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PERFORMANCE ASSESSMENT OF INDUSTRY 4.0 TECHNOLOGIES BASED ON CIRCULAR ECONOMY CONCEPT: A CASE STUDY FOR MANUFACTURING COMPANIES

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ABSTRACT

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Industry 4.0 and Circular Economy are two significant concepts of the last decade. Industrial technologies make supply chain processes easier and effective. Industry 4.0 technologies and digitalization of supply chains have positive effects on the Circular Economy. In this thesis, the benefits of I4.0 technologies on enabling Circular Economy were investigated. The main aim of this thesis is to propose a framework to measure the performance of I4.0 technologies on enabling Circular Economy based on criteria organized by the Triple-Bottom-Line approach. Since the Triple-Bottom-Line approach includes social and environmental subjective criteria; a combined Multi-Criteria Decision-Making approach, Fuzzy Best-Worst and Fuzzy VIKOR Methods, was used for calculation of criteria weights and ranking of the alternatives. A case study was applied to analyze the implementation of the proposed framework for manufacturing companies.

keywords: circular economy, industry 4.0, industry 4.0 technologies, performance assessment, triple-bottom-line, fuzzy best-worst method, fuzzy-vikor method

ÖZ

DÖNGÜSEL EKONOMİ KAVRAMINA DAYALI ENDÜSTRİ 4.0 TEKNOLOJİLERİNİN PERFORMANS DEĞERLENDİRMESİ: ÜRETİM FİRMALARI İÇİN BİR VAKA ÇALIŞMASI

Memiş, İlker
Yüksek Lisans Tezi, Lojistik Mühendisliği
Danışman: Prof. Dr. Yücel Öztürkoğlu
Ocak 2022

Endüstri 4.0 ve Döngüsel Ekonomi, son on yılın iki önemli kavramıdır. Endüstriyel teknolojiler, tedarik zinciri süreçlerini daha kolay ve etkili hale getirir. Endüstri 4.0 teknolojileri ve tedarik zincirlerinin dijitalleşmesi Döngüsel Ekonomi üzerinde olumlu etkilere sahiptir. Bu tezde, E4.0 teknolojilerinin Döngüsel Ekonomiyi etkinleştirmedeki faydaları araştırılmıştır. Bu tezin temel amacı, E4.0 teknolojilerinin Üçlü-Alt-Hat yaklaşımı ile düzenlenen kriterlere dayalı Döngüsel Ekonomiyi etkinleştirme konusundaki performansını ölçmek için bir çerçeve önermektir. Triple-Bottom-Line yaklaşımı sosyal ve çevresel sübjektif kriterleri içerdiğinden; Kriter ağırlıklarının hesaplanması ve alternatiflerin sıralanması için birleştirilmiş Çok Kriterli Karar Verme yaklaşımı, Bulanık En İyi-Kötü ve Bulanık VIKOR Yöntemleri kullanılmıştır. İmalat şirketleri için, önerilen çerçevenin uygulamasını analiz etmek için bir vaka çalışması uygulandı.

Anahtar Kelimeler: döngüsel ekonomi, endüstri 4.0, endüstri 4.0 teknolojileri, performans değerlendirmesi, üçlü-alt çizgi, bulanık en iyi-en kötü yöntem, bulanık-vikor yöntemi

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I would like to show my appreciation to my parents, by thanking them for their unconditional love and support towards me.

İlker Memiş

İzmir, 2022

TEXT OF OATH

I can honestly confirm and declare that my study, titled "Performance Assessment of Industry 4.0 Technologies Based on Circular Economy Concept: A Case Study for Manufacturing Companies" and presented as a Master's Thesis, have been composed without applying to any help conflicting with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn specifically or indirectly from outside sources are demonstrated within the text and listed within the list of references.

İlker Memiş

January 2022

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SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS:

CE	Circular Economy
I4.0	Industry 4.0
TBL	Triple-Bottom-Line
IoT	Internet of Things
BDA	Big Data Analytics
AM	Additive Manufacturing
CPS	Cyber-Physical System
AR	Augmented Reality
VR	Virtual Reality
RFID	Radio Frequency Identification System
MCDM	Multi-Criteria Decision Making
ROI	Return on Investment
BWM	Best-Worst Method
VIKOR	VIsekriterijumska Optimizacija I Kompromisno Resenje
BoD	Board of Directors

SYMBOLS:

c_n	n[th] Criteria
c_B	The Best Criteria
c_W	The Worst Criteria
A_B	Best-to-others vector
A_W	Others-to-worst vector

CHAPTER 1
INTRODUCTION

Increasing consumption which is a result of the population growth of the world leads to the use of more natural resources, but natural resources are finite (Akao and Managi, 2007). High consumption and short life cycle of products result in increases in the global waste amount. According to The Organization for Economic Cooperation and Development (OECD), in 2050, nearly 27 billion tons of waste will be generated globally. This amount was only half of it in 2000 (OECD, 2008). Besides, the world economy is expected to be four times larger than today which requires much more energy to compensate for the growth in 2050 (OECD,2012). This situation increases the importance of sustainable supply chains, and circular economy rather than linear production models (take-make-dispose). The circular economy can be defined as an economic model that aims to use the scarce resources, energy, and end-of-life goods repeatedly in the production processes whether its process or other processes (Korhonen et al., 2018). One of the most famous definitions of CE was made by Ellen Mac Arthur Foundation (2015) as an economic model that has abilities to restore itself by an effective design. The primary goal of a CE, according to Webster (2015), is to maintain the most significant value of goods and materials within the production system. Reverse production systems have an important role in the CE concept. Rapid changes and growth in technology shortened the life cycle of products which turns to waste at the end-of-life (EoL) come up an increasing amount of waste worldwide which increases the significance of the 6R (recycle, repair, reuse, reduce, refuse, and rethink). Elimination of waste is a fundamental issue in waste management for companies and governments. Regarding this issue, politicians have taken various actions to reduce the generation and amount of waste. Germany was one of the first countries that had taken an action on product recovery and introduced the "life cycle of products responsibility" concept (Thierry,1997). After this, many countries have introduced specific legislation. European Union waste management law has a directive on waste which has entered into force in 2008 and which establishes a legal framework for waste treatment activities in the EU. These regulations give responsibility to firms to recycle the waste that they generated because of the production activities and depend on the "polluter pays principle". This approach named extended producer responsibility (EPR) based on the polluter pays principle gives the responsibility of getting back, recycling and properly disposing of the products to their producers after end-of-life (EoL) of the products to decrease the amount of waste generation and save the environment from the hazardous materials and contaminants (Kiddee et al., 2013; Li et al., 2015; Kunz et al., 2018).

Today, companies have to cope with many difficulties while managing to decrease the waste amount generated and improving capabilities to achieve a zero-waste target. Rapid technological developments force to change production systems and require high investments to maintain the competitive level of companies. However, technology helps companies to increase the efficiency of equipment, labor, and energy use in the long term. As a result of more efficient resource usage, elimination of waste and getting close to zero waste in supply chain management is a more achievable object. The use of technology more effectively and circular economy have similar targets to reach sustainable supply chains through ensuring the elimination of waste, increasing productivity and effectiveness of resources, creating less environmental pollution (Zeng et al., 2017; Caliskan et al., 2020).

Industry 4.0 can be defined as a concept designed to create a collective vision on the basis of real-time data-driven measuring, monitoring, and decision making, digital transformation of processes occurring in all phases of the supply chain, providing simple, fast, and flexible solutions (Duman and Akdemir, 2021). A range of technologies including Simulation, Internet of Things (IoT), Big Data Analytics (BDA), Cloud Computing, Additive Manufacturing (AM), Augmented Reality (AR), Autonomous Robots, Vertical & Horizontal Integration, Blockchain, and Cyber Security are identified by Boston Consulting Group under Industry 4.0 concept (Rüßmann et al., 2015). Cyber-Physical Systems (CPSs) are the systems state that connected devices, equipment, sensors, actuators, workpieces, and information systems. These systems are designed to interact with each other to analyze data gathered from activities of physical systems in a virtual world based on computing and communicating infrastructures. (Lu, 2017).

Industry 4.0 has similar aims with CE for some features as more efficient use of resources through automated systems, achieving error-proof production systems which decrease waste generation, and eco-friendly energy usage. In the literature, there is not much research about the combination of these new topics: Industry 4.0 and CE. Also, very limited contributions are available integrating both CE and Industry 4.0 technologies within the perspective of how and what kind of I4.0 technologies can positively affect the implementation of CE (Rosa et al., 2019). Specifically, no contribution can be found in terms of analyzing the effects of I4.0 technologies on the circularity performance of manufacturing companies according to the triple bottom line (TBL) perspective. Therefore, the fundamental aim of this paper is to assess the performance of industry 4.0 technologies on enhancing circular economy within the dimensions of TBL. For this purpose, it is necessary to understand the relationship between industry 4.0 and circular economy. In order to fill this gap, this paper organized to present the findings of the following research questions:

RQ1: What kind of I4.0 technologies may have a role as enablers in implementing the circular economy?

In order to answer this question, a meticulous literature review under the concepts of CE, Industry 4.0 and the integration of these concepts is conducted. Technologies as enablers of I4.0 which have effects on circularity performance of organizations are determined according to literature and experts' opinions from manufacturing industries.

RQ2: Which criteria set should be used for determining the effectiveness of Industry 4.0 technologies on the circular economy?

After reviewing the literature, the criteria set determined from the TBL perspective to evaluate the I4.0 enablers in terms of their effects on sustainability performance.

RQ3: What are the weights of the criteria and rankings of the alternatives?

To evaluate the effectiveness of technological enablers of I4.0 on circularity performance of manufacturing industries, determining the weights of criteria and ranking the alternatives are required. For this purpose, a questionnaire is formed to conduct pairwise comparisons of criteria. Also, another survey is created to collect the opinions from experts about the importance of alternatives based on the effects on criteria. A hybrid multi-criteria decision-making method (MCDM) is used to answer this question. The Fuzzy Best-Worst method is used to determine the weights of the criteria and the Fuzzy Vikor method is used to rank the alternatives.

Following the introduction, Section 2 identifies the theoretical background. Section 3 describes the proposed framework, and Section 4 introduces the methodology. Section 5 discusses the case study for a manufacturing company in the poultry industry and the results. Section 6 proposes the implications and discussions, and finally, Section 7 presents the conclusion and future research directions.

CHAPTER 2
THEORETICAL BACKGROUND

The section highlights the research areas of CE and Industry 4.0. Firstly, the CE was identified briefly, then Industry 4.0 was clarified, and finally, Industry 4.0 as the enabler of CE was represented.

2.1. The Concept of the Circular Economy

The circular economy concept which introduces environment and economic interactions has been first mentioned by Pierce and Turner in 1989 in the literature. They stressed that a linear system should be replaced by a circular system in which the economy and environment are regarded by circular relationships. Since then, many papers conducted about the concept of Circular Economy, but the concept is derived from industrial ecology (IE) and environmental economics which explains the benefits of recycling waste (Jacobsen, 2006; Andersen, 2006; Yuan et al., 2008; Ghisellini et al., 2016). The idea of reducing the use of resources and applying cleaner technology in many industries and eliminating waste is promoted by industrial ecology. (Andersen 1999). The circular economy is a comprehensive concept that includes the basics of industrial ecology in terms of the aim of decreasing scarce natural resources in production processes. Simultaneously, a circular economy has many benefits to the environment, economy, and society. It provides the elimination of harmful ingredients of waste flows for the environment and society, and it creates value without using new natural resources for the economy (Sagnak et al., 2021).

A great amount of research has been presented to investigate the attributes of the circular economy concept since the 1970s. Many authors described how natural resources affects the contemporary linear economy systems to fulfil the requirements of production by serving as inputs and at the same time turning into waste after consumption (Geissdoerfer et al., 2017). Ellen MacArthur Foundation is one of the well-known associations which has purposed to decrease waste and pollution amount created in an economy, to promote circularity of the products, and to vitalize the nature and environment. One of the most famous definitions of circular economy is also made by Ellen MacArthur Foundation (2015) as a universal economic model that can restore itself by an intelligent design. Webster (2015) indicated that the most important purpose of a circular economy is keeping the most noticeable value of the resources, energy, or materials within the economic system by reusing or recycling repeatedly. To achieve these objects of CE, rethinking the production processes from the design phases by redefining the ways of the usage of natural resources is a fundamental factor.

A circular economy model must be created by using renewable resources in the supply chain, providing the lifecycle of the product last longer, and keeping the value of renewable sources in the economy. CE as a concept created based on triple bottom line approach has benefits to the economy in terms of keeping the value of the resources within the systems, society in terms of eliminating harmful residual waste and environment by decreasing the usage of natural resources.

CE concept has gained attention not just by academicians, but also by the governments and policymakers and they have been regulated the industries according to achieve the objectives of CE. Germany government was the first authority that integrated the CE into their national laws with an enactment of a law in 1996: "Closed Substance Cycle and Waste Management Act" (Su et al., 2013). Since then, Japan, Europe, China, and many other countries have introduced specific regulations to implement the circular economy (Geissdoerfer et al., 2017). As the consumption, production and population rising, replacement of the linear economic model with the circular economic models is inevitable. Table 2.1 shows the literature review of the Circular Economy Concept.

Table 2.1. Literature Review of the Circular Economy Concept

Author (Year)	Objective	Research Type
Andersen, 1999	The aim is to analyze the economies of four European Countries (Denmark, Germany, France and, The Netherlands) according to the environmental policies.	Report
Andersen, 2006	The aim is to introduce the significance of environmental economics principles.	Report
Jacobsen, 2006	The aim is to analyze the central industrial symbiotic exchanges using precise economic and environmental statistics in Kalundborg, Denmark	Quantitative Assessment
Yuan et al., 2008	The aim is to examine a new development strategy in Chine	Review
Su et al, 2013	The aim is to go over the Circular Economy concept, current operations, and evaluation.	Review
Ellen MacArthur Foundation, 2015	The aim is to argue the necessity of the concept of Circular Economy and the inadequacy of the linear economy model.	Report
Ghisellini et al., 2016	The aim is to conduct a thorough assessment of the literature over the previous two decades in order to understand the key Circular Economy characteristics.	Review

Table 2.1. (cont'd). Literature Review of the Circular Economy Concept

Geissdoerfer et al., 2017	The aim is to provide conceptual clarity by defining words and synthesizing the many forms of interactions between Circular Economy and Sustainability.	Literature Review
Sagnak et al., 2021	The aim is to find the best location for an E-waste collection center according to the defined criteria set in an emerging economy.	Fuzzy Best-Worst and TOPSIS

2.2. Industry 4.0

Industry 4.0 as a term is initially put forward at the Hannover Fair in 2011. The concept of the "I4.0", which brings together policymakers, academic researchers, and corporate officials, were first proposed as ways to improve the German manufacturing industry's competitiveness (Duman and Akdemir, 2021). Kagermann explained the complement processes that are required to achieve the benefits of Industry 4.0. Industry 4.0 technologies including Cyber-Physical Systems (CPSs) were mentioned in the article entitled "Recommendations for Implementing the Strategic Initiative Industry 4.0". Some application suggestions and potential benefits for the German industries were presented by Kagermann to answer the question of how industry 4.0 technologies will affect the future of the world (Kagermann et al., 2013).

In the literature, many publications on Industry 4.0 context can be found but there is no consensus on the definition of I4.0 among researchers (Lasi et al., 2014; Meisner et al., 2017; Rosa et al., 2019). Industry 4.0 is a paradigm covering a wide range of concepts represented in a system that connects each kind of physical things (machinery, equipment etc.) with embedded electronic devices (sensors, actuators, alarms, annunciators, radio frequency identification etc.) by using the information and communication technologies (ICT; networks, internet, cloud etc.) to the virtual world (Kamble et al., 2018; Rosa et al., 2019). Physical systems and virtual systems can interact with each other by configurations on input parameters or by automated settings of the system with embedded devices to change outputs which make the system highly adaptable to changes. Maximum outputs may be achieved while resources are utilized more efficiently with the benefits of Industry 4.0 technologies (Khan et al., 2021). Industrial manufacturing systems are predicted to function 30 percent quicker and 25% more efficiently under the impact of Industry 4.0 (Rüßmann et al., 2015).

The main drivers of Industry 4.0 are the latest digital technologies. Cyber-Physical Systems (CPS) and Internet of Things are the decisive innovations of Industry 4.0 (Weyer et al., 2015). Specifically, nine technological components were identified by Boston Consulting Group as can be listed in Industry 4.0 context. Industry 4.0 can be seen as a comprehensive framework that includes these technologies and integrations (Schwab, 2016; Meisner et al., 2017). These technologies are additive manufacturing (AM), big data and analytics (BDA), Internet of Things (IoT), simulation, augmented reality (AR), autonomous robots, cloud technology, horizontal/vertical system integration, and cybersecurity (Rüßmann et al., 2015). A cyber-physical system (CPS), cloud computing, and the Internet of Things (IoT) that take the place in the information technology part of Industry 4.0 make the whole factory adaptable and smart (Ivanov et al, 2016).

Cyber-physical systems are industrial automation systems that integrate physical business operations with the virtual world through machine-to-machine communication by using networks as a way of connections (Lu, 2017; Lee, 2008). The physical and digital objects are interconnected, and decentralized decisions can be taken through interactions between these objects in CPS (Manavalan and Jayakrishna, 2019). To transition to I4.0, businesses must have CPS technology that links the real and virtual worlds (Wang and Wang, 2016). Gathering data from machines and equipment, creating an error-proof production, changing the roles of employees for system integration are the fundamental benefits of CPS technology in a business. CPS are supportive systems that gather, transit, and interpret data from the production area and take fast and accurate actions according to data gathered (Prinz et al., 2016). It is getting easier to construct a duplicate of the actual environment and make judgments from afar with a CPS which assist to find out possible errors before they occurred. For example, CPS and intelligent technological devices can enable shop floor workers to troubleshoot the issues regarding the machinery without waiting for the maintenance crew (Prinz et al., 2016).

The Internet of Things (IoT) is connected to CPSs in Industry 4.0 in such a way that the system develops the ability to collect and feed data, adding value to the manufacturing process. IoT enables things to interact and connect via a wired or wireless connection and offers communication tools between smart devices and their interconnections (Zezulka et al., 2016). Radio frequency identification (RFID), software, sensors, processors, tags, actuators and communication technologies can enable the linkages (Bahrin et al, 2016; Nasiri et al., 2017). RFID systems and intelligent sensors are referred to as identification and tracking technologies. In an RFID system, each object has its own unique identification number. Objects can be identified and tracked using RFID tags and readers. RFID system provides real-time data about the objects which have an ID, and it makes it easier to track the number, quality, name, or anything that is determined of the objects (Jia et al., 2012). Sensors on physical items are increasingly being used to record, analyze, and share data with humans and other physical systems. Sensors are used for detecting equipment wear and tear, monitoring inventory levels, detecting quality defects, measuring and controlling temperature levels etc. They have a big potential for the development of systems because they create real-time data and transit the data via modern technologies using IoT (Lin et al., 2016). The Internet of Things (IoT) has attracted the attention of many governments and corporations because of the potential benefits it may provide. With the help of IoT related technologies such as sensors, wireless communication, smartphones many smart objects are interconnected (Xu et al., 2014). Providing digital services to goods, increasing efficiency and security, expanding storage capacity, reducing processing time, enhancing customer satisfaction, and boosting the quality of life, and are all advantages of the Internet of Things (Salkin et al., 2018).

A great amount of data is gathered every second with the help of IoT, named Big Data. An increasing number of things that can connect each other via communication technologies create the need for the platforms where the gathered data is stored, shared, processed and analyzed. Due to a lack of processing capacity, Big Data cannot be handled and analyzed using conventional software programs or personal PCs (Lee et al., 2014). Business organizations must leverage Cloud Computing services or invest in more contemporary technology like Edge Computing (Bajic et al., 2019). The US National Institute of Standards and Technology (NIST) identifies cloud computing as a model that is designed for convenient, and ubiquitous network access to a shared platform of configurable computing resources (Holligan et al., 2017). A browser, a proxy server, a router, a load balancer, a web server, an application server, a database server, a backup server, and a storage server are typical components of a cloud computing system (Rabai et al., 2013).

Cloud-based platforms have several significant advantages; providing easy accessibility to big data from anytime and anywhere, presenting many statistical and machine learning tools, having the unlimited capacity to store the data getting bigger and bigger. Cloud computing resources are a perfect match for handling large data flows because they enable big data applications to grow to manage their complexity (data volume, variety, and velocity) (Xiang et al., 2016). However, the transition to cloud-based platforms from personal computer platforms brings some risks along with these advantages (Rabai et al., 2013). With their expanding use in real-world circumstances, data privacy, security, and integrity have become more important in such systems. Ransomware, Trojans, and viruses, among other things, have been a threat in this domain, causing malicious destruction, theft, and corruption of data. Ensuring the protection of the integrity of data is critical to the systems' trustworthiness. Blockchain technology has been developed in the IoT area and other real-time systems to assure data security (Gill et al., 2019; Gimenez-Aguilar et al., 2021). Blockchain technology allows for the creation of distributed ledgers to which data may be added (Nakamoto, 2008). One crucial point to keep in mind is that trust in the system is dispersed across all nodes within the system because there is no centralized party exist. As a result, a joint agreement among all or a qualifying subset of the relevant nodes is normally required to add new data to the ledgers (Axon et al., 2017). This technology was initially established as the transaction record for the Bitcoin cryptocurrency. However, to have blockchain technology within a cloud system as distributed ledgers is a great capability to secure the communication between integrated information from attackers and hackers, which can increase the reliability of the cloud computing systems (Gill et al., 2019). Table 2.2 shows the research papers which are published between the years 2008 and 2021 based on Industry 4.0 and technologies related to the fourth industrial revolution.

Table 2.2. Literature Review of the Industry 4.0 Technologies

Author (Year)	Objective of the Study	Industry 4.0 Technologies
Lee, 2008	The aim is to analyze the challenges in designing software computing systems that are object-oriented and to determine whether the contemporary computing and networking technologies are adequate to achieve the full potential of CPS or not.	CPS
Jia et al., 2012	The aim is to examine the uses and problems of RFID technology within the IoT context, as well as the basic principles and technological components of RFID and IoT.	IoT
Kagermann et al., 2013	The aim is to present the vision of the new fourth industrial revolution and explain Industry 4.0 based on related systems; components, technologies and so on. Also, the paper examines the potential and actual benefits with example applications and as well as challenges and barriers of Industry 4.0.	Generic Research, IoT, CPS, Cloud Computing, Big Data Analytics, Simulation, Autonomous Robots, Vertical and Horizontal Integration
Rabai et al., 2013	The aim is to analyze the cloud computing model with a proposed mathematical model to measure the security of cloud service providers and subscribers with the help of some factors determined to quantify the risks associated with the security of their assets rather than quantitative analysis.	Cloud computing, Cybersecurity
Lasi et al., 2014	The aim is to analyze the technological and organizational implications of Industry 4.0 while conceptualizing the term Industry 4.0 for managerial operations.	End to end engineering, MES, ERP

Table 2.2. (cont'd). Literature Review of the Industry 4.0 Technologies

Lee et al., 2014	The aim is to propose a systematic framework including the concepts of CPS and decision support systems to utilize advanced prediction tools which analyze big data to make more informed decisions.	CPS, BDA, Cloud Computing
Xu et al., 2014	The aim is to review researches on IoT, especially focusing on industrial IoT (IIOT) applications.	IIoT, Cloud Computing, Artificial Intelligence
Rüßmann et al., 2015	The aim is to present nine key technological components of Industry 4.0 and managerial priorities and explore potential benefits for manufacturers.	BDA, Autonomous Robots, Simulation, Horizontal and Vertical System Integration, IIOT, Cybersecurity, Cloud Technology, Additive Manufacturing, Augmented Reality (AR)
Weyer et al., 2015	The aim is to present an overview of the initiative called "SmartFactoryKL" located in Germany to identify the contemporary solutions for flexibility, modularity, and standardization of Industry 4.0 under the light of the multi-vendor project.	CPS, IoT, Augmented Reality, Advanced Sensors, RFID
Axon et al., 2017	The aim is to construct a public key infrastructure that is privacy-aware of users based on blockchain to increase the control of users on their key data.	IoT, Blockchain
Bahrin et al., 2016	The aim is to present a review of the contemporary technological advances of industrial robotics applications of Industry 4.0 to provide a comprehensive understanding of future engineering studies.	Automation and Robots

Table 2.2. (cont'd). Literature Review of the Industry 4.0 Technologies

Ivanov et al., 2016	The aim is to present a dynamic model and algorithm for scheduling problems of multi-objective, multi-stage and flexible flow-shop in smart factories for the short term.	Collaborative CPS, Mathematical Models
Lin et al., 2016	The aim is to analyze sensor deployment and sleep schedule in a group-based wireless sensor network along a manufacturing line. The research offers a hybrid harmony search and genetic algorithm that integrates deployment and sleep cycles to save energy.	Sensors, IoT, Genetic Algorithm, Simulation
Prinz et al., 2016	The aim is to describe human-machine interactions in the changing manufacturing environment within the context of Industry 4.0, emphasize the importance of learning factories and present learning modules for the smart factories.	CPS, Simulation, MES
Wang and Wang, 2016	The aim is to introduce technological advances in CPS, digital manufacturing and BDA.	CPS, BDA, IoT, Cloud Computing, Simulation, Cybersecurity, AM, Digital Manufacturing
Xiang et al., 2016	The aim is to examine the challenges and potential solutions for service composition and optimal solution (SCOS) in the future for big data, particularly for optimum selection from large-scale composed service execute pathways (CSEP) and presents a two-phase SCOS technique based on a novel case library method.	Cloud Computing, BDA
Zezulka et al., 2016	The aim is to expose industry experts to a significant new technological phenomenon and to explain the cyber-physical and informatics backdrop of the I4.0 platform, as well as the essential processes in the design and implementation of Industry 4.0 systems.	CPS, BDA, IoT

Table 2.2. (cont'd). Literature Review of the Industry 4.0 Technologies

Holligan et al., 2017	The aim is to examine the existing Product Lifecycle Management (PLM) and Data Management (DM) tools available, as well as the upcoming enabling technologies that will enable the next generation of PLM and DM platforms to assist manufacturers in solving the more complex difficulties posed by globalization.	IoT, Cloud Computing, BDA
Lu, 2017	The aim is to review Industry 4.0 as a paradigm and give an overview of the content, breadth, and conclusions of Industry 4.0 by evaluating the available literature in all of the databases within the Web of Science	CPS, IoT, Cloud Computing, BDA
Meissner et al., 2017	The aim is to discuss decentralized control architectures and the features of Industry 4.0. The various characteristics of techniques are compared to I4.0 goals.	CPS, Sensors, BDA
Nasiri et al., 2017	The aim is to analyze technological innovations for sustainability and circular economy and to review the investigations on the effects of IoT on sustainability.	IoT and related technologies; RFID, Sensors etc., BDA, NFC, Web of Things, Semantic Technologies, IP for smart objects
Kamble et al., 2018	The aim is to propose a systematic literature review on Industry 4.0, human-machine interactions, machine-equipment interactions, Industry 4.0 technologies, and sustainability.	CPS, IoT, BDA, Cloud Manufacturing, Simulation, AR, AM, Robotic Systems, Cybersecurity Horizontal and Vertical Integration

Table 2.2. (cont'd). Literature Review of the Industry 4.0 Technologies

Salkin et al., 2018	The aim is to discuss the underlying importance of design concepts and technology, as well as a conceptual framework for Industry 4.0 creation of smart goods and smart processes.	CPS, IoT, BDA, AI, Embedded Electronics, Cloud Systems, Additive Manufacturing, Horizontal and Vertical Integration, Simulation, AR and VR
Bajic et al., 2019	The aim is to present an analysis of Cloud and Edge Computing with comparisons and to discuss the possible benefits and problems presented by these technologies, as well as their implementations in I4.0.	IoT, BDA, Cloud Computing, and Edge Computing
Gill et al., 2019(1)	The aim is to provide a comprehensive review to integrate past innovations and applications studied in the literature and emerging paradigms and technologies such as IoT, AI, and Blockchain in cloud computing.	Cloud Computing, Fog and Edge Computing, IoT, AI, Blockchain
Gill et al., 2019(2)	The aim is to present a fog-enabled Cloud computing resource management system for smart homes considering and optimizing numerous factors concurrently, including reaction time, network bandwidth, energy usage and latency via a Particle Swarm Optimization (PSO) algorithm.	Cloud Computing, Fog and Edge Computing, IoT, BDA
Manavalan and Jayakrishna, 2019	The aim is to examine the many components of Supply Chain Management (SCM), Enterprise Resource Planning (ERP), IoT, and Industry 4.0, as well as the possible prospects for Industry 4.0 transformation in IoT, integrated sustainable supply chains.	CPS, IoT, Cloud Manufacturing, BDA

Table 2.2. (cont'd). Literature Review of the Industry 4.0 Technologies

Rosa et al., 2019	The aim is to propose a systematic literature review to examine the effects of I4.0 technologies on the Circular Economy and to categorize the relationships using an innovative framework developed to emphasize the connections between I4.0 and CE.	CPS, IoT, BDA, AM, Simulation
Duman and Akdemir, 2021	The aim is to propose a qualitative analysis to assess the impact of Industry 4.0 technology components on company performance in terms of profitability, sales, production amount, production amount per capita, capacity utilization rate, production speed, product quality and production cost	CPS, IoT, BDA, Cloud Computing, AM, Robotic Applications, AR
Gimenez-Aguilar et al., 2021	This survey attempts to offer a complete overview of the strategies and aspects proposed for achieving cybersecurity in blockchain-based systems. The aim is to analyze papers related to the issue and industrial applications.	Blockchain, Cybersecurity
Khan et al., 2021	The aim is to map the broad field of sustainability and look at the important research fields that encompass the aforementioned viewpoints within the I4.0 framework.	CPS, IoT, Big Data, AM, Cybersecurity, Autonomous Robots, AR, Simulation

The first objective of this paper is to figure out how I4.0 technologies can affect CE. Technologies can operate as enablers of I4.0 and I4.0 can operate as a CE enabler, according to one common assertion supported by experts. The relationship between I4.0 and CE was described under these phrases: "Digital CE, digital technologies and CE, digitalization and CE or smart CE" (Alcayaga et al., 2019; Kristoffersen et al., 2020; Ranta et al., 2021; Rosa et al., 2019; Ucar et al., 2020).

In section 2.3, research papers investigating and analyzing the relationships between circular economy and industry 4.0 are presented.

2.3. Industry 4.0 as the Enabler of the Circular Economy

Industry 4.0 and Circular Economy are two important research areas for academicians in the last decade. Many published papers can be found in the literature. However, in the confluence of these areas, there is a lot of room for advancement in terms of new research. Only three papers were published in 2017 according to the research of Tseng et al. (2018) which shows a lot of opportunities to enhance the literature. Since 2018, many important papers combining these two important areas have been published.

Lin, (2018) suggested a data-driven innovation framework for smart production design in the CE of the glass recycling sector to enable Industry 4.0. To develop products to satisfy the needs of users and the industry, the framework consists of experimental data collection and smart decision making. The study shows that a systematic model driven by big data and analytics helps structural decision making in product development according to gathered data of user identity and preferences and requirements to enable CE in the early stages of production. Rajput and Singh (2019) have identified a list of 25 enabling and 15 challenging factors to connect CE and Industry 4.0 according to the literature. Data is collected from online surveys that they made with the expertise of the manufacturing sector and academicians. A combined approach of PCA and DEMATEL are applied; PCA is used to factorize the enabling factors into 6 enabler factors and 4 barriers, and DEMATEL is used to analyze cause-effect relationships of these enablers. The paper discussed that these enablers are a necessity to achieve a closed-loop supply chain, therefore monitoring and optimizing resource efficiency and wastage can be possible. Similarly, Abdul-Hamid et al. (2020) have listed challenging factors of Industry 4.0 in CE according to literature and then applied the Fuzzy Delphi Method to analyze linguistic opinions and rank the alternatives. The most challenging factor is found as "lack of automation system virtualization" followed by "unclear economic benefit of digital investments" and "lack of process design". Ozkan-Ozen et al. (2020) identified Circular Supply Chain and Industry 4.0 barriers separately from existing literature and then specified 13 synchronized barriers that are emerged in CSCs in transition from Industry 3.0 to Industry 3.5-Industry 4.0. Fuzzy Analytical Network Process (ANP) has been used to prioritize the synchronized barriers. The most important barrier is found as "lack of knowledge about data management among stakeholders" followed by "lack of understanding of decentralized organizational structure for supplier collaboration" and "lack of IoT facilities for product tracking and recovery". Yadav et al. (2020) identified 28 challenges that obstruct achieving sustainable supply chain management in the automotive industry according to the literature review. Then, solution measures based on CE and I4.0 are determined according to the literature. A hybrid decision-making approach, BWM and ELECTRE, is used to compute the weights of the challenges and rank the solution measures. The most critical challenges are found as "lack of availability of resources including financial, technical and human", "conflict among product sustainability policy and free trade provisions" and "Poor management commitment for the adoption of sustainability". Chauhan et al, (2021) identified 7 criteria related to intersections between IoT technology and CE to achieve a smart healthcare waste disposal system. DEMATEL method was applied to find out the most important factor as "Digitally connected healthcare centers, waste disposal firms, and pollution control board". Gupta et al., (2021) evaluated manufacturing firms based on practices for sustainable business development formed as 3 groups of criteria and 17 sub-criteria. Industry 4.0 technologies were selected as the first criteria, sustainable and clear production was selected as the second criteria and the circular economy was selected as the third criteria. BWM was used to calculate the weights of criteria and the Combined Compromise Solution (CoCoSo) method was used to identify the best performing alternative among manufacturing companies. Kumar et al., (2021a) identified 15 barriers hindering sustainable operations of supply chains in the context of Industry 4.0 and determined 9 sustainability criteria through literature review and experts' opinions. AHP and ELECTRE methods were used to determine the criteria weights and rank the alternatives respectively. "Lack of skilled workers" is found as the most important barrier to achieving sustainable operations of supply chains. On the other hand, Shayganmehr et al., (2021) proposed and validated a novel framework for assessing the importance of Industry 4.0 enablers to develop a circular economy and cleaner production. 6 main Industry 4.0 enablers and 27 sub-enablers are determined. The fuzzy AHP method was used to determine the weights of these enablers for achieving CE and CP. The framework was applied in an Iranian textile manufacturing company to figure out the outcomes. "Technical Capability" was found as the most important enabler to the better implementation of CE. Technical capability enabler composed of 9 sub-criteria including Industry 4.0 technologies such as IoT, big data, additive manufacturing, block chain, cloud computing. This study also differs from previous studies because I4.0 technologies can be viewed as enablers of implementing CE.

Some of these research papers that are published between the years of 2018 and 2021 which are integrating I4.0 with CE, with the methods used to measure the relationship between these two significant notions are shown below in Table 2.3.

Table 2.3. Research Papers about the Relationship between CE and I4.0

Author (Year)	Objective	Method
Lin, 2018	The aim is to create a product design in user experience-based Industry 4.0 technology for glass recycling under a Circular Economy.	Empirical Analysis
Tseng et al., 2018	The aim is to identify the impact of Big Data on to Circular Economy.	Data-driven analysis method
Rajput and Singh, 2019	The aim is to demonstrate the connection points between Industry 4.0 and the Circular Economy.	Principle Component Analysis (PCA) and DEMATEL
Abdul-Hamid et al., 2020	The aim is to obstruct the challenges of Industry 4.0 in circular economy in the context of the palm oil industry.	Fuzzy Delphi Method
Bag et al., 2020	This aim is to explore how Industry 4.0 assets affect smart logistics and further impact dynamic remanufacturing and green manufacturing capability and, the ultimate impact on trade logistics sustainability.	Partial Least Squares based Structural Equation Modelling
Dev et al., 2020	The aim is to give a roadmap to implement the Industry 4.0 and ReSolve model in the Circular Economy concept in the Logistics sector.	Mathematical Modeling
Fatimah et al., 2020	The aim is to create a smart waste management system by using the technologies of Industry 4.0.	Maturity Model
Rajput and Singh, 2020	The aim is to optimize machine allocations to create an Industry 4.0 model for achieving a Circular Economy.	Mixed-Integer Linear Programming (MILP) Model

Table 2.3. (cont'd). Research Papers about the Relationship between CE and I4.0

Yadav et al., 2020	The aim is to create a framework to overcome the challenges of sustainable supply chain management under Circular Economy and Industry 4.0.	Best-Worst Method (BWM) and ELECTRE
Zhou et al., 2020	The aim is to show the environmental and energy-based Industry 4.0 technologies on economic growth in China.	Mathematical Modeling
Abdul-Hamid et al., 2021	The aim is to examine the drivers of Industry 4.0 within the circular economy and the nexus between them from an environmental modernization theory viewpoint.	Fuzzy Delphi Method
Bag et al., 2021	The aim is to create a hypothetical demonstration connecting key assets for Industry 4.0 adoption that are essential to driving innovative progress; and its impact on sustainable production and circular economy capabilities.	PLS-SEM technique
Chauhan et al., 2021	The aim is to meet the healthcare waste yield through a circular economy point of view to achieve the maximum maintenance of material while containing its negative effect on the environment and society.	DEMATEL
Dahmani et al., 2021	The aim is to investigate the relationship between lean eco-design and Industry 4.0 techniques for designing eco-efficient products based on the literature.	Lean design, Eco-design
Dantas et al., 2021	The aim is to identify how to combine Industry 4.0 technologies and Circular Economy practices to achieve Sustainable Development Goals.	Systematic Literature Review
Gupta et al., 2021	The aim is to develop a framework to assess the sustainability performances of production firms according to the concepts of Industry 4.0 and Circular Economy.	Best-Worst Method (BWM) and Delphi Method

Table 2.3. (cont'd). Research Papers about the Relationship between CE and I4.0

Kumar et al., 2021a	The aim is to analyze the barriers of sustainable supply chain operations under Circular Economy and Industry 4.0.	Analytic Hierarchy Process (AHP) and Elimination and Choice Expressing Reality (ELECTRE)
Kumar et al., 2021b	The aim is to identify the barriers of Circular Economy and Industry 4.0 in the Indian agriculture supply chain.	Interpretive structural modelling (ISM) and Analytic Network Process (ANP)
Laskurain-Iturbe et al., 2021	The aim is to identify the effects of Industry 4.0 on the Circular Economy.	Case Study based on a Survey
Mastos et al., 2021	The aim is to demonstrate an Industry 4.0 application for the circular supply chain management.	ReSOLVE model
Shayganmehr et al., 2021	The aim is to create a framework to show the enablers of Industry 4.0 to achieve a Circular Economy.	Fuzzy Analytic Hierarchy Process (AHP)
Spaltini et al., 2021	The aim is to create a framework for understanding the relation between Circular Economy and Industry 4.0.	Multi-Objective Integer Linear Programming (MOILP)

Most of the above-mentioned studies investigate the role of Industry 4.0 in enabling CE. Digital technologies (DTs) that can affect the CE or circularity performance of manufacturing organizations are investigated to answer the first research question of this paper.

In section 2.3.1, the research gaps and problem definition of this paper are presented.

2.3.1. Research Gaps and Problem Definition

Industry 4.0 is a comprehensive term for technological improvements that increase the efficiency and performance of the supply chain in terms of the circular economy. Digital technologies are the main drivers of Industry 4.0 (Rosa et al., 2019). A limited number of studies have investigated the positive relationship between implementing these technologies such as Internet of Things, Big Data and Analytics or 3D Printing etc. and enabling CE (Rajput and Singh, 2019; Rosa et al., 2019; Gupta et al., 2021; Shayganmehr et al., 2021). Only one study focused on prioritizing the I4.0 enablers including subjective concepts to implement and enhance circular economy (Shayganmehr et al., 2021). No studies examine and prioritize technology drivers of Industry 4.0 that affect the circularity performance of manufacturing organizations within the boundaries of the triple bottom line concept. Therefore, the main aim of this study is to assess and prioritize the performance of Industry 4.0 technologies in enabling a circular economy. Eventually, the proposed framework of this study is presented in chapter 3.

CHAPTER 3

THE PROPOSED FRAMEWORK

In this part, a framework is developed to show the flow of the study for assessing the priority of I4.0 technologies in terms of circularity performance of the manufacturing organizations. A detailed literature review is conducted to present the relationships between Industry 4.0 and Circular Economy concepts and to determine I4.0 technologies that have effects on the circularity performance of organizations. The criteria set is assessed according to the literature review and validated by 25 experts. These industry experts are members of the board of directors and other managers of manufacturing organizations. The criteria list includes 3 main criteria and 17 sub-criteria. Economic, social, and environmental criteria are determined as the main criteria according to Triple-Bottom-Line dimensions. Internet of Things (IoT), Cyber-Physical Systems (CPS), Big Data Analytics (BDA), Cloud Computing, Additive Manufacturing (AM) or in other words 3D printer, Autonomous Robots, Augmented Reality (AR), Virtual Reality (VR) and Simulation (Rüßmann et al., 2015) are determined as alternatives. Each alternative is evaluated according to criteria to select the best technology to increase the circularity performance of organizations. Due to high ambiguity in subjective concepts, the Fuzzy Best-Worst Method (BWM) is applied to determine the weights of criteria. Since BWM is a vector-based method, to apply this method, fewer comparisons are needed rather than in Analytical Hierarchy Process (AHP) or Analytical Network Process (ANP) (Gupta et al., 2021). After determining the weights of criteria, the Fuzzy Vikor method is applied to evaluate the alternatives.

Figure 1 presents the proposed framework to show the flow of the study step by step.

Fig. 3.1. The Proposed Framework

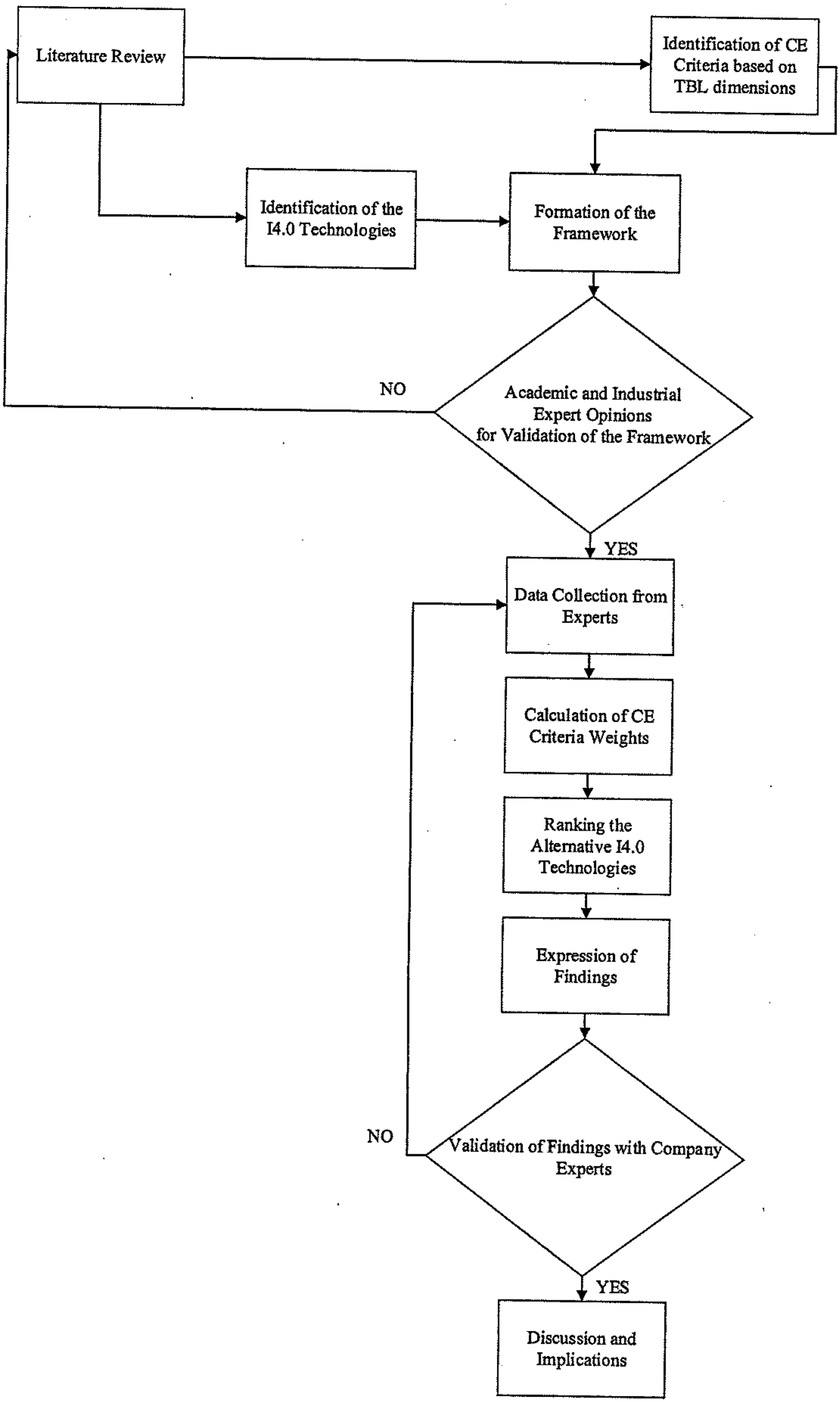

Table 3.1 shows the criteria set and the expressions of the criteria.

Table 3.1. Criteria Set

Criteria Set		
Economic	**Reference**	**Detailed expressions**
Market Share	Sanders et al., 2016	This factor describes created market share through applying innovative and smart technologies.
Return on Investment	Experts' opinions from BoD	Applying I4.0 technologies requires investment in smart machinery, equipment, system, software etc. This factor describes the ratio of the return gained by the investment to the cost of the investment.
Loss of Efficiency	Braccini et al., 2018	Applying I4.0 technologies may decrease the loss of efficiency through optimization of processes, decreasing quality defects, and maximization of material utilization with lesser waste generation.
Operation Cost	Angioletti et al., 2017	This factor describes the cost that occurred in sustainable supply chain operations. Applying I4.0 technologies may decrease the operation cost of the company.
Maintenance Cost	Angioletti et al., 2017	This factor describes the cost occurred in machinery and equipment. Applying I4.0 technologies may decrease maintenance costs.

Table 3.1. (cont'd). Criteria Set

Payback Period	Experts' opinions from BoD	Applying I4.0 technologies requires investment. This factor describes the ratio of the cost of initial investment to the annual cash inflow.
Energy Cost	Ribeiro et al., 2020; Angioletti et al., 2017; Thiede et al., 2018	This factor describes the cost of energy resources. Applying I4.0 technologies may decrease energy costs through increasing resource efficiency.
Personnel Cost	Experts' opinions from BoD	This factor describes the cost of the workforce. Applying I4.0 technologies may change personnel costs by increasing efficiency in processes.
Social		
Generating Job Opportunities	Braccini et al., 2018; Sagnak et al., 2021	This factor describes the new job opportunities created by applying I4.0 technologies in the supply chain.
Work Safety	Oesterreich and Teuteberg, 2016; Pham et al., 2019	This factor describes safe working environments for the employees. Applying I4.0 technologies may decrease the number and dangerous level of safety incidents.
Education and Qualification	Oesterreich and Teuteberg, 2016; Beier et al., 2017; Braccini et al., 2018	This factor describes the new qualifications required to use I4.0 technologies effectively. Applying I4.0 technologies may create educated and qualified roles for the workforce.

Table 3.1. (cont'd). Criteria Set

Society Benefit	Beier et al., 2017; Braccini et al., 2018; Khan et al., 2021	This factor describes generic society benefits including improved workforce conditions, opportunity to work remotely, reduced workloads etc.
Employee Engagement	Oesterreich and Teuteberg, 2016; Sanders et al., 2016	This factor describes employee participation in the operations of the supply chain. Industry 4.0 may increase work satisfaction, leadership roles, professional growth which leads to employee engagement.
Job Reduction	Braccini et al., 2018	This factor describes the jobs and roles which are not required anymore. Applying innovative I4.0 technologies requires new skills and roles for the workforce and may eliminate some roles.
Environmental		
Greenhouse Gas Emission	Pham et al., 2019; Oláh et al., 2020; Ribeiro et al., 2020; Khan et al., 2021	This factor describes the emissions created by industrial operations. Applying I4.0 technologies may decrease emissions through increased energy efficiency, recycling activities and monitoring.
Pollution Prevention and Control	Oláh et al., 2020; Khan et al., 2021; Sagnak et al., 2021	This factor describes the pollution created by industrial operations. Applying I4.0 technologies may decrease pollution by effectively monitoring and controlling.

Table 3.1. (cont'd). Criteria Set

Waste Management	Oláh et al., 2020; Ribeiro et al., 2020; Khan et al., 2021	This factor describes waste created by industrial and supply chain operations. Applying I4.0 technologies decrease waste amount through increasing resource efficiency, reuse, remanufacturing, and recycling activities and green operations.

In the next chapter 4, research methodology with the applied methods; fuzzy BWM and fuzzy VIKOR is introduced.

CHAPTER 4
RESEARCH METHODOLOGY

Multi-criteria decision-making (MCDM) methodologies are used to handle a variety of decision-making issues. This strategy may be used in a variety of fields, including engineering, logistics, supply chain management, manufacturing, healthcare, and sustainable development, among others. MDCM approaches have been proven to be effective in solving complicated multi-criteria issues by several studies. MCDM is concerned with picking the best option from a set of probable options based on a set of criteria or attributes.

4.1. Fuzzy Best-Worst Method

Analytic hierarchy process (AHP), analytic network process (ANP), and simple multi-attribute rating technique (SMART) are the most frequent ways for weighing the criteria. Rezaei (2015) has also invented a new approach named the Best Worst Method (BWM). The weights of decision criteria are determined by comparing the most important and least important criterion to the other decision criteria in BWM. BWM was chosen as the approach to employ in this thesis since it requires fewer comparisons than AHP because it is a vector-based MCDM method. Only 2n-1 comparisons are required to apply BWM while AHP needs n(n-1)/2 comparisons (Gupta et al., 2021). Because there are fewer comparisons, the results may be found in less time and with less difficulty. Furthermore, since the BWM approach employs a mathematical model, it provides robust outcomes rather than other methods.

To calculate decision criteria weights, BWM has five steps to follow (Karimi et al., 2020; Xu et al., 2021; Mostafaeipour et al., 2021; Sagnak et al., 2021; Mohtashami, 2021):

Step 1: Create a set of decision criteria (c_1, c_2,..., c_n).

Step 2: Create a set for each of the most and least important criteria. The most significant and least important criteria are denoted by the letters c_B and c_W, respectively.

Step 3: Compare and contrast the most significant criterion with the others. Because decision-makers rely on linguistic expressions, they should be transformed to fuzzy numbers. Then, using fuzzy numbers, compare the choice criteria. For each value, this fuzzy pairwise comparison should be scored between 1 and 9. The power of the most significant criterion over the other criteria is represented by these ranks. This phase will result in the Best-to-Others vector. $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$ can be used to represent the Best-to-Others vector. a_{Bj} reflects the fuzzy force of the most significant criteria over criterion j because A_B is a fuzzy vector. For instance, a_{BB} = (1, 1, 1).

Step 4: Compare and contrast the least significant criterion with the others. Likewise, verbal assertions of the decision-makers should be transformed to fuzzy integers and the decision criteria compared. Numerical values between 1 and 9 are assessed to rank the pairwise comparison and each criterion has a force over the least important criterion according to assessed values. This phase will result in the Others-to-Worst vector, which can be shown as $A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T$. a_{iW} indicates the fuzzy force of criterion j over the least important criterion, since A_w expresses a fuzzy vector. For instance, a_{WW} = (1, 1, 1).

Step 5: Determine the best fuzzy weights $(\widetilde{w_1^*}, \widetilde{w_2^*}, \dots, \widetilde{w_n^*})$. For each set of criteria, the ideal fuzzy weights are $\widetilde{w}_B/\widetilde{w}_j = \tilde{a}_{Bj}$ and $\widetilde{w}_j/\widetilde{w}_W = \tilde{a}_{jW}$. These should identify the greatest absolute differences $\left|\frac{\widetilde{w}_B}{\widetilde{w}_j} - \tilde{a}_{Bj}\right|$ and $\left|\frac{\widetilde{w}_j}{\widetilde{w}_W} - \tilde{a}_{jW}\right|$ for all j values, with all j values entered into the minimization model. The fuzzy triangular numbers $\widetilde{w}_B$, $\widetilde{w}_W$ and $\widetilde{w}_j$ are fuzzy triangular numbers. All variables should have a value of 0 or more. The total weight should be exactly one. These limitations will be used to develop the mathematical model below.

$$\text{minimize} \qquad \max\left\{\left|\frac{\widetilde{w}_B}{\widetilde{w}_j} - \tilde{a}_{Bj}\right|, \left|\frac{\widetilde{w}_j}{w_W} - \tilde{a}_{jW}\right|\right\}$$

$$s.t.\begin{cases} \sum_{j=1}^{n} R(\widetilde{w}_j) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \dots, n \end{cases}$$

$$\widetilde{w}_B = (l_B^w, m_B^w, u_B^w), \quad \widetilde{w}_W = (l_W^w, m_W^w, u_W^w), \quad \widetilde{w}_j = \left(l_j^w, m_j^w, u_j^w\right),$$

Assume that this model may be transformed into the restricted mathematical model below:

minimize $\tilde{\xi}$

$$s.t. \begin{cases} \sum_{j=1}^{n} R\left(\widetilde{w}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ \left|\dfrac{\widetilde{w}_B}{\widetilde{w}_j} - \tilde{a}_{Bj}\right| \le \tilde{\xi} \\ \left|\dfrac{\widetilde{w}_j}{w_W} - \tilde{a}_{jW}\right| \le \tilde{\xi} \\ \quad l_j^w \ge 0 \\ \quad j = 1, 2, \dots, n \end{cases}$$

$\tilde{\xi} = (l^{\xi}, m^{\xi}, u^{\xi})$.

It can be assumed that $\tilde{\xi}^* = (k^*, k^*, k^*)$ and $k^* \le l^{\xi}$ when $l^{\xi} \le m^{\xi} \le u^{\xi}$. The mathematical model can be transformed to

minimize $\tilde{\xi}$

$$
s.t.\begin{cases}
\sum_{j=1}^{n} R(\widetilde{w}_j) = 1 \\
l_j^w \leq m_j^w \leq u_j^w \\
\left| \dfrac{l_B^w, m_B^w, u_B^w}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\
\left| \dfrac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\
l_j^w \geq 0 \\
j = 1, 2, \dots, n
\end{cases}
$$

The results of the mathematical model will represent the optimal fuzzy weights.

4.2. Fuzzy VIKOR Method

The VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) method, as one of the MCDM methodologies, is a method developed by Opricovic in 1998 (Opricovic, 1998). VIKOR technique supports decision-makers in prioritizing alternatives based on operational factors. The VIKOR technique is designed to be a compromise approach that determines how near an alternative is to the optimal solution. As a result, the most optimum solution will be the one that is closest to the perfect solution while making certain sacrifices. In this study, Fuzzy Vikor is applied to prioritize the I4.0 technologies organized as the alternatives. Table 4.1 shows these technologies and related literature reviews.

Table 4.1. Alternative I4.0 Technologies

I4.0 Technologies	Reference
Internet of Things (IoT)	Rüßmann et al., 2015; Braccini et al., 2018; Moktadir et al., 2018; Pham et al., 2019; Rosa et al., 2019; Duman and Akdemir, 2021; Shayganmehr et al., 2021
Big Data Analytics	Rüßmann et al., 2015; Braccini et al., 2018; Moktadir et al., 2018; Pham et al., 2019; Rosa et al., 2019; Duman and Akdemir, 2021; Shayganmehr et al., 2021
Cloud Computing	Rüßmann et al., 2015; Braccini et al., 2018; Moktadir et al., 2018; Pham et al., 2019; Duman and Akdemir, 2021; Shayganmehr et al., 2021
Additive Manufacturing	Rüßmann et al., 2015; Braccini et al., 2018; Moktadir et al., 2018; Nascimento et al., 2018; Rosa et al., 2019; Duman and Akdemir, 2021; Shayganmehr et al., 2021
Autonomous Robots	Rüßmann et al., 2015; Braccini et al., 2018; Moktadir et al., 2018; Duman and Akdemir, 2021;
Augmented Reality	Rüßmann et al., 2015; Moktadir et al., 2018; Duman and Akdemir, 2021;
Virtual Reality	Rüßmann et al., 2015; Moktadir et al., 2018;
Cyber-Physical Systems	Rüßmann et al., 2015; Moktadir et al., 2018; Pham et al., 2019; Rosa et al., 2019; Duman and Akdemir, 2021;
Simulation	Rüßmann et al., 2015; Moktadir et al., 2018; Rosa et al., 2019

Opricovic presented a fuzzy logic adaptation for the VIKOR approach in 2007. The following are the five steps in the fuzzy VIKOR approach:

Step 1: Establishing a fuzzy decision matrix consisting of triangular fuzzy numbers.

A fuzzy multi-criteria decision making problem can be defined for m alternatives and n criteria as a matrix format as shown below:

$$\begin{array}{c} \\ a_1 \\ \vdots \\ a_m \end{array} \begin{pmatrix} c_1 & \cdots & c_n \\ x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

Step 2: Calculation of the fuzzy best value and the fuzzy worst value of all criteria.

If higher values are desirable for a criterion, then the criterion is beneficial (e.g., Return on Investment).

If lower values are desirable for a criterion, then the criterion is non-beneficial (e.g., Job Reduction).

$BC = The\ beneficial\ criteria$

$NBC = The\ Non - beneficial\ criteria$

$X_i^+ = (MaxX_{ij}$ if $j \in BC; MinX_{ij}$ if $j \in NBC) \quad i = 1,..,m \ , \ j = 1,..,n$

$X_i^- = (MinX_{ij}$ if $j \in BC; MaxX_{ij}$ if $j \in NBC) \quad i = 1,..,m \ , \ j = 1,..,n$

Step 3: Computing the S_i and R_i values.

S_i is the separation measure of a_i from fuzzy best value.

R_i is the separation measure of a_i from fuzzy worst value.

$S_i = \sum_{j=1}^{n}(W_j * \frac{X_i^+ - X_{ij}}{X_i^+ - X_i^-})$ for all l, m, u.

$R_i = Max_j \ (W_j * \frac{X_i^+ - X_{ij}}{X_i^+ - X_i^-})$ for all l, m, u.

Step 4: Calculation of S^*, S^-, R^*, R^- values.

$S^* = MinS_i$ for all l, m, u.

$S^- = MaxS_i$ for all l, m, u.

$R^* = MinR_i$ for all l, m, u.

$R^- = MaxR_i$ for all l, m, u.

Step 5: Calculation of Q_i values for each alternative.

$Q_i = v * (S_i - S^*) / (S^- - S^*) + (1 - v) * (R_i - R^*) / (R^- - R^*)$ for all l, m, u.

where v can be varied from 0 and 1. Usually, $v = 0{,}5$ is preferred.

Step 6: Defuzzification of Q_i values for each alternative.

Deffuzified Q_i values $= \frac{l}{6} + 4 * \frac{m}{6} + \frac{u}{6}$ for all alternatives.

Step 7: Sorting Q_i values from lowest value to highest value for each alternative to determine the rank of alternatives. The alternative which has the lowest Q_i value is selected as the best alternative.

CHAPTER 5
THE CASE STUDY

This case study introduces the implementation of the methodology to analyze how I4.0 technologies affect CE. The criteria set is defined as 3 main criteria, and 17 sub-criteria as the dimensions of TBL. 3 main criteria include economic, social and environmental criteria. 9 different I4.0 technologies are determined as the alternative solutions to match the needs of the criteria. Alternatives are IoT, BDA, Cloud Computing, AM, Autonomous Robots, AR, VR, CPS and Simulation. Alternatives are determined according to a detailed literature review as shown in Table 5 above.

This case study is applied in ABC manufacturing organization operating in the poultry industry in Izmir. The company has over 3500 employees employed in its integrated facilities. The main facilities are 11 breeding facilities, 3 incubation facilities, 1 slaughterhouse, 1 further processing plant, 1 feed mill, and 3 regional directorates and sub-regional directorates. The company is also working with 3rd party organizations for the transportation of the products and over 500 hencoops. The organization has a strong capital structure since the debt ratio is too low and EBITDA and growth ratio in 2020 is relatively high among other organizations operating in the same industry. Also, the company is still investing in technologies in transition to I4.0 and the circular business model. Measuring sustainability performance of the digital transition of the company was an important problem to help the strategic decisions for next years. With the permission and approval of the Board of Directors, data were collected through pairwise comparisons with 5 experts from the organization. These experts are the Chief Executive Officer, Chief Financial Officer, Production Director, Live Production Director, and Quality Management Manager of the company. All experts have experience more than 10 years in the same industry.

The proposed framework is applicable to similar studies to investigate the relationship between I4.0 technologies and CE principles organized as TBL dimensions. However, results are unique for this company and cannot be generalized.

In the following section 5.1, the implementation of the study is expressed step by step according to the presented framework.

5.1. Implementation

First of all, a set of criteria is created according to the literature review and validated by 25 experts as mentioned before. This criteria set can be seen in table 3.1.

For the calculations of weights for sub-criteria, the best criteria and the worst criteria were determined. All the experts agreed that the best criterion is "return on investment", and the worst criterion is "job reduction". Then, a survey is created for getting the weights of the criteria and given to five experts from the poultry industry. This survey can be seen in table 5.1.

Table 5.1. Survey for the Criteria Weights

Expert 1	Market Share	Return on Investment	Loss of Efficiency	Operation Cost	Maintenance Cost	Payback Ratio	Energy Cost	Personnel Cost
Market Share								
Return on Investment								
Loss of Efficiency								
Operation Cost								
Maintenance Cost								
Payback Ratio								
Energy Cost								
Personnel Cost								
Generating Job Opportunities								
Work Safety								
Education and Qualification								
Society Benefit								
Employee Engagement								
Job Reduction								
Greenhouse Gas Emission								
Pollution Prevention and Control								
Waste Management								

Table 5.1. (cont'd). Survey for the Criteria Weights

Expert 1	Generating Job Opportunities	Work Safety	Education and Qualification	Society Benefit	Employee Engagement	C14 Job Reduction	Greenhouse Gas Emission	Pollution Prevention and Control	Waste Management
Market Share									
Return on Investment									
Loss of Efficiency									
Operation Cost									
Maintenance Cost									
Payback Ratio									
Energy Cost									
Personnel Cost									
Generating Job Opportunities									
Work Safety									
Education and Qualification									
Society Benefit									
Employee Engagement									
Job Reduction									
Greenhouse Gas Emission									
Pollution Prevention and Control									
Waste Management									

Then, a ranking scale is defined according to triangular fuzzy numbers. The ranking scale can be seen in table 5.2.

Table 5.2. Ranking Scale

Linguistic Measurement Scale	Equivalent Numbers	Triangular Fuzzy Numbers
Equal Importance	1	1,1,3
Weakly More Important	3	1,3,5
Fairly More Important	5	3,5,7
Strongly More Important	7	5,7,9
Absolutely More Important	9	7,9,9

According to the given scale, experts filled the required blank parts of the survey. The pairwise comparisons data of expert 1 can be seen in Appendix. After this step, two main matrices are created which are "Best-to-Others" and "Others-to-Worst" matrices. These matrices can be seen in tables 5.3 and 5.4.

Table 5.3. Best-to-Others Matrix

Best to Others	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**	**a8**	**a9**	**a10**	**a11**	**a12**	**a13**	**a14**	**a15**	**a16**	**a17**
	5	1	7	3	7	3	7	9	9	5	3	9	9	9	7	3	7
	5	1	5	7	9	1	9	5	5	7	1	9	7	9	5	5	3
a2	5	1	7	9	9	5	7	3	1	7	1	5	5	9	5	3	3
	9	1	1	3	5	7	7	9	9	7	9	5	5	9	3	3	3
	7	1	9	9	7	9	9	9	3	1	1	7	9	9	7	3	7

Table 5.4. Others-to-Worst Matrix

Others to Worst	**a13**				
a1	5	5	7	5	1
a2	9	9	9	9	9
a3	5	3	7	5	3
a4	3	7	7	9	9
a5	7	7	1	3	7
a6	9	9	5	7	7
a7	7	5	7	7	7
a8	5	7	9	5	5
a9	3	3	9	3	9
a10	7	1	5	3	9
a11	9	9	3	3	9
a12	3	5	3	5	7
a13	7	1	3	7	7
a14	1	1	1	1	1
a15	5	5	5	9	9
a16	7	7	7	9	9
a17	7	7	7	9	9

The next step is converting these statements to fuzzy numbers according to table 5.2.

The converted "Best-to-Others" and "Others-to-Worst" matrices can be seen in tables 5.5 and 5.6.

Table 5.5. Converted Best-to-Others Matrix

Best to Others	a1			a2			a3			a4			a5		
a2	3	5	7	1	1	3	5	7	9	1	3	5	5	7	9
	3	5	7	1	1	3	3	5	7	5	7	9	7	9	9
	3	5	7	1	1	3	5	7	9	7	9	9	7	9	9
	7	9	9	1	1	3	1	1	3	1	3	5	3	5	7
	5	7	9	1	1	3	7	9	9	7	9	9	5	7	9

Table 5.5. (cont'd). Converted Best-to-Others Matrix

a6			a7			a8			a9			a10			a11		
1	3	5	5	7	9	7	9	9	7	9	9	3	5	7	1	3	5
1	1	3	7	9	9	3	5	7	3	5	7	5	7	9	1	1	3
3	5	7	5	7	9	1	3	5	1	1	3	5	7	9	1	1	3
5	7	9	5	7	9	7	9	9	7	9	9	5	7	9	7	9	9
7	9	9	7	9	9	7	9	9	1	3	5	1	1	3	1	1	3
a12			a13			a14			a15			a16			a17		
7	9	9	7	9	9	7	9	9	5	7	9	1	3	5	5	7	9
7	9	9	5	7	9	7	9	9	3	5	7	3	5	7	1	3	5
3	5	7	3	5	7	7	9	9	3	5	7	1	3	5	1	3	5
3	5	7	3	5	7	7	9	9	1	3	5	1	3	5	1	3	5
5	7	9	7	9	9	7	9	9	5	7	9	1	3	5	5	7	9

Table 5.6. Converted Others-to-Worst Matrix

Others to Worst	a13			a13			a13			a13			a13		
a1	3	5	7	3	5	7	5	7	9	3	5	7	1	1	3
a2	7	9	9	7	9	9	7	9	9	7	9	9	7	9	9
a3	3	5	7	1	3	5	5	7	9	3	5	7	1	3	5
a4	1	3	5	5	7	9	5	7	9	7	9	9	7	9	9
a5	5	7	9	5	7	9	1	1	3	1	3	5	5	7	9
a6	7	9	9	7	9	9	3	5	7	5	7	9	5	7	9
a7	5	7	9	3	5	7	5	7	9	5	7	9	5	7	9
a8	3	5	7	5	7	9	7	9	9	3	5	7	3	5	7
a9	1	3	5	1	3	5	7	9	9	1	3	5	7	9	9
a10	5	7	9	1	1	3	3	5	7	1	3	5	7	9	9
a11	7	9	9	7	9	9	1	3	5	1	3	5	7	9	9
a12	1	3	5	3	5	7	1	3	5	3	5	7	5	7	9
a13	5	7	9	1	1	3	1	3	5	5	7	9	5	7	9

Table 5.6. (cont'd.) Converted Others-to-Worst Matrix

a14	1	1	3	1	1	3	1	1	3	1	1	3	1	1	3
a15	3	5	7	3	5	7	3	5	7	7	9	9	7	9	9
a16	5	7	9	5	7	9	5	7	9	7	9	9	7	9	9
a17	5	7	9	5	7	9	5	7	9	7	9	9	7	9	9

After this step, these five different surveys of experts should be combined. To combine these values, the following formula is used:

$x^* = (\prod_{j=1}^{5} x_{i,j})^{1/5}$

By using the formula combined matrices are set and can be seen in tables 5.7 and 5.8.

Table 5.7. Combined Best-to-Others Matrix

Best to Others	a2		
a1	3.936283	6.015201	7.740265
a2	1	1	3
a3	3.499708	4.663175	6.870516
a4	3.004922	5.515249	7.114322
a5	5.164776	7.236528	8.558815
a6	2.536517	3.936283	6.108504
a7	5.720332	7.740265	9
a8	4.003899	6.423382	7.609552
a9	2.713085	4.139189	6.108504
a10	3.271947	4.434583	6.870516
a11	1.475773	1.933182	4.139189
a12	4.663175	6.765573	8.139256
a13	4.663175	6.765573	8.139256
a14	7	9	9
a15	2.954177	5.164776	7.236528
a16	1.245731	3.322699	5.348052
a17	1.903654	4.21029	6.325269

Table 5.8. Combined Others-to-Worst Matrix

Others to Worst	a13		
a1	2.667269	3.876159	6.213432
a2	7	9	9
a3	2.141127	4.359695	6.433921
a4	4.14598	6.533719	8.001806
a5	2.626528	4.003899	6.423382
a6	5.164776	7.236528	8.558815
a7	4.514402	6.544439	8.558815
a8	3.936283	6.015201	7.740265
a9	2.177906	4.655537	6.325269
a10	2.536517	3.936283	6.108504
a11	3.214096	5.799546	7.114322
a12	2.141127	4.359695	6.433921
a13	2.626528	4.003899	6.423382
a14	1	1	3
a15	4.21029	6.325269	7.740265
a16	5.720332	7.740265	9
a17	5.720332	7.740265	9

After creating these combined "Best-to-Others" and "Others-to-Worst" matrices set, the next step is to calculate the weights with the mathematical model below using IBM ILOG Optimization Studio Software. Figure 5.1 shows the model set into the software.

Figure 5.1. BWM Model

```
int J = ...;
range j = 1..J;

float d1[j] = ...;
float d2[j] = ...;
float d3[j] = ...;
float e1[j] = ...;
float e2[j] = ...;
float e3[j] = ...;

dvar float+ L[j] ;
dvar float+ M[j] ;
dvar float+ U[j] ;
dvar float+ k;

minimize k;

subject to{

  forall (b in j)
    abs(L[2] - d1[b] * U[b]) <= k ;

  forall (b in j)
    abs(M[2] - d2[b] * M[b]) <= k;

  forall (b in j)
    abs(U[2] - d3[b] * L[b]) <= k;

  forall (b in j)
    abs(L[b] - e1[b] * U[13]) <= k;

  forall (b in j)
    abs(M[b] - e2[b] * M[13]) <= k;

  forall (b in j)
    abs(U[b] - e3[b] * L[13]) <= k;

   (sum(b in j) L[b]/6) + (sum(b in j) (M[b]*4)/6) + (sum(b in j) U[b]/6) == 1;

   forall (b in j)
    L[b] >= 0;
   forall (b in j)
    L[b] <= M[b];
   forall (b in j)
    M[b] <= U[b];
   k >= 0 ;

}
```

The combined matrix data is imported from Microsoft Excel to the software for the calculation of the weights. The data file of the model is shown below in Figure 5.2.

Figure 5.2. Data for Fuzzy Weight Calculations

```
J=17;
SheetConnection sheet("BWM and Vikor.xlsx");

d1 from SheetRead(sheet, "'Model'!A2:A18");
d2 from SheetRead(sheet, "'Model'!B2:B18");
d3 from SheetRead(sheet, "'Model'!C2:C18");

e1 from SheetRead(sheet, "'Model'!D2:D18");
e2 from SheetRead(sheet, "'Model'!E2:E18");
e3 from SheetRead(sheet, "'Model'!F2:F18");

L to SheetWrite (sheet, "'Model'!J2:J18");
M to SheetWrite (sheet, "'Model'!K2:K18");
U to SheetWrite (sheet, "'Model'!L2:L18");
```

Fuzzy criteria weights are calculated by running the model. The results can be seen in Table 5.9.

Table 5.9. Criteria Weights

Weights	L	M	U
a1	0.035201	0.045297	0.046146
a2	0.090823	0.181645	0.181645
a3	0.039658	0.051903	0.051903
a4	0.038298	0.049403	0.060449
a5	0.031835	0.03517	0.03517
a6	0.044605	0.06922	0.071612
a7	0.030274	0.031754	0.031754
a8	0.035806	0.042418	0.045367
a9	0.044605	0.065826	0.066951
a10	0.039658	0.055516	0.055516
a11	0.065826	0.123085	0.123085
a12	0.033476	0.038953	0.038953
a13	0.014322	0.01873	0.023407
a14	0.025949	0.025949	0.025949
a15	0.037652	0.052755	0.061488
a16	0.050947	0.082002	0.145814
a17	0.043076	0.064715	0.095419

This calculation was the last step in the BWM method. Criteria weights are calculated and the next step is ranking the alternatives using the Fuzzy VIKOR method. Another survey was created for ranking the alternatives. Pairwise comparisons of each alternative overall criteria set one by one were made by the same five experts in the first phase. The blank survey given to the experts for pairwise comparisons can be seen in Appendix. Pairwise comparison data of expert 1 can be seen in Appendix.

Experts filled the survey with linguistic scales shown in Table 5.2. These linguistic variables were converted to triangular fuzzy numbers. All these converted matrices for 5 experts can be seen in Appendix.

After this step, the five surveys were combined by taking the averages of all rows. The combined matrix can be seen in Table 5.10.

Table 5.10. The Combined Matrix

Alternatives/Criteria	u1			u2			v1			v2			v3			v4			v5			v6		
Internet of Things (IoT)	6,12	8,14	9	4,83	6,88	8,56	4,36	6,43	8,14	3,68	5,72	7,74	3,94	6,02	7,74	4,08	6,12	8,14	5,16	7,24	8,56	4,66	6,77	8,14
Big Data Analytics	4,83	6,88	8,56	5,52	7,61	8,56	5,16	7,24	8,56	4,51	6,54	8,56	4,66	6,77	8,14	3,94	6,02	7,74	4,66	6,77	8,14	5,72	7,74	9
Cloud Computing	2,95	5,16	7,24	2,54	4,9	6,77	1,9	4,21	6,33	2,81	5,24	7,11	2,81	5,24	7,11	3,94	6,02	7,74	5,52	7,61	8,56	2,14	4,36	6,43
Additive Manufacturing	2,67	4,83	6,88	2,67	3,88	6,21	2,95	5,16	7,24	2,95	5,16	7,24	2,14	3,5	5,81	2,95	5,16	7,24	2,37	3,74	6,11	1,55	2,95	5,16
Autonomous Robots	2,14	2,81	5,24	1,9	4,21	6,33	1,9	3,38	5,71	1,9	3,38	5,71	2,63	4,99	7,11	1,93	4,08	6,12	1,38	3,55	5,62	3,68	5,72	7,74
Augmented Reality	1	1,55	3,68	1,25	2,14	4,36	1,55	2,37	4,66	1,55	3,68	5,72	1,25	2,14	4,36	1	1,55	3,68	1	1,55	3,68	1	1,55	3,68
Virtual Reality	1,55	1,9	4,21	1,55	2,95	5,16	1,55	2,37	4,66	1	1,55	3,68	1,25	1,72	3,94	1,55	2,95	5,16	1,25	2,67	4,83	1,25	2,14	4,36
Cyber Physical Systems	1,72	3,94	6,02	3,5	5,81	7,61	2,71	5,16	6,77	2,95	5,16	7,24	3,16	5,43	7,24	4,36	6,43	8,14	5,35	7,36	9	2,95	5,16	7,24
Simulation	1,72	3,94	6,02	1,72	2,54	4,9	1	1,93	4,08	1,25	2,14	4,36	1,9	3,38	5,71	2,67	4,83	6,88	2,63	4,99	7,11	3,27	4,43	6,87

Alternatives/Criteria	u3			u4			u5			u6			u7			v7			v8			u8			u9		
Internet of Things (IoT)	4,99	7,11	8,14	5,16	7,24	8,56	5,72	7,74	9	6,54	8,56	9	5,16	7,24	8,56	5,72	7,74	9	3,94	6,02	7,74	4,36	6,43	8,14	4,36	6,43	8,14
Big Data Analytics	3,94	6,02	7,74	5,52	7,61	8,56	7	9	9	5,16	7,24	8,56	3,94	6,02	7,74	4,66	6,77	8,14	3,94	6,02	7,74	4,21	6,33	7,74	3,94	6,02	7,74
Cloud Computing	1,55	3,68	5,72	2,37	4,66	6,77	2,81	5,24	7,11	3,74	6,11	7,61	3,16	5,43	7,24	2,95	5,16	7,24	3,38	5,71	7,24	2,95	5,16	7,24	3,62	5,91	8
Additive Manufacturing	1,25	1,72	3,94	1,55	2,95	5,16	1,72	2,04	4,43	1,72	2,54	4,9	3,27	5,52	7,61	1,25	2,67	4,83	2,95	5,16	7,24	1,55	1,9	4,21	2,95	5,16	7,24
Autonomous Robots	1,38	2,85	5,08	1,72	3,16	5,43	2,14	3,5	5,81	1,38	1,84	4,14	2,67	3,88	6,21	1,25	1,72	3,94	2,63	3,21	5,8	3	5	7	1,25	2,67	4,83
Augmented Reality	1,93	2,63	4,99	1,25	1,38	3,55	1,25	2,67	4,83	1,25	2,14	4,36	1,55	3,68	5,72	1,25	2,14	4,36	1,55	1,9	4,21	1,93	3,27	5,52	1,55	2,37	4,66
Virtual Reality	1,55	1,9	4,21	1,55	2,37	4,66	3	5	7	2,41	3,62	5,91	1	1,93	4,08	1,55	1,9	4,21	1,55	3,68	5,72	1	2,41	4,51	1,93	3,27	5,52
Cyber Physical Systems	3	5,52	7,11	1,84	4,14	6,02	4,15	6,53	8	5,16	7,24	8,56	2,71	5,16	6,77	6,54	8,56	9	3,88	6,21	8	2,29	4,58	6,43	4,99	7,11	8,14
Simulation	2,14	2,81	5,24	1,55	1,9	4,21	2,95	5,16	7,24	2,14	3,5	5,81	1,9	2,71	5,16	3,27	5,52	7,61	4,51	6,54	8,56	1,55	2,95	5,16	2,95	5,16	7,24

The best and worst numbers were selected as follows:

Find best (X_{ij})max for beneficial, (X_{ij})min for non-beneficial.

Find worst (X_{ij})min for beneficial, (X_{ij})max for non-beneficial.

The best and worst values were selected for each criterion and shown in Table 5.11.

Table 5.11. The Best and Worst Values for the Criteria Set

	u1			u2			v1			v2			v3			v4			v5			v6		
Best	6	8	9	6	8	9	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4
Worst	1	2	4	1	2	4	5	7	9	5	7	9	5	7	8	4	6	8	6	8	9	6	8	9

Table 5.11. (cont'd). The Best and Worst Values for the Criteria Set

	u3			u4			u5			u6			u7			v7			v8			u8			u9		
Best	5	7	8	6	8	9	7	9	9	7	9	9	5	7	9	1	2	4	2	2	4	4	6	8	5	7	8
Worst	1	2	4	1	1	4	1	2	4	1	2	4	1	2	4	7	9	9	5	7	9	1	2	4	1	2	5

The next step was calculating the S_i and R_i values for each criterion. To calculate these values, criteria weights were taken from Table 5.9 and applied the following formulas using data from Table 5.10 and Table 5.11:

$S_i = \sum_{j=1}^{n}(W_j * \frac{x_i^{+} - x_{ij}}{x_i^{+} - x_i^{-}})$ for all l, m, u.

$R_i = Max_j \ (W_j * \frac{x_i^{+} - x_{ij}}{x_i^{+} - x_i^{-}})$ for all l, m, u.

where W_j represents the weights for j criterion, X_i^{+} represents the best value for j criterion and X_i^{-} represents the worst value for the j criterion.

Table 5.12. shows the S_i values and Table 5.13. shows the R_i values.

Table 5.12. S_i Values

Si		
L	M	U
0,234973	0,374151	0,383774
0,299885	0,3863891	0,404877
0,409773	0,5589023	0,537608
0,661268	0,7195134	0,557171
0,563141	0,6206553	0,52153
0,701534	0,6507417	0,427957
0,620077	0,606048	0,431877
0,414004	0,5237625	0,528291
0,610963	0,6722823	0,535801

Table 5.13. R_i Values

Ri		
L	M	U
0,040837747	0,064748	0,071612
0,03965753	0,063283	0,065204
0,077571862	0,089886	0,065204
0,145814099	0,124012	0,060647
0,096618508	0,112914	0,076857
0,181645135	0,181645	0,090823
0,146819026	0,154638	0,084325
0,063289398	0,06922	0,071612
0,158119103	0,168511	0,080781

After S_i *and* R_i values are observed, S^*, S^-, R^*, R^- values could be calculated by getting maximum and minimum S_i *and* R_i values as shown in Chapter 4.2. Table 5.14 shows S^*, S^-, R^*, R^- values for each alternative.

Table 5.14. S^*, S^-, R^*, R^- Values

	Si			Ri		
Alternatives	L	M	U	L	M	U
Internet of Things (IoT)	0,23	0,37	0,38	0,04	0,06	0,07
Big Data Analytics	0,30	0,39	0,40	0,04	0,06	0,07
Cloud Computing	0,41	0,56	0,54	0,08	0,09	0,07
Additive Manufacturing	0,66	0,72	0,56	0,15	0,12	0,06
Autonomous Robots	0,56	0,62	0,52	0,10	0,11	0,08
Augmented Reality	0,70	0,65	0,43	0,18	0,18	0,09
Virtual Reality	0,62	0,61	0,43	0,15	0,15	0,08
Cyber Physical Systems	0,41	0,52	0,53	0,06	0,07	0,07
Simulation	0,61	0,67	0,54	0,16	0,17	0,08
S*, R*	0,23	0,37	0,38	0,04	0,06	0,06
S-, R-	0,70	0,72	0,56	0,18	0,18	0,09

The fifth step was calculating the Q_i values for each alternative by using data taken from Table 5.12, Table 5.13 and Table 5.14. To calculate Q_i values, the equation is used that was mentioned in Step 5 in Chapter 4.2.

Table 5.15 shows the Q_i values for each alternative.

Table 5.15. Q_i values

	Qi (v=0.5)		
Alternatives	L	M	U
Internet of Things	0,004156	0,006189	0,181686
Big Data Analytics	0,069565	0,017718	0,136365
Cloud Computing	0,320841	0,379853	0,519101
Additive Manufacturing	0,830672	0,756541	0,5
Autonomous Robots	0,552273	0,566534	0,665817
Augmented Reality	1	0,900435	0,627405
Virtual Reality	0,790067	0,721643	0,531037
Cyber Physical Systems	0,275081	0,241679	0,598408
Simulation	0,820092	0,87614	0,771995

After obtaining the Q_i values, defuzzification could be done by summing the L/6, 4*M/6 and U/6 as shown in Step 6 in Chapter 4.2. After defuzzification, we were able to achieve a single value for each alternative to evaluate them. Table 5.16. shows the defuzzified values of all Q_i values for the alternatives.

Table 5.16. Defuzzified Q_i values

	Qi (v=0.5)			
Alternatives	L	M	U	Defuzzified Qi
Internet of Things (IoT)	0,004156	0,006189	0,181686	0,035099
Big Data Analytics	0,069565	0,017718	0,136365	0,046133
Cloud Computing	0,320841	0,379853	0,519101	0,393226
Additive Manufacturing	0,830672	0,756541	0,5	0,726139
Autonomous Robots	0,552273	0,566534	0,665817	0,580704
Augmented Reality	1	0,900435	0,627405	0,871524
Virtual Reality	0,790067	0,721643	0,531037	0,701279
Cyber Physical Systems	0,275081	0,241679	0,598408	0,306701
Simulation	0,820092	0,87614	0,771995	0,849441

Now, these alternatives can be ranked according to defuzzied values shown in table 5.16. The lowest value identifies the best alternative and the highest value identifies the worst alternative. Other alternatives are ranked respectively from the lowest defuzzied value to the highest defuzzied value they have.

Table 5.17 shows the ranks of the I4.0 technologies.

Table 5.17. Ranking the Alternatives

Alternatives	Defuzzied Qi Values	Rank
Internet of Things (IoT)	0,035099	1
Big Data Analytics	0,046133	2
Cloud Computing	0,393226	4
Additive Manufacturing	0,726139	7
Autonomous Robots	0,580704	5
Augmented Reality	0,871524	9
Virtual Reality	0,701279	6
Cyber Physical Systems	0,306701	3
Simulation	0,849441	8

According to the ranks of the alternatives shown in table 5.17, Internet of Things (IoT) is selected as the most effective technology on the circular economy criteria, followed by Big Data Analytics and Cyber-Physical Systems. The company should prioritize these I4.0 technologies to achieve the best performance in CE. The main reason behind this result is that these technologies are also the main technical drivers of the paradigm of the I4.0. Therefore, other technological solutions like cloud computing systems or 3d printers should not be prioritized before applying IoT and BDA effectively. Other I4.0 technologies can be seen as supportive technologies to achieve higher circularity levels. Meanwhile, it should not be forgotten that all these technologies are complements of I4.0 and collaboration of these technologies may serve better outcomes for circular economy performance. Chapter 6 includes details of the results of this study, discussions on the findings and managerial implications.

CHAPTER 6

DISCUSSIONS AND IMPLICATIONS

Industry 4.0 and Circular Economy are two significant paradigms that change the dynamics of the business environment. In the transition to CE from a linear economy, companies face many challenges while closing the loop of business operations. Also, in transition to I4.0 from I3.0, companies have to cope with a highly competitive environment. Today's technology presents disruptive opportunities for supply chains to overcome challenges in competition and companies have to invest in these technologies to create competitive advantages through providing lean solutions for the needs of markets. I4.0 technologies help companies to enable a circular economy at the same time. One of the most important aspects that shows the aims of I4.0 and CE are positively correlated is both concepts target to eliminate inefficiencies in their principles.

In this paper, a novel framework for assessing the performance of the Industry 4.0 technologies in enabling Circular Economy in the context of Triple Bottom Line criteria. The framework comprised 9 enabler technologies found in the literature which have positive effects on the CE performance of organizations. To evaluate the effectiveness of these technologies on CE performance, 3 main criteria and 17 sub-criteria were formed according to literature and expert opinions in the context of TBL. The distinctive features of this framework are CE enablers are chosen from I4.0 technologies and to assess the effectiveness of these technologies, criteria set is formed based on TBL and weighted by MCDM methods. Conceptually, the significance of these enabler technologies on CE is supported by Braccini et al. (2018), Jabbour et al. (2018), Rosa et al. (2019), and Shayganmehr et al. (2021). In this thesis, these technologies are evaluated in terms of CE performance. The most efficient technology was found as the Internet of Things followed by Big Data Analytics and Cyber-Physical Systems. Although these technologies may have not directly positive impacts on the circularity of products and services in terms of recycling, or reuse etc., they have common potential to determine the circularity of the processes, provide comprehensive digital infrastructure for supply chains to increase resource efficiency, and support decision-making mechanism to make the processes more sustainable. Because of that, these technologies have been found as the most important ones in this study as same in line with the experts' opinions.

Digitalization of CE can be ensured by IoT appliances within smart industrial environments (Rosa et al., 2019). IoT provides dynamic monitoring and controlling tools for complex supply chains; presents abilities to detect resource inefficiencies within the systems and provide smart sustainable solutions. For example, temperature sensors are used to automatically switch on-off or set degrees of the coolers to increase energy efficiency and to protect product quality or RFID systems are used to automatically identify, track and monitor objects which provides real-time controlling for the operators which increase efficiency and decrease the need for reuse and recycling. IoT also provides an enormous amount of data for smart decisions. Smart machines are interacting with each other for achieving the determined target with the help of information and communication technologies (ICT). Today, over 10 million devices are connected to the internet. IoT has great potential for enabling CE. The findings of this study are supported with implications supported by the company's operations in the case study and past studies.

In this thesis, the most important criterion is found as return on investment (ROI) according to experts' opinions because they have concerns on the economic dimensions of investing in technologies to enable CE. IoT technology is found feasible in terms of ROI for many operations in this company. The company has been using many IoT appliances. Intelligent Reporting, Inspection & Selection system (IRIS) is in use for determining quality defects and assessing the direction of products through distribution lines in production units. A digital camera, LED Lighting and smart recognition software are the components of this system. The software is connected with the camera through the internet and uses shape, color and texture data to decide the direction of the product through distribution lines. Also, the software decides whether products have quality defects or not. If a quality defect is determined by the software, the product has left the production line for reprocessing or recycling. This system can be a perfect example of how IoT increases production efficiency, decreases resource inefficiencies and supports sustainable operations with recycling or reusing products while providing satisfying ROI. Similar smart solutions can be used for other industrial products. Generally, real-time monitoring and controlling of the products and machine-to-machine communication using IoT can help better decision making for desired outcomes.

IoT can be used for monitoring the performance of energy conversion systems. Energy prices depend on many factors and may vary in non-stabilized local market conditions according to major economic conditions. Energy conversion systems can be used for the management of energy resources effectively. IoT can help decision-makers to improve energy efficiency by providing data and monitoring the system. In the context of the company in this thesis, an energy conversion system is used for generating electrical energy from natural gas. IoT ensures monitoring performance of the system which helps to decide at which level energy should be converted in a period. In addition to this, monitoring energy efficiency can be useful for renewable green energy resources to provide economic benefits while providing zero negative impacts on the environment.

Smart routing optimization can be ensured by using RFID and GPS through tracking and monitoring the transactions. These systems can easily be applied in terms of economic feasibility. Decreasing CO_2 emissions and increasing energy efficiency are possible through decreasing the number and distance of travel. This is in line with the implications of Sagnak et al. (2021). The company in this thesis is using GPS and temperature sensors for tracking and monitoring the conditions of products while products are travelling long distances. To protect cold chain logistics, IoT has a vital role for the company. Tracking and monitoring solutions through IoT can be much more important for the firms which are operating in fast-moving consumer goods (FMCG) industries.

Data acquisition through IoT technologies provides many opportunities for the managers in lifecycle assessment of products, waste management, and inefficiencies. This is in line with the study of Esmaeilian et al., (2018) and Rosa et al., (2019). Esmaeilian et al. stated that IoT can help to develop new waste management strategies in smart cities. Rosa et al. stated that IoT can be useful for assessing the environmental impacts of business operations.

Generally, the proposed framework can provide guidance for decision-makers which technologies should be prioritized for transition to CE and determine their influences on CE criteria. In addition, this paper answers the question of which I4.0 technologies have positive impacts on CE. This framework also can help managers to determine the performance of I4.0 technologies on their sustainability operations. The proposed framework in this thesis is also a comprehensive summary for the managers in how to measure the effectiveness of I4.0 technologies in achieving desired CE performance criteria.

CHAPTER 7
CONCLUSIONS

Sustainability concerns and Industry 4.0 are two major topics that receive high attention from academicians, managers, and policy-makers in the last decade. Although these two paradigms have completely individual meanings and importance, many positive correlations can affect one another (Rosa et al., 2019). Most of the time, the I4.0 concept is investigated around technologies as the components of the concept. I4.0 technologies have measurable economic, environmental, and social benefits on the sustainability of companies. However, there is still evidence gap on which technologies have positive effects for enabling CE in terms of these 3 dimensions of TBL. Also, it is not clarified that how the effects of I4.0 technologies on CE in terms of TBL criteria can be measured in the literature. To fill these gaps, this thesis organized to propose a framework for prioritizing the I4.0 technologies in terms of their effects on the CE performance of manufacturing companies. This study focuses on the problems of which technologies have which degree of positive effects on which CE criteria. The criteria set have 3 main, 17 sub-criteria. The main criteria include economic, environmental and social criteria which are the Triple Bottom Line dimensions. Internet of Things (IoT), Big Data Analytics (BDA), Cloud Computing, Additive Manufacturing (AM), Autonomous Robots, Augmented Reality (AR), Virtual Reality (VR), Cyber-Physical Systems (CPS), and Simulation are the alternative I4.0 technologies. To prioritize alternatives and select the best one, each alternative was judged in terms of each criterion.

Since criteria require qualitative measurements, a survey was created to obtain data about the importance of criteria through pairwise comparisons. To determine the weights of each criterion, the fuzzy Best-Worst Method (BWM) was used. A survey was also created to determine the relative importance of the alternatives over the criteria. Then, the fuzzy VIKOR method is used to identify the rankings of the alternative technologies. Fuzzy BWM has been used for the first time for determining the effectiveness of I4.0 technologies on CE. The proposed framework is the main contribution of this study to select the best technology in terms of circularity performance of manufacturing companies by the association of CE and I4.0 concepts. Return on investment is found as the most significant factor followed by pollution prevention and control, and education and qualification; and employee engagement is found as the least significant criterion followed by job reduction, and energy cost. Among all alternatives, the Internet of Things (IoT) was found as the best alternative for enabling CE followed by Big Data Analytics (BDA) and Cyber-Physical Systems (CPS).

This thesis includes a case study implemented in a single manufacturing company. This can be identified as the limitation of this paper. Future studies may follow the proposed framework to determine the relative effectiveness of I4.0 over the circular economy performance of companies operating in different industries. Also, data used in this thesis was gathered by subjective judgements which make the findings of this thesis specific for this company. Further researches may focus on measuring the performance of specific alternative solutions provided by I4.0 on the sustainability operations of the companies. Industrial comparisons may be useful for providing a better understanding of the effectiveness of I4.0 on CE.

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APPENDIX

Table A1: Pairwise Comparisons of Expert 1 for Calculation of Criteria Weights

Expert 1	Market Share	Return on Investment	Loss of Efficiency	Operation Cost	Maintenance Cost	Payback Period	Energy Cost	Personnel Cost	Generating Job Opportunities	Work Safety	Education and Qualification	Society Benefit	Employee Engagement	Job Reduction	Greenhouse Gas Emission	Pollution Prevention and Control	Waste Management
Market Share														5			
ROI	5	1	7	3	7	3	7	9	9	5	3	9	9	9	7	3	7
Loss of Effic.														5			
Operat. Cost														3			
Maint. Cost														7			
Payback Period														9			
Energy Cost														7			
Person. Cost														5			
Job Opport.														3			
Work Safety														7			
Educat. Qualif.														9			
Society Benefit														3			
Employ.Engagement														7			
Job Reduc.														1			
GGE														5			
PPC														7			
WM														7			

Table A2: The Blank Table for Pairwise Comparisons

Alterna. /Criteria	Market Share	Return on Investment	Loss of Efficiency	Operation Cost	Maintenance Cost	Payback Period	Energy Cost	Personnel Cost	Generating Job Opportunities	Work Safety	Education and Qualification	Society Benefit	Employee Engagement	Job Reduction	Greenhouse Gas Emission	Pollution Prevention and Control	Waste Management
IoT																	
Big Data Analytics																	
Cloud Computing																	
Additive Manufac.																	
Auton. Robots																	
Augment. Reality																	
Virtual Reality																	
CPS																	
Simulation																	

Table A3: Pairwise Comparisons Data of Expert 1 for Ranking the Alternatives

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	Very High	Very High	Average	High	Average	High	Very High	Average	Average	Very High	High	High	Average	High	Average	Very High	Average
Big Data Analytics	High	High	Very High	High	High	Average	Very High	High	Very High	High	Very High	High	Average	Very High	Average	Very High	Average
Cloud Computing	High	Average	High	Very High	High	Average	Very High	Average	Low	High	Low	Very High	Very High	Low	Low	High	Low
Additive Manufacturing	Low	Average	Average	High	High	High	Very Low	Low	Average	Average	High	High	Low	Very Low	Average	Very Low	High
Autonomous Robots	Average	High	Very Low	Low	High	Low	Low	Average'	High	Low	Average	Very Low	Average	Low	High	Average	Low
Augmented Reality	Low	Low	Low	Low	Low	Low	Very Low	Very Low	Very Low	Very Low	Very Low	Average	Low	Very Low	Very Low	Average	Average
Virtual Reality	Very Low	Very Low	Very Low	Very Low	Very Low	Low	Very Low	Low	Very Low	Average	Average	Very Low	Very Low	Very Low	Average	Low	Average
Cyber Physical Systems	Average	High	Average	Low	High	Very High	High	High	Very High	Very High	Low	High	Very High	Very High	High	Low	Average
Simulation	Low	High	Very Low	Very Low	Very Low	Low	Low	High	Average	Very Low	Average	Very Low	High	Low	High	Average	Average

Table A4: Converted Matrices into Fuzzy Sets for VIKOR Calculations

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	7 9 9	7 9 9	3 5 7	5 7 9	3 5 7	5 7 9	7 9 9	3 5 7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Big Data Analytics	5 7 9	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cloud Computing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Additive Manufacturing	1 3 5	3 5 7	3 5 7	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Autonomous Robots	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Augmented Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Virtual Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cyber Physical Systems	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Simulation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Big Data Analytics	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cloud Computing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Additive Manufacturing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Autonomous Robots	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Augmented Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Virtual Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cyber Physical Systems	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Simulation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Big Data Analytics	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cloud Computing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Additive Manufacturing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Autonomous Robots	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Augmented Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Virtual Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cyber Physical Systems	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Simulation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Big Data Analytics	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cloud Computing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Additive Manufacturing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Autonomous Robots	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Augmented Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Virtual Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cyber Physical Systems	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Simulation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Alternatives/Criteria	u1	u2	v1	v2	v3	v4	v5	v6	u3	u4	u5	u6	u7	v7	v8	u8	u9
Internet of Things (IoT)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Big Data Analytics	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cloud Computing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Additive Manufacturing	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Autonomous Robots	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Augmented Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Virtual Reality	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Cyber Physical Systems	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Simulation	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]