2)
3. Data and Information Technology Integration (BDA 3)
4. Change Management (BDA 4)
5. Feasibility Study on Big Data Analytics (BDA 5)
6. Organizational Openness (BDA 6)
7. Synchronization of Processes (BDA 7)
8. Adequate System Capabilities (BDA 8)

Question 3:

Based on the best criteria selected in Section 2 Question 1 provide the importance of that best criteria over the following criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Best to Best comparison is equally Important).

Best Technology selected as per Question 1: ___________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BDA 1						
2. BDA 2						
3. BDA 3						
4. BDA 4						
5. BDA 5						
6. BDA 6						
7. BDA 7						
8. BDA 8						

Question 4:

Based on the worst criteria selected in Section 2 Question 2 provide the importance of following criteria over the worst criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Worst to Worst comparison is equally Important).

Worst Technology selected as per Question 2: ___________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BDA 1						
2. BDA 2						
3. BDA 3						
4. BDA 4						
5. BDA 5						
6. BDA 6						
7. BDA 7						
8. BDA 8						

Section 3: Subcategory Enablers (Moderators) Internet of Things

Description: The presence of these enablers in an organization will help in the successful implementation of Internet of Things and therefore help in improving the Supply Chain performance. Based on the same parameters as above answer the following questions.

Question 1:

Select the best criteria from the following criteria, the presence of which will have the most impact in improving the performance of Internet of things.

1. Cloud Centric IOT for Logistics and Manufacturing (IOT 1)
2. Enterprise Modelling/Manufacturing (IOT 2)
3. Radio Frequency Identification (IOT 3)
4. Sensor Networks (IOT 4)
5. NFC, QR Codes, structured Data, Beacons & Bluetooth (IOT 5)
6. Software Defined Networking (IOT 6)
7. Big Data Supported Manufacturing (IOT 7)

Question 2:

Select the worst criteria from the following criteria, the presence of which will have the least impact in improving the performance of Internet of Things.

1. Cloud Centric IOT for Logistics and Manufacturing (IOT 1)
2. Enterprise Modelling/Manufacturing (IOT 2)
3. Radio Frequency Identification (IOT 3)
4. Sensor Networks (IOT 4)
5. NFC, QR Codes, structured Data, Beacons & Bluetooth (IOT 5)
6. Software Defined Networking (IOT 6)
7. Big Data Supported Manufacturing (IOT 7)

Question 3:

Based on the best criteria selected in Section 3 Question 1 provide the importance of that best criteria over the following criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Best to Best comparison is equally Important).

Best Technology selected as per Question 1: ________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. IOT 1						
2. IOT 2						
3. IOT 3						
4. IOT 4						
5. IOT 5						
6. IOT 6						
7. IOT 7						

Question 4:

Based on the worst criteria selected in Section 3 Question 2 provide the importance of following criteria over the worst criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Worst to Worst comparison is equally Important).

Worst Technology selected as per Question 2: ___________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. IOT 1						
2. IOT 2						
3. IOT 3						
4. IOT 4						
5. IOT 5						
6. IOT 6						
7. IOT 7						

Section 4: Subcategory Enablers (Moderators) Industry 4.0

Description: The presence of these enablers in an organization will help in the successful implementation of Industry 4.0 and therefore help in improving the Supply Chain performance. Based on the same parameters as above answer the following questions.

All questions are mandatory, and the most relevant single entry should be selected.

Question 1:

Select the best criteria from the following criteria, the presence of which will have the most impact in improving the performance of Industry 4.0.

1. E-Supply Chain Management (IDY 1)
2. Tracking and Localization of Products (IDY 2)
3. Additive Manufacturing and 3D Printing (IDY 3)
4. Innovative Business Models (IDY 4)
5. Effective Management of Technologies (IDY 5)

Question 2:

Select the worst criteria from the following criteria, the presence of which will have the least impact in improving the performance of Internet of Things.

1. E-Supply Chain Management (IDY 1)
2. Tracking and Localization of Products (IDY 2)
3. Additive Manufacturing and 3D Printing (IDY 3)
4. Innovative Business Models (IDY 4)
5. Effective Management of Technologies (IDY 5)

Question 3:

Based on the best criteria selected in Section 4 Question 1 provide the importance of that best criteria over the following criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Best to Best comparison is equally Important).

Best Technology selected as per Question 1: _____________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. IDY 1						
2. IDY 2						
3. IDY 3						
4. IDY 4						
5. IDY 5						

Question 4:

Based on the worst criteria selected in Section 4 Question 2 provide the importance of following criteria over the worst criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Worst to Worst comparison is equally Important).

Worst Technology selected as per Question 2: ___________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. IDY 1						
2. IDY 2						
3. IDY 3						
4. IDY 4						
5. IDY 5						

Section 5: Subcategory Enablers (Moderators) Block Chain Technology

Description: The presence of these enablers in an organization will help in the successful implementation of Block Chain Technology and therefore help in improving the Supply Chain performance. Based on the same parameters as above answer the following questions.

<u>All questions are mandatory, and the most relevant single entry should be selected.</u>

Question 1:

Select the best criteria from the following criteria, the presence of which will have the most impact in improving the performance of Block Chain Technology.

1. Transparency and Visibility (BCT 1)
2. Validation of Data and Transactions (BCT 2)
3. Automation using Smart Contracts (BCT 3)
4. Integrity of the Products (BCT 4)
5. Standardization and Automation of Processes (BCT 5)
6. Real Time Information (BCT 6)

Question 2:

Select the worst criteria from the following criteria, the presence of which will have the least impact in improving the performance of Block Chain Technology.

1. Transparency and Visibility (BCT 1)
2. Validation of Data and Transactions (BCT 2)
3. Automation using Smart Contracts (BCT 3)
4. Integrity of the Products (BCT 4)
5. Standardization and Automation of Processes (BCT 5)
6. Real Time Information (BCT 6)

Question 3:

Based on the best criteria selected in Section 5 Question 1 provide the importance of that best criteria over the following criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Best to Best comparison is equally Important).

Best Technology selected as per Question 1: ____________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BCT 1						
2. BCT 2						
3. BCT 3						
4. BCT 4						
5. BCT 5						
6. BCT 6						

Question 4:

Based on the worst criteria selected in Section 5 Question 2 provide the importance of following criteria over the worst criteria. Also provide the degree of confidence for each ranking ranging from 50% to 100%. (Worst to Worst comparison is equally Important).

Worst Technology selected as per Question 2: ____________________________________

Criteria	Equally Important	Weakly Important	Fairly Important	Very Important	Absolutely Important	Degree of Confidence
1. BCT 1						
2. BCT 2						
3. BCT 3						
4. BCT 4						
5. BCT 5						
6. BCT 6						

Appendix-B

Data Collected for Main Enablers:

Table B-1 Best to Other Vector Values for Main Category Enabler

S. No.	Data Collected from	Best Criteria	Comparison of the Best Criteria with Other Criteria			
			BDA	IOT	IDY	BCT
1	Expert 1	BDA	EI	VI	FI	WI
			(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.9)	(2/3,1,3/2;0.8)
2	Expert 2	BCT	AI	VI	WI	EI
			(7/2,4,9/2;1)	(5/2,3,7/2;0.9)	(2/3,1,3/2;0.8)	(1,1,1;1)
3	Expert 3	BDA	EI	AI	WI	VI
			(1,1,1;1)	(7/2,4,9/2;0.8)	(2/3,1,3/2;0.7)	(5/2,3,7/2;0.7)
4	Expert 4	BCT	VI	WI	FI	EI
			(5/2,3,7/2;0.9)	(2/3,1,3/2;0.8)	(3/2,2,5/2;0.8)	(1,1,1;1)
5	Expert 5	IOTs	FI	EI	AI	VI
			(3/2,2,5/2;0.7)	(1,1,1;1)	(7/2,4,9/2;0.9)	(5/2,3,7/2;1)
6	Expert 6	BDA	EI	WI	FI	AI
			(1,1,1;1)	(2/3,1,3/2;0.9)	(3/2,2,5/2;0.7)	(7/2,4,9/2;0.8)

Table B-2 Other to Worst Vector Values for Main Category Enablers

S. No.	Data Collected from	Worst Criteria	Comparison of Other Criteria with Worst Criteria			
			BDA	IOT	IDY	BCT
1	Expert 1	IOT	VI	EI	WI	FI
			(5/2,3,7/2;0.8)	(1,1,1;1)	(2/3,1/3/2;0.9)	(3/2,2,5/2;0.8)
2	Expert 2	BDA	EI	FI	VI	AI
			(1,1,1;1)	(3/2,2,5/2;0.8)	(5/2,3,7/2;0.8)	(7/2,4,9/2;1)
3	Expert 3	IOT	AI	EI	WI	FI
			(7/2,4,9/2;0.8)	(1,1,1;1)	(2/3,1,3/2;0.8)	(3/2,2,5/2;0.9)
4	Expert 4	BDA	EI	WI	FI	VI
			(1,1,1;1)	(2/3,1,3/2;0.8)	(3/2,2,5/2;1)	(5/2,3,7/2;0.9)
5	Expert 5	IDY	VI	AI	EI	WI
			(5/2,3,7/2;0.6)	(7/2,4,9/2;0.9)	(1,1,1;1)	(2/3,1,3/2;0.7)
6	Expert 6	BCT	AI	FI	VI	EI
			(7/2,4,9/2;0.8)	(3/2,2,5/2;0.8)	(5/2,3,7/2;0.7)	(1,1,1;1)

Block Chain Technology:

Table B-3 Best to Other Vector Values for Subcategory Enablers of BCT

S. No.	Expert	Best Criteria	Comparison of Best Criteria with other criteria					
			BCT 1	BCT 2	BCT 3	BCT 4	BCT 5	BCT 6
1	Expert 1	BCT 1	EI	FI	WI	VI	AI	FI
			(1,1,1;1)	(3/2,2,5/2;0.9)	(2/3,1,3/2;0.9)	(5/2,3,7/2;1)	(7/2,4,9/2;1)	(3/2,2,5/2;0.8)
2	Expert 2	BCT 3	EI	VI	EI	WI	AI	FI
			(1,1,1;0.8)	(5/2,3,7/2;0.7)	(1,1,1;1)	(2/3,1,3/2;0.8)	(7/2,4,9/2;0.9)	(3/2,2,5/2;0.9)
3	Expert 3	BCT 6	EI	VI	AI	WI	WI	EI
			(1,1,1;0.8)	(5/2,3,7/2;0.8)	(7/2,4,9/2;0.9)	(2/3,1,3/2;0.8)	(2/3,1,3/2;0.7)	(1,1,1;1)
4	Expert 4	BCT 1	EI	FI	WI	EI	VI	EI
			(1,1,1;1)	(3/2,2,5/2;0.8)	(2/3,1,3/2;0.8)	(1,1,1;0.6)	(5/2,3,7/2;1)	(1,1,1;0.9)
5	Expert 5	BCT 4	FI	FI	WI	EI	VI	FI
			(3/2,2,5/2;0.6)	(3/2,2,5/2;0.7)	(2/3,1,3/2;0.9)	(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.8)
6	Expert 6	BCT 3	WI	FI	EI	WI	AI	FI
			(2/3,1,3/2;0.7)	(3/2,2,5/2;0.6)	(1,1,1;1)	(2/3,1,3/2;0.8)	(7/2,4,9/2;0.9)	(3/2,2,5/2;0.8)

Table B-4 Other to Worst Vector Values for Subcategory Enablers of BCT

S. No.	Expert	Worst Criteria	Comparison of Other Criteria with Worst Criteria					
			BCT 1	BCT 2	BCT 3	BCT 4	BCT 5	BCT 6
1	Expert 1	BCT 5	AI	FI	VI	FI	EI	WI
			(7/2,4,9/2;1)	(3/2,2,5/2;0.8)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.7)	(1,1,1;1)	(2/3,1,3/2;0.9)
2	Expert 2	BCT 5	VI	WI	AI	VI	EI	FI
			(5/2,3,7/2;0.7)	(2/3,1,3/2;0.9)	(7/2,4,9/2;0.9)	(5/2,3,7/2;0.8)	(1,1,1;1)	(3/2,2,5/2;1)
3	Expert 3	BCT 3	VI	FI	EI	VI	VI	AI
			(5/2,3,7/2;0.9)	(3/2,2,5/2;0.8)	(1,1,1;1)	(5/2,3,7/2;0.7)	(5/2,3,7/2;0.8)	(7/2,4,9/2;0.9)
4	Expert 4	BCT 5	VI	FI	FI	WI	EI	WI
			(5/2,3,7/2;1)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(2/3,1,3/2;0.7)	(1,1,1;1)	(2/3,1,3/2;0.6)
5	Expert 5	BCT 5	EI	FI	EI	VI	EI	WI
			(1,1,1;0.6)	(3/2,2,5/2;0.7)	(1,1,1;0.9)	(5/2,3,7/2;0.8)	(1,1,1;1)	(2/3,1,3/2;0.6)
6	Expert 6	BCT 5	VI	FI	AI	VI	EI	FI
			(5/2,3,7/2;0.9)	(3/2,2,5/2;0.7)	(7/2,4,9/2;0.9)	(5/2,3,7/2;0.7)	(1,1,1;1)	(3/2,2,5/2;0.6)

Industry 4.0:

Table B-5 Best to Other Vector Values for Subcategory Enablers of IDY

S. No.	Expert	Best Criteria	Comparison of Best Criteria with other criteria				
			IDY 1	IDY 2	IDY 3	IDY 4	IDY 5
1	Expert 1	IDY 2	WI	EI	AI	FI	WI
			(2/3,1,3/2;0.8)	(1,1,1;1)	(7/2,4,9/2;0.9)	(3/2,2,5/2;0.7)	(2/3,1,3/2;0.8)
2	Expert 2	IDY 2	FI	EI	AI	WI	FI
			(3/2,2,5/2;0.7)	(1,1,1;1)	(7/2,4,9/2;0.9)	(2/3,1,3/2;1)	(3/2,2,5/2;0.8)
3	Expert 3	IDY 5	VI	FI	FI	AI	EI
			(5/2,3,7/2;0.9)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(7/2,4,9/2;0.9)	(1,1,1;1)
4	Expert 4	IDY 1	EI	VI	WI	AI	FI
			(1,1,1;1)	(5/2,3,7/2;0.9)	(2/3,1,3/2;0.9)	(7/2,4,9/2;1)	(3/2,2,5/2;0.7)
5	Expert 5	IDY 3	AI	EI	EI	FI	EI
			(7/2,4,9/2;1)	(1,1,1;0.7)	(1,1,1;1)	(3/2,2,5/2;0.9)	(1,1,1;0.6)
6	Expert 6	IDY 1	EI	EI	FI	VI	FI
			(1,1,1;1)	(1,1,1;0.6)	(3/2,2,5/2;0.9)	(5/2,3,7/2;0.8)	(3/2,2,5/2;1)

Table B-6 Other to Worst Vector Value for Subcategory Enablers of IDY

S. No.	Expert	Worst Criteria	Comparison of Other Criteria with Worst Criteria				
			IDY 1	IDY 2	IDY 3	IDY 4	IDY 5
1	Expert 1	IDY 3	VI	AI	EI	FI	VI
			(5/2,3,7/2;0.8)	(7/2,4,9/2;0.9)	(1,1,1;1)	(3/2,2,5/2;0.7)	(5/2,3,7/2;0.9)
2	Expert 2	IDY 3	FI	AI	EI	VI	FI
			(3/2,2,5/2;0.9)	(7/2,4,9/2;0.9)	(1,1,1;1)	(5/2,3,7/2;0.7)	(3/2,2,5/2;0.7)
3	Expert 3	IDY 4	FI	WI	VI	EI	AI
			(3/2,2,5/2;0.8)	(2/3,1,3/2;0.8)	(5/2,3,7/2;0.9)	(1,1,1;1)	(7/2,4,9/2;0.9)
4	Expert 4	IDY 4	AI	EI	VI	EI	FI
			(7/2,4,9/2;1)	(1,1,1;0.8)	(5/2,3,7/2;0.8)	(1,1,1;1)	(3/2,2,5/2;0.9)
5	Expert 5	IDY 1	EI	VI	AI	VI	VI
			(1,1,1;1)	(5/2,3,7/2;0.9)	(7/2,4,9/2;1)	(5/2,3,7/2;0.8)	(5/2,3,7/2;0.7)
6	Expert 6	IDY 4	VI	WI	FI	EI	FI
			(5/2,3,7/2;0.8)	(2/3,1,3/2;0.9)	(3/2,2,5/2;0.8)	(1,1,1;1)	(3/2,2,5/2;0.7)

Internet of Things:

Table B-7 Best to Other Vector Values for Subcategory Enablers of IOT

S. No.	Expert	Best Criteria	Comparison of Best Criteria with other criteria						
			IOT 1	IOT 2	IOT 3	IOT 4	IOT 5	IOT 6	IOT 7
1	Expert 1	IOT 4	VI	FI	FI	EI	FI	FI	AI
			(5/2,3,7/2;0.9)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(1,1,1;1)	(3/2,2,5/2;0.7)	(3/2,2,5/2;0.7)	(7/2,4,9/2;1)
2	Expert 2	IOT 1	EI	VI	FI	FI	WI	FI	FI
			(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.7)	(2/3,1,3/2;0.7)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.7)
3	Expert 3	IOT 3	FI	AI	EI	WI	VI	WI	FI
			(3/2,2,5/2;0.8)	(7/2,4,9/2;0.9)	(1,1,1;1)	(2/3,1,3/2;0.8)	(5/2,3,7/2;0.9)	(2/3,1,3/2;0.7)	(3/2,2,5/2;0.8)
4	Expert 4	IOT 3	WI	FI	EI	FI	EI	AI	WI
			(2/3,1,3/2;0.6)	(3/2,2,5/2;0.6)	(1,1,1;1)	(3/2,2,5/2;0.7)	(1,1,1;1)	(7/2,4,9/2;0.8)	(2/3,1,3/2;0.9)
5	Expert 5	IOT 4	VI	FI	FI	EI	VI	AI	WI
			(5/2,3,7/2;0.6)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(1,1,1;1)	(5/2,3,7/2;0.7)	(7/2,4,9/2;0.9)	(2/3,1,3/2;0.7)
6	Expert 6	IOT 3	WI	EI	EI	FI	FI	VI	FI
			(2/3,1,3/2;1)	(1,1,1;1)	(1,1,1;1)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(5/2,3,7/2;0.9)	(3/2,2,5/2;0.7)

Table B-8 Other to Worst Vector Values for Subcategory Enablers of IOT

S. No.	**Expert**	**Worst Criteria**	**Comparison of Other Criteria with Worst Criteria**						
			IOT 1	IOT 2	IOT 3	IOT 4	IOT 5	IOT 6	IOT 7
1	Expert 1	IOT 7	WI	FI	FI	AI	WI	WI	EI
			(2/3,1,3/2;0.8)	(3/2,2,5/2;0.9)	(3/2,2,5/2;0.8)	(7/2,4,9/2;1)	(2/3,1,3/2;0.7)	(2/3,1,3/2;0.7)	(1,1,1;1)
2	Expert 2	IOT 2	VI	EI	FI	FI	FI	FI	WI
			(5/2,3,7/2;0.8)	(1,1,1;1)	(3/2,2,5/2;0.9)	(3/2,2,5/2;1)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.9)	(2/3,1,3/2;0.8)
3	Expert 3	IOT 2	FI	EI	AI	VI	WI	FI	WI
			(3/2,2,5/2;0.8)	(1,1,1;1)	(7/2,4,9/2;0.9)	(5/2,3,7/2;0.8)	(2/3,1,3/2;0.9)	(3/2,2,5/2;0.9)	(2/3,1,3/2;0.7)
4	Expert 4	IOT 6	VI	VI	AI	WI	FI	EI	VI
			(5/2,3,7/2;0.7)	(5/2,3,7/2;0.7)	(7/2,4,9/2;0.8)	(2/3,1,3/2;0.9)	(3/2,2,5/2;0.8)	(1,1,1;1)	(5/2,3,7/2;0.7)
5	Expert 5	IOT 6	WI	EI	VI	AI	EI	EI	FI
			(2/3,1,3/2;0.8)	(1,1,1;0.6)	(5/2,3,7/2;0.7)	(7/2,4,9/2;0.9)	(1,1,1;0.9)	(1,1,1;1)	(3/2,2,5/2;0.6)
6	Expert 6	IOT 6	WI	FI	VI	WI	FI	EI	WI
			(2/3,1,3/2;0.8)	(3/2,2,5/2;0.9)	(5/2,3,7/2;0.9)	(2/3,1,3/2;0.8)	(3/2,2,5/2;0.7)	(1,1,1;1)	(2/3,1,3/2;0.8)

Big Data Technology:

Table B-9 Best to Other Vector Values for Subcategory Enablers of BDA

S. No.	Expert	Best Criteria	Comparison of Best Criteria with other criteria							
			BDA 1	BDA 2	BDA 3	BDA 4	BDA 5	BDA 6	BDA 7	BDA 8
1	Expert 1	BDA 2	FI	EI	VI	VI	WI	VI	AI	FI
			(3/2,2,5/2;0.9)	(1,1,1;1)	(5/2,3,7/2;0.7)	(5/2,3,7/2;0.8)	(2/3,1,3/2;1)	(5/2,3,7/2;1)	(7/2,4,9/2;0.8)	(3/2,2,5/2;0.8)
2	Expert 2	BDA 4	WI	EI	FI	EI	VI	FI	FI	WI
			(2/3,1,3/2;0.8)	(1,1,1;0.9)	(3/2,2,5/2;0.9)	(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.7)	(2/3,1,3/2;0.9)
3	Expert 3	BDA 3	FI	FI	EI	VI	WI	EI	FI	EI
			(3/2,2,5/2;0.7)	(3/2,2,5/2;0.6)	(1,1,1;1)	(5/2,3,7/2;0.8)	(2/3,1,3/2;0.7)	(1,1,1;0.9)	(3/2,2,5/2;0.9)	(1,1,1;0.7)
4	Expert 4	BDA 3	FI	EI	EI	AI	FI	VI	FI	EI
			(3/2,2,5/2;0.9)	(1,1,1;0.9)	(1,1,1;1)	(7/2,4,9/2;1)	(3/2,2,5/2;0.7)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.6)	(1,1,1;0.7)
5	Expert 5	BDA 1	EI	EI	WI	WI	AI	WI	VI	VI
			(1,1,1;1)	(1,1,1;0.7)	(2/3,1,3/2;0.7)	(2/3,1,3/2;0.9)	(7/2,4,9/2;1)	(2/3,1,3/2;0.6)	(5/2,3,7/2;0.7)	(5/2,3,7/2;0.6)
6	Expert 6	BDA 1	EI	VI	WI	WI	AI	FI	FI	WI
			(1,1,1;1)	(5/2,3,7/2;0.7)	(2/3,1,3/2;0.6)	(2/3,1,3/2;0.6)	(7/2,4,9/2;0.9)	(3/2,2,5/2;0.8)	(3/2,2,5/2;0.9)	(2/3,1,3/2;1)

Table B-10 Other to Worst Vector Values for Subcategory Enablers of BDA

S. No.	Expert	Worst Criteria	Comparison of Other Criteria with Worst Criteria							
			BDA 1	BDA 2	BDA 3	BDA 4	BDA 5	BDA 6	BDA 7	BDA 8
1	Expert 1	BDA 7	VI	AI	EI	FI	VI	FI	EI	FI
			(5/2,3,7/2;0.9)	(7/2,4,9/2;0.8)	(1,1,1;0.8)	(3/2,2,5/2;0.7)	(5/2,3,7/2;1)	(3/2,2,5/2;1)	(1,1,1;1)	(3/2,2,5/2;0.8)
2	Expert 2	BDA 5	FI	FI	WI	VI	EI	WI	FI	FI
			(3/2,2,5/2;0.8)	(3/2,2,5/2;0.8)	(2/3,1,3/2;0.9)	(5/2,3,7/2;0.8)	(1,1,1;1)	(2/3,1,3/2;0.9)	(3/2,2,5/2;0.9)	(3/2,2,5/2;0.7)
3	Expert 3	BDA 4	FI	WI	VI	EI	FI	FI	EI	WI
			(3/2,2,5/2;0.8)	(2/3,1,3/2;0.8)	(5/2,3,7/2;0.8)	(1,1,1;1)	(3/2,2,5/2;0.9)	(3/2,2,5/2;0.7)	(1,1,1;0.9)	(2/3,1,3/2;0.9)
4	Expert 4	BDA 4	WI	VI	AI	EI	VI	FI	VI	VI
			(2/3,1,3/2;0.8)	(5/2,3,7/2;0.8)	(7/2,4,9/2;1)	(1,1,1;1)	(5/2,3,7/2;0.8)	(3/2,2,5/2;0.7)	(5/2,3,7/2;0.7)	(5/2,3,7/2;0.9)
5	Expert 5	BDA 5	AI	VI	VI	FI	EI	VI	FI	WI
			(7/2,4,9/2;1)	(5/2,3,7/2;0.8)	(5/2,3,7/2;0.6)	(3/2,2,5/2;0.9)	(1,1,1;1)	(5/2,3,7/2;0.7)	(3/2,2,5/2;0.6)	(2/3,1,3/2;0.7)
6	Expert 6	BDA 5	AI	WI	VI	FI	EI	VI	FI	FI
			(7/2,4,9/2;0.9)	(2/3,1,3/2;0.7)	(5/2,3,7/2;0.7)	(3/2,2,5/2;0.8)	(1,1,1;1)	(5/2,3,7/2;0.6)	(3/2,2,5/2;0.6)	(3/2,2,5/2;0.7)