ADOPTION OF INDUSTRY 4.0 FOR SUSTAINABLE MANUFACTURING

by

Parham Dadash Pour

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Declaration of Authorship

I declare that this thesis is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

Signed………………*Parham Dadash Pour*……………………….

Date…………………28/April/2022………………………………

Approval Signatures

We, the undersigned, approve the Master's Thesis of Parham Dadash Pour.

Thesis Title: Adoption of Industry 4.0 for Sustainable Manufacturing

Date of Defence: 25/April/2022

Name, Title and Affiliation	**Signature**
Dr. Mohammad Nazzal Associate Professor, Department of Mechanical Engineering Thesis Advisor	
Dr. Basil Darras Associate Professor, Department of Mechanical Engineering Thesis Co-Advisor	
Dr. Mohammad Hamdan Professor, Department of Mechanical Engineering Thesis Committee Member	
Dr. Mahmoud Awad Associate Professor, Department of Industrial Engineering Thesis Committee Member	
Dr. Mamoun Abdel-Hafez Head Department of Mechanical Engineering	
Dr. Lotfi Romdhane Associate Dean for Graduate Affairs and Research College of Engineering	
Dr. Fadi Aloul Dean College of Engineering	
Dr. Mohamed El-Tarhuni Vice Provost for Research and Graduate Studies Office of Research and Graduate Studies	

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Dedication

To my family…

Abstract

The Fourth Industrial Revolution (Industry 4.0) intends to help different industries monitor, control, and run their production systems efficiently. Most of the currently available Industry 4.0 implementation frameworks focus on providing users with an implementation plan that do not include information regarding technology selection or readiness assessment. In this work, a comprehensive Industry 4.0 implementation framework is developed to help manufacturing firms improve their current state of production. The framework developed consists of five main stages. These stages are gap analysis, Industry 4.0 technology selection, Industry 4.0 readiness assessment, Industry 4.0 reference architecture selection, and pilot project assessment. An Industry 4.0 technology selection model is developed that uses Fuzzy Analytical Hierarchy Process (FAHP) to assign weights to the production, social, economic, and environmental indicators. Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is used to aggregate the results and rank the technology alternatives based on their scores. Furthermore, a novel Industry 4.0 readiness tool is developed to assess how capable the facility is to implement Industry 4.0 technologies. A case study was carried out by applying the developed Industry 4.0 technology selection and readiness assessment procedures on an aluminium extrusion factory. Cyber-Physical Systems, Big Data Analytics, and Autonomous/Industrial Robots were the top three ranked technologies to be implemented having closeness coefficient scores of 0.964, 0.928, and 0.601, respectively. The firm obtained a readiness score of 45.8% based on the developed readiness assessment model revealing that the firm is at an intermediate readiness level.

Keywords: Industry 4.0; Multi Criteria Decision Making; Sustainable Manufacturing; Fuzzy Logic; Technology Selection.

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List of Abbreviations

AHP	Analytical Hierarchy Process
AM	Additive Manufacturing
ANP	Analytical Network Process
B2B	Business-to-Business
CM	Cloud Manufacturing
COPRAS	Complex Proportional Assessment
CPS	Cyber Physical Systems
DoE	Design of Experiment
FAHP	Fuzzy Analytical Hierarchy Process
FDT	Fuzzy Decision Tree
FNIS	Fuzzy Negative Ideal Solution
FPIS	Fuzzy Positive Ideal Solution
FTOPSIS	Fuzzy Technique for Order of Preference by Similarity to Ideal Solution
GP	Goal Programming
GRI	Global Report Initiative
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
ISO	International Organization for Standardization
IVRA	Industrial Value Chain Reference Architecture
KPI	Key Performance Indicator
LASFA	LAsim Smart FActory
MCDM	Multi-Criteria-Decision-Making

OAT	One-Factor-At-a-Time
PPE	Personal and Protective Equipment
RAMI 4.0	Reference Architectural Model Industrie 4.0
RFID	Radio Frequency Identification
SAW	Simple Additive Weighting
SITAM	Stuttgart IT-Architecture for Manufacturing
SME	Small and Medium Sized Enterprise
TBL	Triple Bottom Line
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WSN	Wireless Sensor Network

Chapter 1. Introduction

1.1. Introduction

In this chapter, an overview on the topic of Industry 4.0 is provided in which different Industry 4.0 technologies are introduced. Next, the specific objectives and the main contributions of this thesis to the literature are presented. Lastly, the organization of this thesis is laid out.

1.2. Overview

The world has gone through three different phases of industrialization. Started by the mid-eighteenth century in Great Britain, the first industrial revolution took place by the introduction of steam engines into different industries which led to the emergence of different industries across Europe [1]. The second industrial revolution started around 1870 and lasted for a century. Introduction of electricity and mass production were the two most important features of this revolution. The third industrial revolution also known as the “Digital” revolution occurred in the late 1960s, in which computers played a significant role in the automation of different industries [2]. Figure 1-1 illustrates different industrial revolutions throughout history.

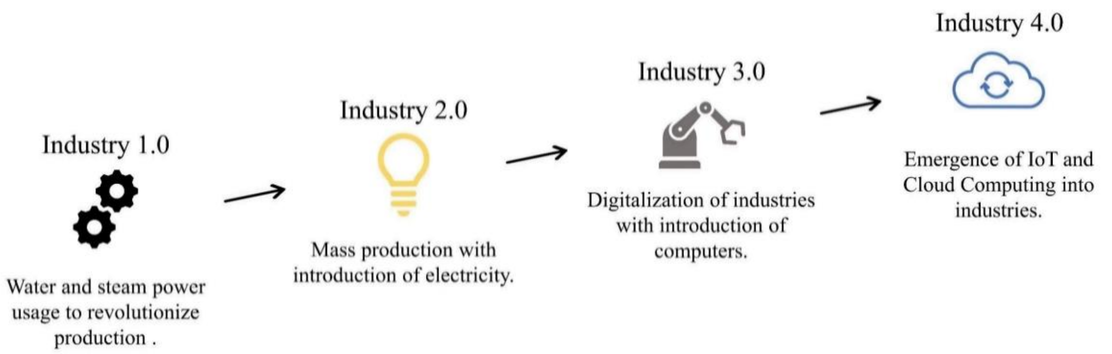


Figure 1-1: Different Industrial Revolutions.

The core of Industry 4.0 is its contributing technologies. Internet of Things (IoT), Cyber Physical Systems (CPS), and Additive Manufacturing (AM) are few examples of such technologies. The benefits of implementing such technologies into different types of firms is optimizing different dimensions involved in the production. For example, research done by Nara et al. on Brazil’s plastic industry showed the positive influence of Industry 4.0 technologies implementation mostly on economic dimension followed by the environmental and social dimensions [3]. Increase in customer satisfaction by having a better response to their needs is an indicator of social dimension. Decreased solid waste, reduced greenhouse gas emissions, and more sustainable energy management are considered as indicators for environmental dimension [4]. Figure 1-2 shows the main Industry 4.0 technologies.

Figure 1-2: Industry 4.0 Technologies.

1.3. Thesis Objectives

Implementation of Industry 4.0 on manufacturing firms will positively affect environmental, social, and economic dimensions of sustainability. Currently, there is a research gap existing in literature on a comprehensive framework or roadmap for Industry 4.0 implementation/transformation. Most roadmaps developed are either theoretical without quantitative analysis or are too complex, which disables Small and Medium Sized Enterprises (SMEs) from following along and successfully upgrading to Industry 4.0. Hence, the main aim of this thesis is to develop an Industry 4.0 implementation framework that covers different aspects related to Industry 4.0 such as technology selection, readiness assessment, and reference architecture selection.

1.4. Research Contribution

The main contributions of this thesis work are summarized as below:

- Create an Industry 4.0 implementation framework that covers different aspects of Industry 4.0 such as technology selection, readiness assessment, and reference architecture selection.

- Discuss possible solutions that Industry 4.0 technologies provide to tackle challenges brought by pandemic on manufacturing sector.
- Develop a novel Industry 4.0 technology selection model and implement it on a case study.
- Build a novel Industry 4.0 readiness assessment model and implement it on a case study.

1.5. Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 of the thesis includes a literature review on different Industry 4.0 technologies and different components/procedures associated with Industry 4.0. Chapter 3 presents the developed framework and the methodology behind it. Chapter 4 showcases the results obtained from the case study implementation. Lastly, chapter 5 concludes the thesis and talks about the work to be carried out in future.

Chapter 2. Background and Literature Review

A detailed literature review is required to understand the characteristics of Industry 4.0 and its technologies functionalities. In this chapter, important Industry 4.0 technologies characteristics, and their contributions in solving pandemic challenges have been discussed. Further, a literature review on different Industry 4.0 attributes such as readiness/maturity models, reference architectures, and technology selection frameworks have been conducted. Lastly, some of the currently available Industry 4.0 roadmaps have been shown and discussed in this chapter.

2.1. Industry 4.0 Technologies

In this section, a brief description of each Industry 4.0 technology is provided. These technologies include Big Data Analytics, Cloud Computing, Cyber Physical Systems, Internet of Things, Computer Simulations, Blockchain, Autonomous/Industrial Robots, and Additive Manufacturing. Industry 4.0 technologies can play a positive role in the transition to sustainable manufacturing. The reduction of the environmental impact of a product by light weighting, use of clean energy resources, waste elimination, recycling, and embracing Industry 4.0 technologies and circular economy principles is becoming a high priority for manufacturing companies [5-34].

2.1.1. Big data analytics

It is known that this technology helps in speeding up different processes while making sure of reducing production complexity [35]. Another main advantage of Big Data Analytics is corelating data in order to determine the influence of certain variables in the production structure [36]. Big Data Analytics technology also play an important role in manufacturing and production sectors of supply chain. Real-time data monitoring and analysis is one of the most crucial aspects of Industry 4.0. Real-time data acquisition from manufacturing sector can reduce the costs of faulty production unit and can prevent mistakes in production that are happening continuously. In order to analyse and sort real-time data acquired from different machines and services within the industry, a powerful tool is needed to handle such huge amount of data poured at once. Hence, Big Data Analytics technology can be implemented into the industry to handle and analyse data successfully. From such analysis, feedbacks can be created and sent to the production line to make necessary changes.

2.1.2. Cloud computing

The adoption of this CPS technology into manufacturing sector is by two means of either direct adaptation of the Cloud Computing technology or adaptation in form of Cloud Manufacturing (CM). Cloud Computing technology can provide flexible commerce transactions alongside the ease of scaling up/down the production per demand. Moreover, Cloud Computing facilitates in creating more transparent communication in the organization [37]. One challenge to industries is huge amount of data that is obtained and needed to be stored. Storing data in traditional ways require considerable amount of storing devices and physical space. Hence, Cloud Computing technology is integrated into different factories to accommodate for above mentioned issues. Another crucial role of Cloud Computing in industries is its ability to collect and process data which eases the data transfer among industries [36]. Therefore, Cloud Computing can enable industries to communicate with one another. Making communications possible among industries helps in determining shortcomings in production of certain products which might affect another industry's production. Most of industry 4.0 technologies like IoT, Additive Manufacturing, Autonomous Robots are based on real-time data acquisition and collection. Thus, Cloud Computing is used as the main database to increase the speed of data transfer among different sectors within one industry.

2.1.3. Cyber physical systems

Cyber Physical Systems or CPS often refer to a group of embedded systems, controllers, sensors, and connection networks which enable the connection between physical and digital world [38]. CPS acts as a core of Industry 4.0 technologies due to dependability of other technologies to it.

2.1.4. Internet of things

Initially, Internet of Things (IoT) was known for the technology which can help in tracking different products (objects) within different manufacturing stages. By time, the idea of IoT has enhanced and described as a tool or technology which connect physical with digital world. This linking between two different worlds become possible by use of transducers and sensors. The role of sensors is to obtain information from physical world whereas actuators are responsible to act upon given instructions. As mentioned earlier, IoT is known as technology for tracking objects. These objects are characterized into four main groups of Trackable Objects, Data Objects, Interactive Objects, and Smart Objects [39]. Trackable Objects were things which would have contain simple RFID chips in order to provide information about the location of the product. Data Objects refers to things which can produce data using sensors and provide information to user on the current state of the product. With more developments in technology, Interactive Objects have been created which are able to collect information using sensors and react to the situation using actuators. Finally, Smart Objects are identified as things which are able to process data obtained from sensors and take action upon the condition with help of transducers [39].

2.1.5. Computer simulations

Computer Simulation is a technology that uses algorithms to give predictions about possible outcomes regarding different case scenarios [40]. Nowadays, simulations have transformed from static to dynamic environment with rise of real time data collection and cloud technologies. Different scenarios can be programmed in order to be simulated based on different variables. These variables can differ from machine's conditions to labour issues and resources limitations [36]. Simulating different scenarios can help industries to have improved control over their resources. Computer generated models of new products can be simulated before the product is first manufactured. Hence, implementing Computer Simulation technology into industries can possibly reduce raw material usage and faulty production costs while increasing the overall quality of the product manufactured.

2.1.6. Blockchain

Development of technology and immerse use of different technologies within industries has itself brought new challenges to industries. One such challenge for firms is protecting digital data within the industry from possible cyber-attacks. Blockchain is an Industry 4.0 technology which is mainly responsible for facilitating data security within the industry of interest. It is known that Blockchain can affect industries in other different aspects rather than data security. One such aspect is at enterprise level which Blockchain technology can make a trusted network for the industry to have connection with different manufacturers [41]. Transparency in data transaction, decentralization of an industry, and process automation are other different features associated with Blockchain technology. Transparency feature leads to having a more agile industry which all sectors are enabled to access real-time data. With help of Blockchain, data is transferred directly from peer-to-peer leading to a decentralized industry in which different sectors are less dependent on one another [42].

2.1.7. Autonomous and industrial robots

Industrial Robots are becoming more integrated into different industries due to the advantages that they can provide. As an example, robots are used in hazardous production environment which due to safety reasons, humans are not permitted to enter. Robots used in such applications have ability to collaborate with humans remotely [43].

2.1.8. Additive manufacturing

Additive Manufacturing is one of the emerging technologies in Industry 4.0. With help of this technology, computer-made 3D models can be produced through placing consecutive layers of material. Previously, Additive Manufacturing was mainly used for creating fast and less expensive prototypes for testing purposes. These prototypes were used in different industries to reduce material waste and costs [36]. To make a workpiece using Additive Manufacturing technology, the model should be 3D designed, printed, and post processed if required. The post processing step involves different manufacturing processes such as machining, heat-treatment, polishing, and painting [44,45]. Figure 2-1 illustrates steps required for having a successful implementation of Additive Manufacturing into a firm. Table 2-1 summarizes the positive impacts of Industry 4.0 technologies on manufacturing firms.

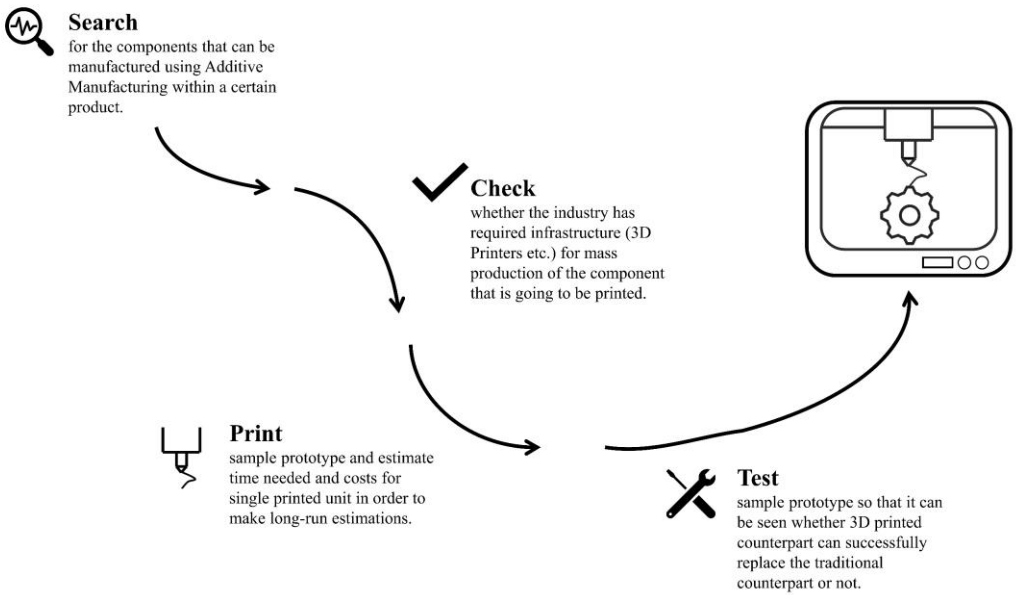


Figure 2-1: Additive Manufacturing Roadmap.

Table 2-1: Industry 4.0 Technologies Possible Impact on Manufacturing Firms.

Index	Name	Description
T1	Big Data Analytics	Being able to handle and analyze raw data is becoming important for different industries. The Big Data Analytics technology can help to evaluate and examine the obtained data form production floor in order to assist decision makers.
T2	Cloud Computing	Data storage is becoming a new concern for many industries with rapid advancements in the technology. Hence, Cloud Computing can be used to provide an additional storage space for industries to store important data.
T3	Cyber Physical Systems	Group of technologies which enable the connection between digital and physical components within one manufacturing firm allowing the digitalization of the production line.
T4	Internet of Things	Internet of Things (IoT) is one of the crucial technologies in Industry 4.0 that can act as a bridge between different components among the industry. IoT usually involves Wireless Sensor Networks (WSN) and RFID chip technology to make the connection possible.
T5	Computer Simulations	Use of computer simulations can save industries time and money. Prior to producing a unit, simulations can be performed to obtain results which are highly similar to the actual results. With that, industries can visualize the defects and problems before starting the actual production which leads in saving time and funds. Computer simulations can also appear in terms of digital twin which also enable other beneficial features for the firms.
T6	Blockchain	One of the main abilities of Blockchain technology is enabling secure B2B transactions among different industries by eliminating the intermediaries in between through the digital distributed ledgers.
T7	Autonomous and Industrial Robots	Industrial and Autonomous Robots are becoming an integral element in different industries. Being able to perform tasks remotely and autonomously without human contribution can increase the agility of the production within the firm.
T8	Additive Manufacturing	Additive Manufacturing is a rapidly growing technology used in Industry 4.0 since it can benefit different firms in sustainability and economic dimensions. Improvement in product life cycle is another important contribution of Additive Manufacturing technology.

2.2. Application of Industry 4.0 Technologies in Overcoming Pandemic Challenges on Manufacturing Sector

Industry 4.0 gained more popularity at time of the COVID-19 pandemic. Many researchers shifted their focus on how Industry 4.0 technologies can assist in overcoming some of the challenges brought by pandemic to the manufacturing sector in specific. Figure 2-2 illustrates some of the challenges brought by pandemic on manufacturing firms.

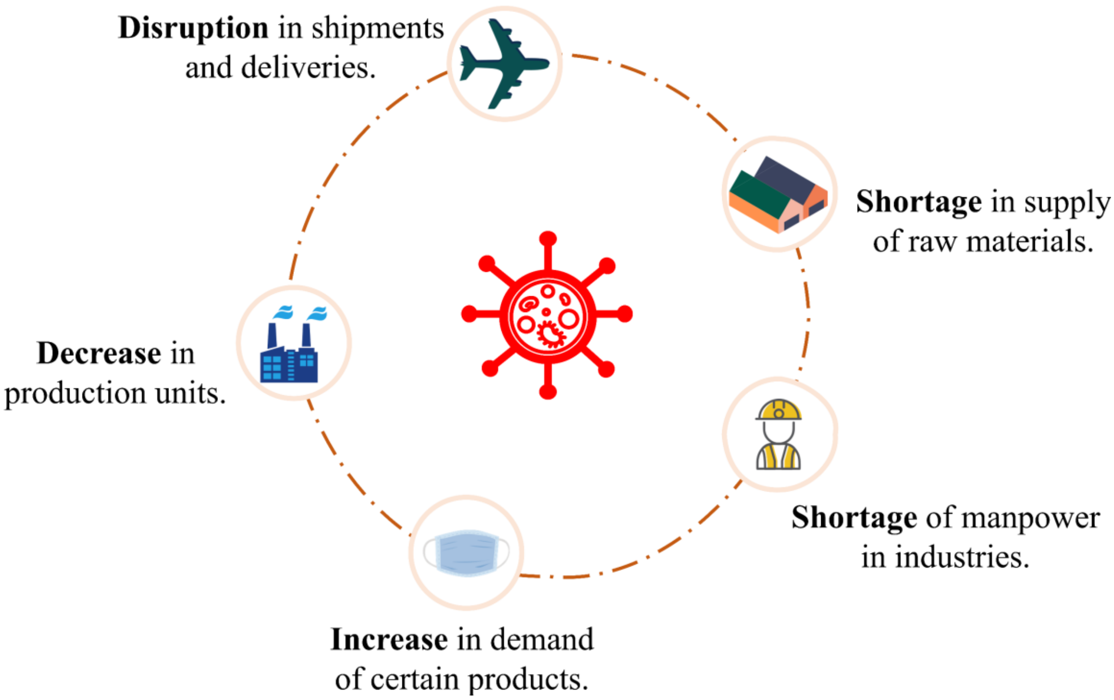


Figure 2-2: Challenges Brought by Pandemic on Manufacturing Sector [46].

Most of the countries implemented air travel ban which affected the shipping of materials and goods worldwide. According to UNICEF [47], different airlines tried to interchange the cargo flights with passenger flights to compensate for losses occurred during peak of pandemic period [47]. Due to virus outbreak, demand for certain products have been increased which brought operational challenges to many manufacturing firms. Another important challenge of the pandemic on manufacturing firms was the shortage of raw material which consequently led to a decrease in production units. China is considered as Tier 1 and Tier 2 supplier for many manufacturing firms worldwide. Hence, factories closure in China can have a domino effect on other manufacturing firms specially in industries such as bioengineering and opto-electronics [48]. Table 2-2 summarizes some examples of challenges that have been brought by COVID-19 on different industries. Disruption in supply chain and shortage of manpower were among the top two most common challenges faced by industries.

Table 2-2: Examples of COVID-19 Pandemic Challenges on Different Sectors.

Studied Sector	**Contribution**
Agricultural sector	The paper talked about challenges brought by COVID-19 on agriculture sector in China. Shortage of manpower, disruption in sales, and reductions in harvest are considered as main causing factors to such problem [49].
Textile industries	The study discussed the impact of COVID-19 on textile and clothing industries. The paper talked about the importance of China and its domino effect on clothing manufacturers all around the world since China is considered as the main supplier for different clothing materials such as: synthetic fibers, polyurethane tapes, dyes, etc. [50].
Medium-sized enterprises	The paper discussed the impact of COVID-19 on Pakistan's Medium Sized Enterprises and economy. Reports have shown that Pakistan's exports have been decreased by 50% due to COVID-19 which also led to a decrease in the total revenue of the country by one third. Factories closure due to lockdown restrictions in Pakistan had also an impact on Pakistan's economy in which only 50 out of 2700 factories remained functioning during lockdown in Karachi [51].
Personal and Protective Equipment manufacturing firms	The study evaluated the impact of COVID-19 on supply chain of Personal and Protective Equipment (PPE) around the world and Republic of Ireland in more details. In order to fight the shortage of PPE, the study found that implication of technology can possibly increase the production sustainability in a way that meets the increased demands of PPEs at times of pandemics [52].

Implementation of different Industry 4.0 technologies on manufacturing sector can provide a possible solution to different challenges mentioned earlier. As an example, many manufacturers have used Additive Manufacturing technology to make PPEs such as face shields, faces masks, and nasopharyngeal swabs in order to successfully address the increased demand [53]. Computer simulations can simulate scenarios that might occur at times of pandemics which in return helps decision makers better prepare for the unforeseen crisis. Big Data Analytics can be used in different ways to assist in tackling pandemic challenges. One such ways is usage of machine learning and neural networks for predicting consumer behavior at times of pandemics. Blockchain technology can be utilized to track products and Cloud Computing can be used to facilitate collaboration between different firms at times pandemics. Different Industry 4.0 technologies can also work simultaneously in order to overcome pandemic challenges. As an example, Big Data Analytics can be used to study consumer behavior at times of pandemics. This knowledge helps in creating a predictive algorithm. Predictive analytics is a known phenomenon in literature which refers to an analytics that provides a foresight about the future based on current available data [54]. This predictive algorithm can be expanded using Cloud Computing and preserved using Blockchain. Figure 2-3 represents the schematics of how Industry 4.0 technologies can work alongside one another in order to solve a pandemic challenge.

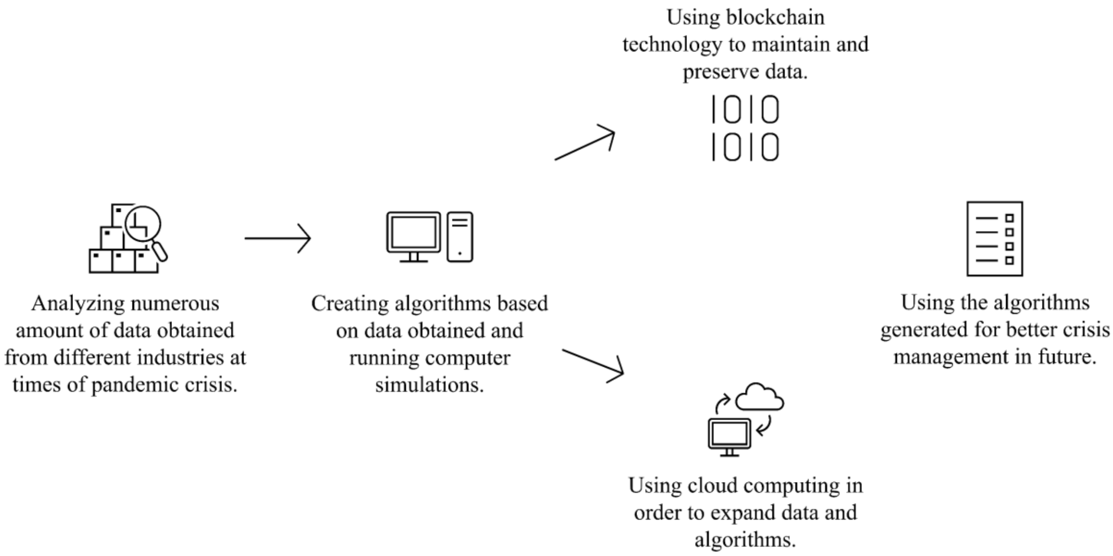


Figure 2-3: Predictive Algorithm Creation Schematics [46].

2.3. Industry 4.0 Technology Selection Frameworks

One of the important aspects in Industry 4.0 implementation is the technologies selection. Often, there is a challenge associated with deciding on which technologies to choose from by manufacturing firms. Hence, the demand for having an approach on how to select the technologies have been increased. Currently, there are quite a few frameworks available in literature for advanced manufacturing/Industry 4.0 technologies selection. As an example, Hamzeh et al. [55], have proposed a technology selection framework for the manufacturing firms which is uniquely designed for Industry 4.0 technologies. In this framework, the manufacturing owners will first evaluate the current situation of the production floor which is then followed by identifying the critical factors (strengths and weaknesses) of the firm. Next, a time range on fixing the weaknesses is defined based on firm's business strategies and goals. Then, the technologies are selected and evaluated thoroughly in different aspects. These aspects include social, financial, and environmental dimensions. Lastly, the risks involved with implementing such technologies on production floor are assessed by means of a risk assessment method which includes two main factors of manufacturing operational risks and information security [55].

Another example of frameworks available on literature is the framework developed by Evans, Lohse, and Summers [56], which uses Fuzzy Decision Tree (FDT) analysis for selecting the manufacturing technologies instead of traditional Multi-Criteria-Decision-Making (MCDM) analysis. The authors argued that using this method will lead to less dependency on experts' intuitive feelings (subjective perspectives) involved while making a decision [56]. In more details, this method uses historic technology decision data that is available to the industry to form the FDT. The outcome of the FDT will be the technologies ranked based on their attained score. The main disadvantage of this approach is that the historical decision-making data is mostly and only available for large manufacturing firms that allocate great funds toward implementations of technologies whereas in case of SMEs these data are too costly to be obtained and analysed.

MCDM analysis are widely used in developing a technology selection framework for manufacturing firms. One example is the framework developed by Yurdakul [57] which uses Analytical Hierarchy Process (AHP) and Goal Programming (GP) methods to select between the computer-integrated manufacturing technology alternatives [57]. Tansel Ic has also developed a framework for computer-integrated manufacturing technologies selection which uses TOPSIS and Design of Experiment (DoE) methods to rank between different technologies under study [58].

2.4. Industry 4.0 Readiness and Maturity Models

Often, there is a common ground between "Readiness" and "Maturity" models but still some differences exist to make a differentiation between two models. Maturity models capture and measure the company's maturity on a specific target, whereas readiness models are mostly used as the start point of a development project [59]. An example of Industry 4.0 readiness model is the model created by Pacchini et al. [60]. In their model, for each statement (question), there are four possible answers that can be selected by the firm's decision makers. Each enabling technology has its own sets of questions and prescribed possible answers to select from. Finally, based on the answers which are eventually the maturity levels, the total degree of readiness can be calculated as below [60]:

$$g_n = \frac{\sum Points\ obtained\ from\ the\ evaluation\ of\ technology\ (e)}{Maximum\ points\ possible} \tag{1}$$

$$D_R = \frac{g_1 + g_2 + g_3 + \ldots + g_n}{n} = \frac{\sum_1^n g_n}{n} \tag{2}$$

where g_n is the adoption degree of technology (n) and D_R is the readiness degree of the company.

In order to account for importance of the dimension under study to the specific industry, some maturity models available in literature also account for the weight of the dimension. As an example, Rafael et al. have proposed an Industry 4.0 maturity model that can be used for machine tool industries. In their framework, they have included six main dimensions (Employees, Smart Operations, Data Driven, Smart Factory, Strategy, and Optimization) that capture the essence of every manufacturing industry. For each dimension, there are multiple sub-dimensions defined. Each sub-dimension includes an assessment question which have to be answered by industry's decision maker. Figure 2-4 shows the Industry 4.0 maturity model developed by Rafael et al. [61]. The answer should be in term of maturity level where level 0 corresponds to no implementation and level 5 is the highest score which showcases that the industry is already fully developed in the sub-dimension of interest under Industry 4.0 constraints. Finally, the results of different dimensions are aggregated and final score as format of maturity level of industry is determined. Moreover, a radar chart which is shown in Figure 2-5 is also created based on maturity level obtained for each dimension to further showcase the degree of maturity of the industry on a specific defined dimension [61]. As an example, in the case study performed by Rafael et al., the firm under study achieved the highest level of maturity in the employees dimension by reaching to the target according to the radar chart shown in Figure 2-5. On the other hand, there is a huge gap existing between the target and maturity level obtained for the smart product dimension which indicates that the firm under study requires more investment and development toward this specific dimension.

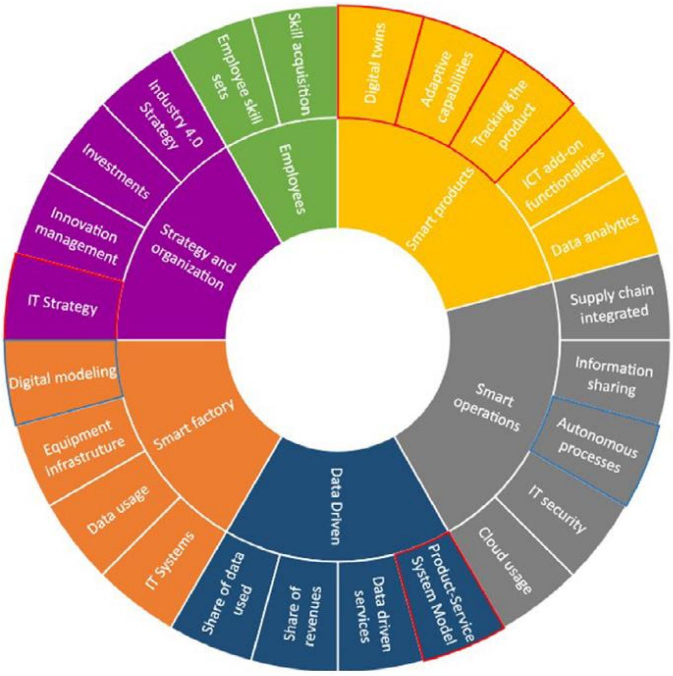


Figure 2-4: Industry 4.0 Maturity Model Developed in [61] Schematic.

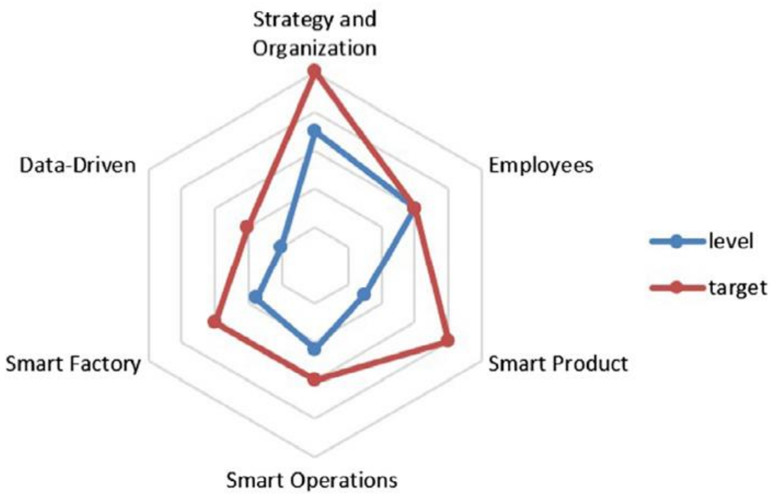


Figure 2-5: Sample Radar Chart after Industry 4.0 Maturity Assessment [61].

More complicated maturity and readiness models are also available in literature. As an example, Caiado et al. [62], have proposed an Industry 4.0 maturity model that uses fuzzy rule-base to evaluate the outcome and is specific for operations and supply chain management [62]. Another example is the Industry 4.0 readiness assessment model created by Bastos et al. in which a preliminary knowledge in the RAMI 4.0 reference architecture is required prior answering the questionnaire [63].

2.5. Industry 4.0 Reference Architectures

In order to build a unified system in which industries can understand each other's functionality better, Industry 4.0 reference architectures are created. Choosing a correct Industry 4.0 reference architecture is a crucial step in implementation of Industry 4.0 technologies within one firm. RAMI 4.0, SITAM, IVRA, and IIRA are few examples of Industry 4.0 reference architectures available in literature [64]. IVRA is one the reference architectures available in literature developed by Industrial Value Chain Initiative. This reference architecture consists of Smart Manufacturing Unit system, General Function Block, and Function Mapping. The General Function Block can be considered as the most important component since it makes the visualization of industry's activities possible. This block consists of three different axes named as: Demand/Supply Flow, Knowledge/Engineering Flow, and Hierarchical Levels [65].

RAMI 4.0 which stands for Reference Architectural Model Indsutrie 4.0 is one of the widely used Industry 4.0 reference architectures. RAMI 4.0 includes three main axes that encapsulate the essence of every firm's functionality. One unique feature of RAMI 4.0 is the usage of ISO standards in describing different aspects of reference architecture. Figure 2-6 demonstrates the RAMI 4.0 reference architecture schematics.

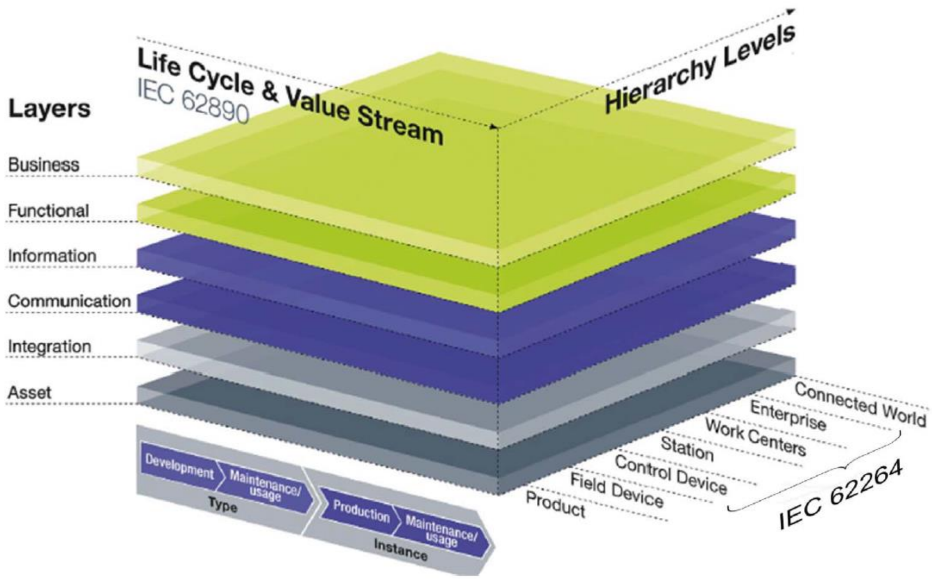


Figure 2-6: RAMI 4.0 Reference Architecture [38].

The right axis is named as "Hierarchy Levels" which shows different components included in the production until the supply. In this axis, four categories (Control Device, Station, Work Centers, and Enterprise) are from IEC 62264 which is an ISO standard for enterprise-control system integration. The other three categories are Product, Field Device and Connected World. The Product refer to the actual product or workpiece that is going to be manufactured. The Field Device is the smart machinery within the firm which enable the smart and intelligent manufacturing. Lastly, the Connected World category refer to the networking of the industry with other firms beyond the production [38]. The Life Cycle and Value Stream Axis is based on IEC 62890 which is a standard used for life cycle management. This axis divides into two main sections of Type and Instance. The first section is about the development and design phase of the product whereas the second section refers to the product, its maintenance and recycling. Lastly, the vertical axis consists of six different layers of 'Business', 'Functional', 'Information', 'Communication', 'Integration', and 'Asset'. These layers enable the digital mapping of the physical entities available in an industry and represent the functionality and business processes of an industry [38].

2.6. Industry 4.0 Roadmaps/Frameworks

In order to implement Industry 4.0 technologies within the manufacturing firms, a roadmap or framework should be followed. Currently available roadmaps/frameworks in literature often do not contain any details or quantitative evaluations. The most important problem associated with currently available Industry 4.0 roadmaps is their lack of incorporating different aspects included within the Industry 4.0 paradigm such as: readiness assessment, technology selection, and reference architecture selection. One of the examples of roadmaps is the work done by Javaid Butt [66] in which there are seven different phases for successful implementation of Industry 4.0 technologies in a manufacturing firm. The seven phases of this roadmap proposed by Javaid Butt are shown in Figure 2-7.

Another available strategic roadmap for Industry 4.0 is proposed by Ghobakhloo [67], in which the roadmap is divided into six different dimensions each consisting of a certain roadmap. Looking into Ghobakhloo's roadmap, the preliminary stages of the roadmap focus more on managerial, business, and human resources aspects and later stages focus more on infrastructure and Industry 4.0 technologies.

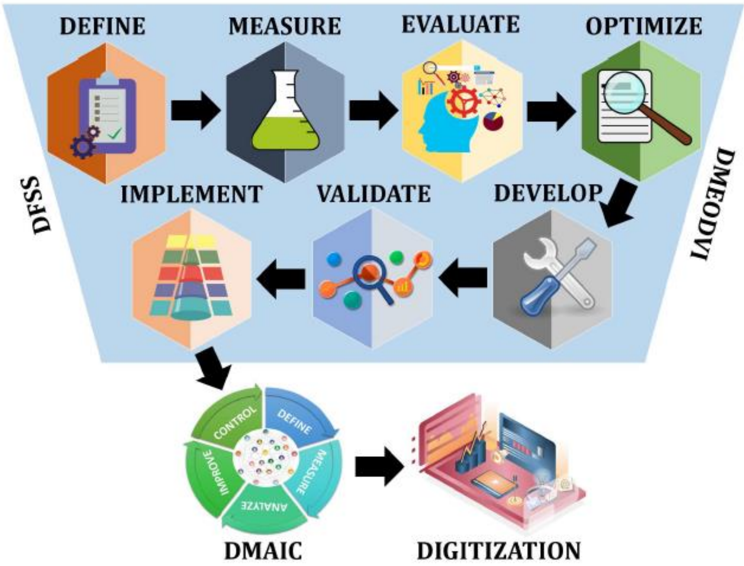


Figure 2-7: Industry 4.0 Roadmap Developed in [66].

An available framework in literature is the work done by Qin et al. [68], in which a categorical framework for Industry 4.0 has been proposed. In their developed framework, three automation level and three intelligence level have been identified. The three automation levels are named as machine, process, and factory. The three intelligence levels are named as control, integration, and intelligence. The combination of automation and intelligence levels create nine applications which showcase the degree of accomplishing Industry 4.0 [68]. The proposed roadmap by Qin et al. is shown in Figure 2-8.

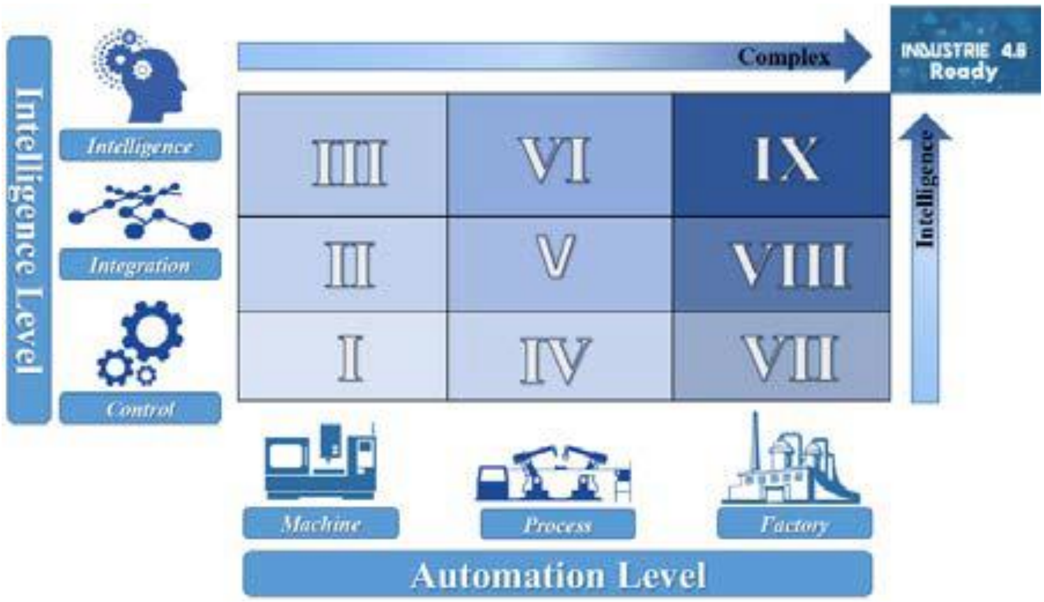


Figure 2-8: Categorical Framework for Industry 4.0 Developed in [68].

Cotrino et al. [69] introduced an Industry 4.0 roadmap which is specifically designed for SMEs. Their roadmap includes six steps shown in Figure 2-9. In the very first step, the reasons that lead to decreasing the overall production efficiency is determined. This step is similar to gap analysis which is a well-known concept. Next, long-term planning is made, and Industry 4.0 technologies are selected based on the amount of funds available and other requirements. Then a pilot prototype is implemented, and the performance of the prototype is measures. If the performance of prototype is acceptable, operators in production lines are trained to learn about Industry 4.0 functionalities. In second last step, new KPIs will be introduced and measured. Finally, the Industry 4.0 technologies are implemented on the production line.

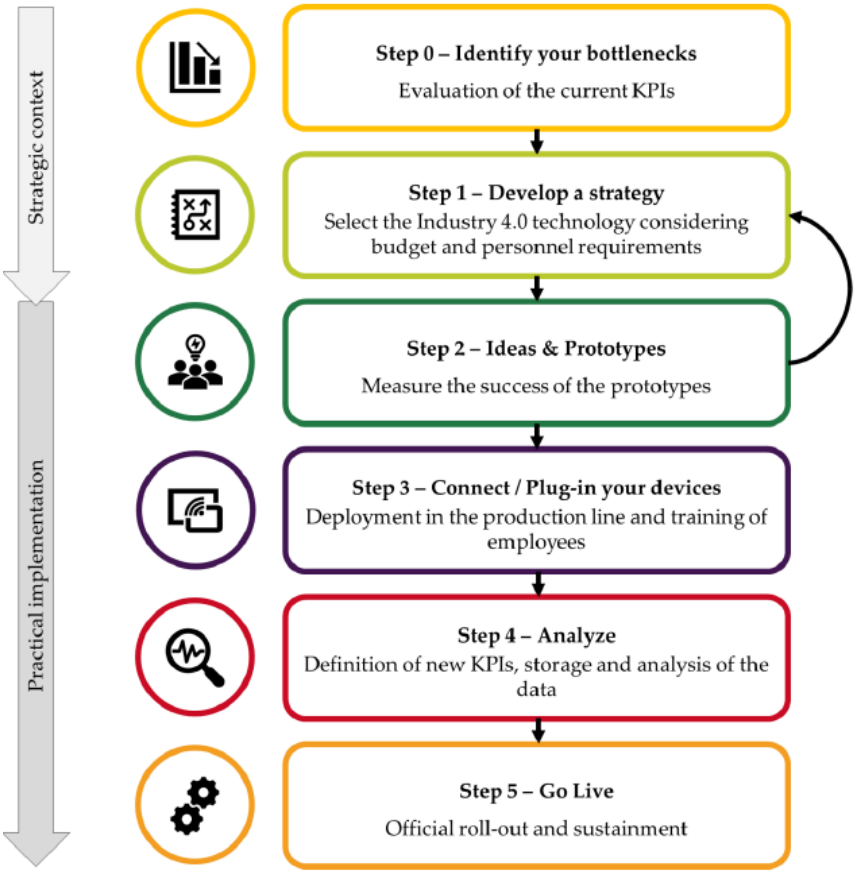


Figure 2-9: Industry 4.0 Roadmap for SMEs Proposed in [69].

As it can be seen in all the above examples, currently available roadmaps and frameworks for Industry 4.0 implementations lack detailed quantitative analysis and step by step approach which is easy to understand. Furthermore, most of such roadmaps do not include any information about readiness assessment, reference architecture, and correct technology selection methods and procedures.

Chapter 3. Methodology and Framework Development

In this chapter, the fully developed framework is shown. The framework is divided into small sections in order to ease the discussion and methodology behind the stages described in the framework.

3.1. Fully Developed Framework

Starting from the top, the decision makers will first gather and store data on current state of the manufacturing firm. Different qualitative/quantitative KPIs can be identified at this stage to be measured and be used for the later assessment of the pilot project. After measuring the KPIs, it is crucial to check whether the measured KPIs meet the specified targets or not. If targets are met, then there is no reason in implementing Industry 4.0 technologies. If targets are not met (gap exist), then the firm can move to next stage of the framework to find solutions to the gaps through implementations of the Industry 4.0 technologies. Next, Industry 4.0 technologies are selected based on experts' opinions and MCDM analysis. The very first step in the technology selection is to assign weights for the pre-selected criteria. Different objective/subjective methods can be utilized for the weight assignment. Once the weights are calculated, different MCDM methods can be utilized to aggregate results for technology selection. After selecting the technologies, a readiness model is selected from literature and the required questionnaire is filled. If the readiness percentage based on the given scale of model was within the acceptable range, then decision makers can proceed to choose an Industry 4.0 reference architecture. If not, some procedures are followed, and readiness score is evaluated again. After choosing the Industry 4.0 reference architecture, the decision makers will implement a pilot project and will assess the outcome of the pilot project. The assessment is made by combining data obtained prior to pilot project and after it. These data are analysed by means of MCDM analysis and decision is made based on results on whether the pilot project was successful or not. If successful, then the industry can move on implementing the Industry 4.0 technologies at full scale. If not, some modifications have to be made and the previously described steps must be repeated. Figure 3-1 represents the full developed framework which consists of five different stages named as gap analysis, technology selection, readiness assessment, reference architecture selection, and pilot project assessment.

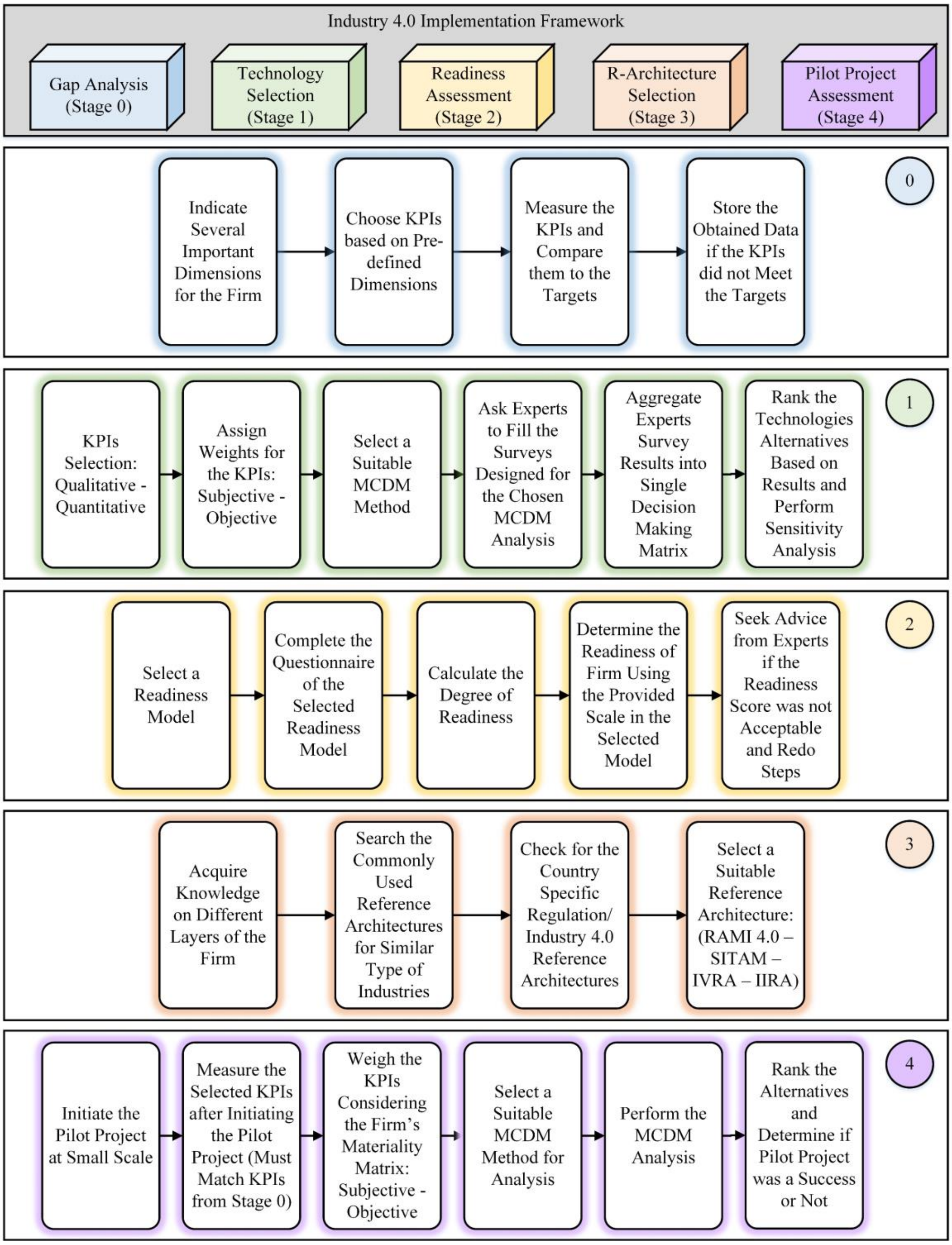


Figure 3-1: Developed Framework for the Industry 4.0 Implementations.

3.2. Gap Analysis

The very first stage in the framework is to acquire data from the current state of the manufacturing firm and compare them to the pre-defined targets. This stage is important since the data measured and obtained from this stage are later used in the pilot project assessment to measure the success of the pilot project. For this stage, different important dimensions are first selected and considered. These dimensions cover different areas important to the manufacturing firm such as sustainability, operations, and finances. After selecting the dimensions, KPIs are selected. The selected KPIs are then measured through standards, expert's opinions, or measuring devices. These measured KPIs are then compared to the pre-defined targets to analyse whether a gap exist or not. If targets are not met, the data from KPIs measurement are stored to be used later in the assessment of the pilot project section. Some examples of KPIs that can be chosen are shown in the pilot project assessment section.

3.3. Industry 4.0 Technology Selection Section

Selecting the appropriate technology can lead to a greater positive outcome after implementing the Industry 4.0 technologies into a manufacturing firm. In terms of functionality and operationality, not all manufacturing firms are same. Hence, not all manufacturing firms require to use all the proposed technologies by Industry 4.0. The novelty in this framework is incorporating MCDM analysis into the technology selection procedure alongside using the expert's opinion. This incorporation will reduce the subjective/intuitive assessment of experts on given questionnaire. It has to be mentioned that the MCDM analysis being done in this section differs from traditional MCDM analysis. To recall, MCDM analysis are known to rank the alternatives based on the given data available. In the context of Industry 4.0 technology selection that means that each manufacturing firm must first implement each technology one at a time on the firm, measure the defined KPIs, and then rank the technology alternatives and select amongst them. This method is not feasible at least for SMEs since it requires huge amount of funds and immerse amount of time to implement each technology one at time and then perform measurements. Due to this reason, the MCDM analysis on this section is being done on the results obtained from the questionnaire filled by the experts. Details on different MCDM methods that can be utilized for this part will be later discussed in the pilot project assessment section. Below are the defined steps for the Industry 4.0 technology selection section:

- KPIs Selection and Weight Assignment: At the beginning of technology selection section, quantitative/qualitative KPIs are selected based on their importance to the manufacturing firm under study. Next, the selected KPIs have to be further differentiated from one another by means of weight assignment.

Entropy and AHP weighting methods are the two most prominent methods available in literature that can be used.

- Expert's Input in the Questionnaire: As mentioned earlier, the MCDM analysis is performed on obtained results from experts' opinions. Hence, a questionnaire must be created which asks experts to provide score on degree of impact of each Industry 4.0 technology on each selected KPI.
- Aggregation of Results using MCDM Analysis: After obtaining the filled-out questionnaires, an average decision matrix is created. Next, MCDM analysis is performed on the average decision matrix to aggregate the results. The final outcome from the analysis will be the technologies ranks based on their impact in all of the pre-defined KPIs. It is obvious that the technologies with highest rankings are preferred to be chosen for the given manufacturing firm.
- Sensitivity Analysis: In order to check the effect of independent variables on particular dependent variable, sensitivity analysis is performed. Linear Regression Analysis, Differential Sensitivity Analysis are two examples of sensitivity analysis methods that can be used for this part.

3.4. Industry 4.0 Readiness Assessment Section

In this section, the decision makers will choose a readiness model available in literature and fill the given questionnaire. It has to be mentioned that most of currently available models in literature account for implementation of all Industry 4.0 technologies within the firm. Hence, the decision makers should modify the chosen readiness model based on the technologies selected in previous section. After filling the questionnaire, the degree of readiness is calculated. If the readiness score was on acceptable range according to the model chosen, then the firm can proceed to the next stage in the Industry 4.0 implementation framework. If not, some steps have to be taken prior to doing the readiness assessment once again. Gathering information on topic of Industry 4.0 technology enablers is one of such steps. Another step is to seek advice from experts in the field on how to improve the current state of the industry. Finally, more investments can be made toward upgrading the equipment within the firm so that different technologies can be implemented on them.

3.5. Industry 4.0 Reference Architecture Selection Section

In chapter 2, the importance of having an Industry 4.0 reference architecture has been described. In short, the main objective of having a reference architecture is to ease communication, enable B2B connection, understand the business functionality, and enhance the feedback provision. Below are the main steps needed to be taken for this section of framework:

- Knowledge/Information Acquisition: Acquiring knowledge in product life cycle, different industry layers, and the value chain is important in understanding the basics of every currently available Industry 4.0 reference architecture.
- Regulations and Samples Check: In order to choose a suitable Industry 4.0 reference architecture, two important considerations exist. First consideration is to check the reference architectures chosen by similar type of manufacturing firms to the firm under study. This can help decision makers to get a clear vision on how the business is broken down in different sections using certain reference architecture. The second consideration is to check the country specific regulations and reference architectures created and then proceed to choose the suitable reference architecture. As an example, if all the firms in certain country use same Industry 4.0 reference architecture model, then it advisable for decision makers to choose the same reference architecture to ease the domestic B2B communications.
- Reference Architecture Selection: Decision makers proceed to select the suitable reference architecture based on findings of previous steps.

3.6. Pilot Project Assessment

The pilot project assessment section has the highest amount of the importance in the proposed framework since it can show whether the decisions made in previous sections of the framework were correct and accurate or not. The assessment utilizes MCDM methods to analyse the obtained data and rank between two states of the manufacturing firm; one prior to the implementation of Industry 4.0 technologies, and one after the technology implementations. The pilot project is considered successful if the assessment results indicate that manufacturing firm’s performance in different dimensions after the technology implementations has been enhanced. Following subsections showcase the detailed breakdown of every step needed to be taken place for the pilot project assessment.

3.6.1. KPIs selection

The key performance indicators selected to be studied must match the indicators chosen in the very first stage of the framework which was "Gap Analysis". Generally, there are three main sustainable development dimensions known as Triple Bottom Line (TBL). These three dimensions are Economic, Social, and Environmental. The economic dimension focuses on the financial aspects of one firm such as profits and losses, earnings, and spendings. The social dimension focuses on employees and consumers. Lastly, the environmental dimension looks into different sustainability aspects regarding the production procedures and product's life cycles. Table 3-1 tabulates sample of KPIs shown for each TBL dimensions.

Table 3-1: Examples of TBL KPIs [70].

Economic	**Environmental**	**Social**
Value Addition and Revenue Product Quality Preventive Maintenance	CO_2 Emissions Energy Consumptions Waste Streams Sustainable Packaging	Employee Satisfaction Employee Safety Consumer Satisfaction

3.6.2. Materiality matrix creation

Materiality matrices are used in materiality analysis of a given business or firm. Materiality assessment help firms to identify their most important topics/issues on hand that affects both stakeholders and the business. Usually, the traditional materiality matrix consists of two axes which the x-axis is the impact of the topic on the business and y-axis is the importance of the topic to the stakeholders. The newer version of materiality matrix proposed by Global Reporting Initiative (GRI) also includes the significance of economic, environmental, and social impact of topics alongside their importance to stakeholders [71]. In context of Industry 4.0 implementation framework, this materiality matrix can be created by each firm to showcase the degree of impact/importance of each selected KPI on TBL dimensions and stakeholders. This materiality matrix helps the experts in following steps to better judge about the weight of each KPI for MCDM analysis. Figure 3-2 showcases a sample materiality matrix.

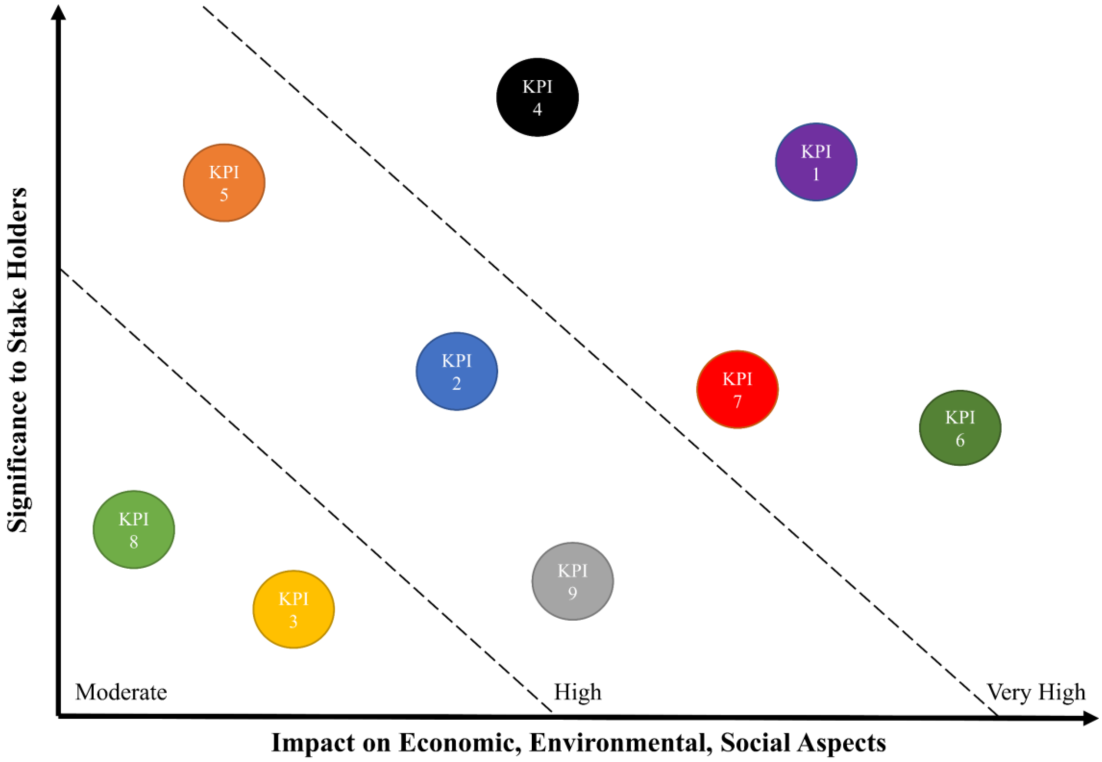


Figure 3-2: Sample Materiality Matrix.

3.6.3. KPIs weight assignment

After selecting the KPIs and creating the materiality matrix, weights can be assigned to the indicators. The weighting process can be either subjective or objective. The subjective weighting techniques depend on experts' opinions, and in this specific framework, it also depends on the materiality matrix created at the previous step. On the other hand, the objective weighting methods use quantitative analysis and perform pair wise comparison between indicators to assign the appropriate weight. Analytical Hierarchical Process (AHP), Analytic Network Process (ANP), and Entropy Weight Method are few examples of objective weighting methods used for weighting the indicators.

3.6.3.1. Analytical hierarchical process

One of the most well-known weighting technique in MCDM analysis is the AHP method. Making pairwise comparison as ratios between the set of indicators is the most important aspect of the AHP method [72]. This pairwise comparison is made using the fundamental scale of absolute numbers shown in Table 3-2.

Table 3-2: Fundamental Scale for AHP Method Proposed by Saaty [72].

Absolute Scale	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over another	One activity is slightly favored over another.
5	Essential or strong importance	One activity is strongly favored over another.
7	Very strong importance	One activity is very strongly favored over another.
9	Extreme importance	One activity is extremely favored over another.
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When comparison is needed.

The results obtained from the comparisons are placed in square matrix A shown as below:

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \quad (3)$$

For the matrix, the following relationships must be satisfied [73].

$$a_{ij} = \frac{1}{a_{ji}} \quad and \quad a_{ii} = 1 \quad (4)$$

Next, the eigenvalues of matrix A are calculated using the following equation:

$$det(A - \lambda I) = 0 \quad (5)$$

where matrix I is the identity matrix with the rank similar to the matrix A. Next, the weights of each indicator can be calculated using the following equation.

$$Aw = \lambda_{max} w \quad (6)$$

In order to evaluate the pairwise comparison, the matrix consistency index and the relative consistency ratio can be calculated as below [73].

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (7)$$

$$CR = \frac{CI}{R} \quad (8)$$

R is a constant value based on the rank of matrix *A* and its values are shown in Table 3-3.

Table 3-3: AHP Method R Coefficient Values [73].

n	1	2	3	4	5	6	7	8	9	10
R	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

The acceptable range for consistency ratio value is less than 0.1 according to AHP method and if values outside of this range is obtained, pairwise comparison must be repeated [74].

3.6.3.2. *Entropy weight method*

Entropy weight method is another popular weighting technique developed by C. E. Shannon which is used in different engineering and social economy fields [75]. At the very first step of entropy analysis, the decision matrix has to be created considering having (*m*) alternatives and (*n*) criteria [76].

$$X = [X_{ij}] = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{pmatrix} \tag{9}$$

where *Xij* is often referred to as performance value of the alternatives.

Next, the decision matrix is required to be normalized by the following equation.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{10}$$

The entropy value can then be calculated using the equation below where *i*=1, 2, ..., *m* and *j*=1, 2, ..., *n*.

$$e_j = -\frac{1}{ln(m)} \sum_{i=1}^{m} r_{ij} ln r_{ij} \tag{11}$$

At last, the weight vectors can be calculated using the equation below where *j*=1, 2, ..., *n*.

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)} \tag{12}$$

3.6.4. Data aggregation and alternatives ranking using MCDM analysis

Up until this point of the pilot project assessment, different KPIs have been selected and weighted with help of different methods discussed earlier. MCDM analysis are now used in order to aggregate the data obtained and rank between alternatives which is the firm's performance prior and after the technology implementations. There are variety of MCDM analysis available in literature which can be used in this sub-section. In the following part, few important MCDM methods are discussed and the procedure for results aggregation is shown for each method in more details.

3.6.4.1. SAW method

The simplest MCDM method developed is the Simple Additive Weighting (SAW) method. In this method, the decision matrix is normalized, and a weight vector is created which lead to finding the overall score for each available alternative [77]. This method is highly suggested and presented first since its simplicity can enable decision makers without background on MCDM analysis follow the steps clearly. The SAW method procedures are represented below [77].

The decision matrix shown in equation (9) has to be normalized using the following relations.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{x_j^+} & j \in \Omega_{max} \\ \frac{x_j^-}{x_{ij}} & j \in \Omega_{min} \end{cases} \tag{13}$$

In which the x_j^+ is the maximum value of x_{ij} in the *j^th^* column of benefit criteria, and x_j^- is the minimum value in the *j^th^* column of cost criteria. Ω_{max} and Ω_{min} are sets of benefit and cost criteria. Next, for each criteria weights are assigned and the ranking score for the ith alternative is calculated.

$$W = [w_1, w_2, \ldots\ldots\ldots, w_n] \tag{14}$$

$$S_i = \sum_{j=1}^{n} w_j \, r_{ij} \tag{15}$$

The alternative with the highest value for the ranking score will be ranked the highest between the alternatives.

3.6.4.2. TOPSIS method

Technique for Order of Preference by Similarity to Ideal Solution also known as TOPSIS is one of the available MCDM methods in the literature. This quantitative method was proposed by Hwang and Yoon to solve for multi-criteria decision-making problems [76]. In TOPSIS, the alternative that has the shortest Euclidean distance from the positive ideal solution and longest distance from the negative ideal solution is considered as the best alternative available to select [76]. The procedure for TOPSIS method is given as below [75, 76].

Set up a performance matrix for (m) alternatives and (n) criteria similar to the one shown in equation (9).

Next, normalize the decision matrix using the following equation.

$$\overline{X_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \tag{16}$$

Create the normalized decision matrix which also takes the weights into consideration shown as below.

$$\overline{V_{ij}} = w_j \times \overline{X_{ij}} = \begin{pmatrix} \overline{x_{11}} \times w_1 & \cdots & \overline{x_{1n}} \times w_1 \\ \vdots & \ddots & \vdots \\ \overline{x_{m1}} \times w_m & \cdots & \overline{x_{mn}} \times w_m \end{pmatrix} \tag{17}$$

The best positive and negative ideal solutions are then calculated as below.

$$A^+ = \{(max_i V_{ij} | j \in J), (min_i V_{ij} | j \in J')\} = \{V_1^+, V_2^+, \dots\dots\dots, V_n^+\} \tag{18}$$

$$A^- = \{(min_i V_{ij} | j \in J), (max_i V_{ij} | j \in J')\} = \{V_1^-, V_2^-, \dots\dots\dots, V_n^-\} \tag{19}$$

In above equations, J represent the benefit criteria and J prime is the non-benefit criteria.

The Euclidean distance can then be calculated by following equations which showcase the distance from the ideal best and worst values.

$$S_i^+ = \left[\sum_{j=1}^{m} (V_{ij} - {V_j}^+)^2\right]^{0.5} \qquad where\ i = 1, 2, \dots\dots\dots, n \tag{20}$$

$$S_i^- = \left[\sum_{j=1}^{m} (V_{ij} - {V_j}^-)^2\right]^{0.5} \qquad where\ i = 1, 2, \dots\dots\dots, n \tag{21}$$

Lastly, the relative closeness is calculated using the equation below.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \qquad (22)$$

The range of values for this index is between 0 and 1. Alternatives are ranked based on their relative closeness score. The closer the value is to 1, the higher will be the rank of the alternative. Likewise, the closer the value is to 0, the lower the rank of the alternative will be.

3.6.4.3. COPRAS method

The Complex Proportional Assessment method also known as COPRAS is another MCDM method that can be used to assess the success of the pilot project. The COPRAS method is often known for its simplicity in calculation and very simple procedures. The steps for COPRAS method are shown below [78].

After obtaining the decision matrix *X* similar to the one shown in equation (9), the matrix can be normalized using equation (10). Next, the weights are incorporated into normalized matrix using the following equation.

$$y_{ij} = w_j \times r_{ij} \qquad (i = 1, 2, \ldots\ldots\ldots, m\ ;\ j = 1, 2, \ldots\ldots\ldots\ldots, n) \qquad (23)$$

The sums of weighted normalized scores (WNS) are calculated using below equations.

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \qquad (24)$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \qquad (25)$$

The comparative significance for each alternative is calculated as below.

$$Q_i = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{1}{S_{-i}}} \qquad (26)$$

Lastly, the utility level is calculated by using the following equation.

$$U_i = \frac{Q_i}{Q_{max}} \times 100 \qquad (27)$$

The alternatives in the study are ranked in the descending order based on their obtained utility level.

3.6.5. Sensitivity analysis

Errors can happen in all sorts of measurements and analysis. These errors are amplified in MCDM analysis where qualitative and quantitative indicators co-exist. Hence, there need to be an analysis performed to make sure that previous steps were accurate and correct. One of the simplest and most well-known sensitivity analysis is the one-factor-at-a-time (OAT) method in which one single parameter is changed per turn while keeping the other parameters constant [79]. The limitation with this specific type of sensitivity analysis is that it can results in high biases for non-linear systems. When sensitivity analysis is completed, the decision maker will have a list which includes the sensitivity rankings of the input parameter sorted by the amount of impact they have on the output [80]. For all the sensitivity analysis, below generalized model is used [80].

$$X = (X_1, X_2, \ldots\ldots, X_n) \tag{28}$$

$$Y = f(X) \tag{29}$$

where X is the independent variables (input), and Y is the single dependent variable (output).

3.6.5.1. Linear regression analysis

One of the simple available sensitivity analysis is the linear regression analysis which constructs a linear relationship between independent variables and dependent variable. As the name implies, this method is not applicable for systems where the relationship between inputs and output is non-linear [79]. Below is the process on how to obtain the sensitivity measure [79].

$$y = b_0 + \sum_{i=1}^{n} b_i\, x_i \tag{30}$$

The regression coefficients b_i are estimated using the least square method. The absolute regression coefficient (SRC) is calculated as below.

$$SRC_i = \left| b_i \frac{\widehat{s_i}}{s} \right| \tag{31}$$

In the above equation ($\widehat{s_i}$) is the standard deviation for x_i, and the (s) is the standard deviation for y.

3.6.5.2. Differential sensitivity analysis

The differential sensitivity is another important method of sensitivity analysis. In reality, the sensitivity coefficient the ratio of change in output due to the change in a single input while holding all the other parameters constant [80]. For this method, the variance of the dependent variable Y is calculated as below [80].

$$V(Y) = \sum_{i=1}^{n} (\frac{\partial Y}{\partial X_i})^2 \ V(X_i) \tag{32}$$

The problem associated with solving the above equation is the amount of effort that is needed for solving the partial derivatives of complex functions. If the relationship between the independent variables and dependent variable is defined by an explicit algebraic equation, then the sensitivity coefficient calculation will become much simpler shown as below.

$$\phi_i = \frac{\partial Y}{\partial X_i} (\frac{X_i}{Y}) \tag{33}$$

where the ϕ_i is the sensitivity coefficient and factor $\frac{X_i}{Y}$ is used to remove the effects of units.

The partial derivatives can be approximated as finite difference if and only if large sets of equations exist. In this case, the equation for the sensitivity coefficient will be modified as below.

$$\phi_i = \frac{\%\Delta Y}{\%\Delta X_i} \tag{34}$$

3.6.5.3. Sensitivity index

This simple method determines the sensitivity by varying one single input from its minimum value to its maximum value. The sensitivity index is basically the output percentage difference and is calculated as below [80].

$$SI = \frac{D_{max} - D_{min}}{D_{max}} \tag{35}$$

D_{min} and D_{max} are the minimum and maximum output values respectively.

3.7. Final Decision and Industry 4.0 Technologies Implementation

After performing all the previous steps, the decision makers can finally decide whether the pilot project was successful or not. If successful, then Industry 4.0 technologies can be implemented on bigger scales. If the results from pilot project favored the state of firm prior to pilot technology implementations, then some procedures listed as below can be taken place prior to re-performing the analysis for another trial.

- Elimination of Factors Leading to Unsuccessful Pilot Trial: Using the help from experts, decision makers can identify the possible factors that led to unsuccessful pilot project and eliminate them accordingly.
- Removal of Similar KPIs from the Assessment: Some technologies affect specific dimensions/KPIs of the manufacturing firm. For example, Additive Manufacturing can have huge impact on sustainability dimension while having a low impact on financial dimension. Now if most of the KPIs defined are based on financial dimensions, the performance of pilot project which have implemented Additive Manufacturing will be deemed to be poor, whereas if most KPIs defined are based on sustainability dimension, the pilot project will be seemed to be a success. Hence, trying to balance the number of KPIs defined for each TBL dimensions, can possibly lead to more accurate results from pilot project assessment.
- Implementation of Different Readiness Model: Most of the readiness models available in literature are for general cases. Hence, some readiness models might not be able to capture all aspects of certain manufacturing firm leading to in-accurate readiness percentage analysis. Therefore, different readiness model can be selected to ensure the degree of readiness of the firm prior to the technology implementations.
- Increase in Number of Experts Used in Technology Selection Section: Choosing incorrect technologies is one of the most obvious factors leading to having an unsuccessful pilot project. Hence, increase in the number of experts used in for the technology selection section can increase the accuracy of the results obtained for the technologies rankings.

Chapter 4. Case Study Implementation

Due to the limited availability of time and resources, only two sections of the developed Industry 4.0 framework have been implemented on a real case study. Decision makers from an aluminium extrusion factory located in Jordan have been contacted to fill the required surveys. The methodology behind the work and results obtained for Industry 4.0 technology selection and Industry 4.0 readiness assessment sections are discussed in this chapter.

4.1. Industry 4.0 Technology Selection Methodology and Implementation

As discussed in earlier chapters, Industry 4.0 technology selection problem can be counted as a MCDM problem since different technologies (alternatives) are selected based on different KPIs (criteria). Since technology selection involves subjective type of assessment, fuzzy MCDM methods are preferred over the conventional MCDM methods. The most well-known fuzzy MCDM approach to a given problem is the combined fuzzy AHP and fuzzy TOPSIS method. In this method, fuzzy AHP is used for criteria weighting and fuzzy TOPSIS is used for technology ranking and selection. Figure 4-1 illustrates the steps needed to be taken in the proposed Industry 4.0 technology selection model. Initially a team of experts is formed, and different important criteria which are the KPIs that the firm is trying to improve are selected. Next, fuzzy AHP and fuzzy TOPSIS surveys are distributed among the experts. After collecting the responses, fuzzy pairwise comparison matrix is created to compute the fuzzy geometric mean values. The fuzzy geometric mean values help in determining the fuzzy local and global weights which can be later converted to crisp weight values to be used in later steps. From the fuzzy TOPSIS survey, fuzzy decision matrix is created which is then multiplied by crisp weight values from fuzzy AHP method. The weighted decision matrix is normalized which helps in calculating FPIS and FNIS values. Finally, the positive and negative distance values are calculated which help in obtaining the closeness coefficient for each technology. Technologies are finally ranked and selected based on their closeness coefficient scores. In this specific model, 8 Industry 4.0 technologies and total of 10 sub-criteria have been considered. These technologies and selected criteria/sub-criteria can be altered at any time by firm owners based on their requirements and functionalities.

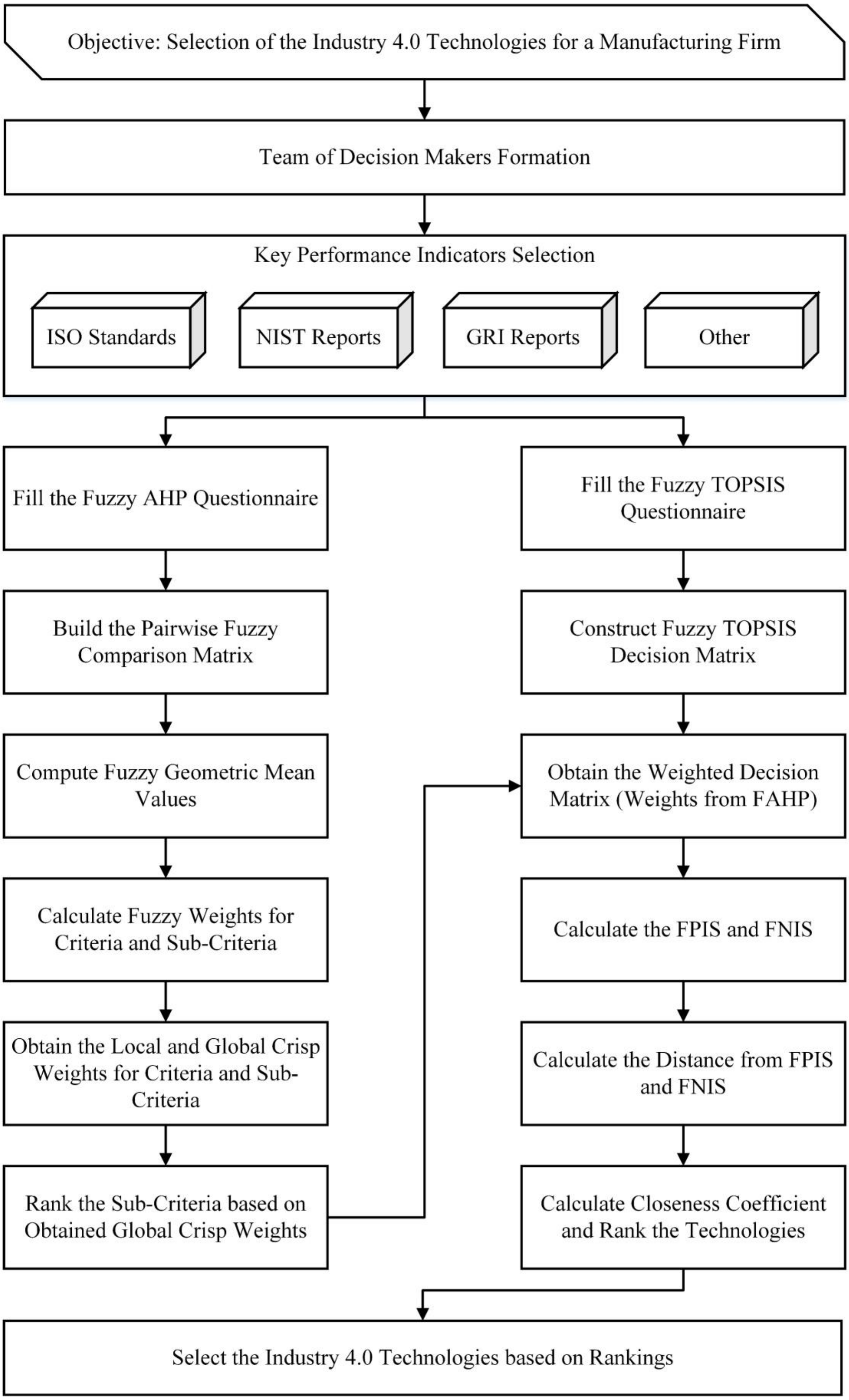


Figure 4-1: Developed Model for the Industry 4.0 Technology Selection.

4.1.1. KPI selection for criteria and sub-criteria assignment

There are different indices available in literature which can be used as valid sources for KPIs. For this specific model, the KPIs have been collected from ISO22400, GRI sustainability reporting standards (2021), and conventional financial ratios [81-84]. These KPIs are counted as sub-criteria in this model which are divided into four main criteria of production, environmental, social, and economic. Figure 4-2 illustrates the selected criteria/sub-criteria and Industry 4.0 technologies.

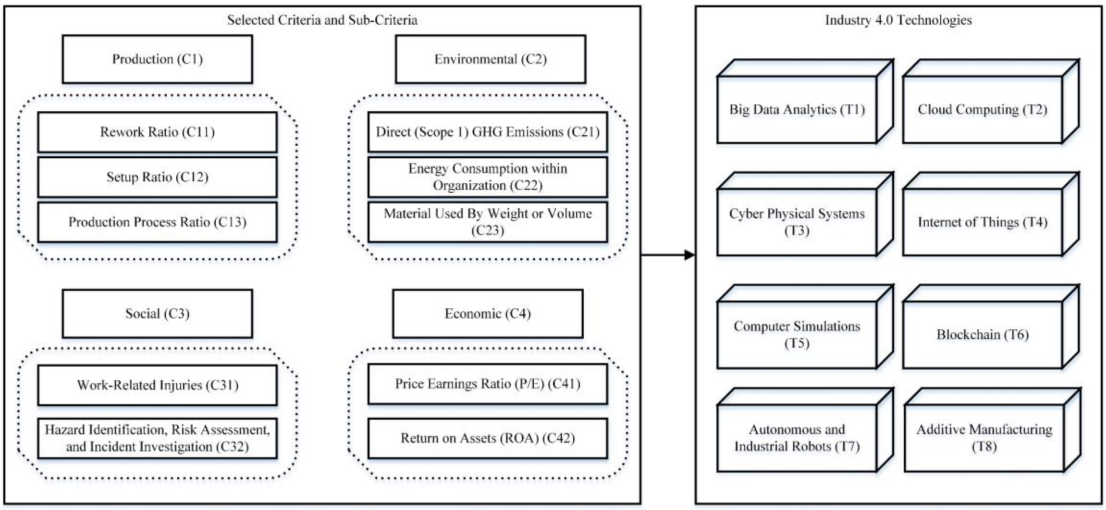


Figure 4-2: Considered Criteria and Technologies for Technology Selection Model.

4.1.2. Fuzzy AHP for criteria/sub-criteria weight assignment

Fuzzy AHP is a modified version of AHP method which fuzzy sets are used to obtain criteria weights. The geometric mean approach proposed by Buckley has been used in this model due to its simplicity [85]. In order to obtain weights using fuzzy AHP, linguistic variables should be first defined. Table 4-1 showcases the linguistic variables (membership functions) used in fuzzy AHP for criteria weighting. The steps for fuzzy AHP analysis are presented in this sub-section [86-87].

Table 4-1: Membership Functions Defined for Fuzzy AHP Method [88].

Linguistic Term	Notation	Fuzzy Value
Equally Important	ELI	(1, 1, 1)
Very Weakly Important	VWI	(1, 2, 3)
Weakly Important	WI	(2, 3, 4)
Weakly to Moderate Important	WMI	(3, 4, 5)
Moderate Important	MI	(4, 5, 6)
Moderate to Strongly Important	MSI	(5, 6, 7)
Strongly Important	SI	(6, 7, 8)
Very Strongly Important	VSI	(7, 8, 9)
Extremely Important	EI	(8, 9, 10)

From the collected survey, a fuzzy AHP decision matrix can be constructed as [86-87]:

$$\tilde{A} = [\tilde{x}_{ij}] = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (\frac{1}{u_{12}}, \frac{1}{m_{12}}, \frac{1}{l_{12}}) & (1,1,1) & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (\frac{1}{u_{1n}}, \frac{1}{m_{1n}}, \frac{1}{l_{1n}}) & (\frac{1}{u_{2n}}, \frac{1}{m_{2n}}, \frac{1}{l_{2n}}) & \cdots & (1,1,1) \end{bmatrix} \quad (36)$$

Table 4-2 showcases the obtained decision matrix based on survey results for criteria weights assignments.

Table 4-2: Decision Matrix Created for Criteria.

	C1	**C2**	**C3**	**C4**
C1	ELI	WI	WMI	ELI
C2	WI^{-1}	ELI	ELI	WMI^{-1}
C3	WMI^{-1}	ELI	ELI	WI^{-1}
C4	ELI	WMI	WI	ELI

Next, the fuzzy geometric mean is calculated for each row of data using equation below:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{x}_{ij}\right)^{1/n} \quad (37)$$

In the above equation, (*n*) represents the total number of criteria. Table 4-3 presents the calculations obtained for geometric mean values.

Table 4-3: Calculated Geometric Mean Values.

	C1	**C2**	**C3**	**C4**	$\tilde{\boldsymbol{r}}_{\boldsymbol{i}}$
C1	(1, 1, 1)	(2, 3, 4)	(3, 4, 5)	(1, 1, 1)	(1.57, 1.86, 2.11)
C2	(1/4, 1/3, 1/2)	(1, 1, 1)	(1, 1, 1)	(1/5, 1/4, 1/3)	(0.47, 0.54, 0.64)
C3	(1/5, 1/4, 1/3)	(1, 1, 1)	(1, 1, 1)	(1/4, 1/3, 1/2)	(0.47, 0.54, 0.64)
C4	(1, 1, 1)	(3, 4, 5)	(2, 3, 4)	(1, 1, 1)	(1.57, 1.86, 2.11)
Total $\tilde{\boldsymbol{r}}_{\boldsymbol{i}}$					(4.08, 4.80, 5.51)
(Total $\tilde{\boldsymbol{r}}_{\boldsymbol{i}}$**)$^{-1}$**					(0.18, 0.21, 0.25)

The fuzzy geometric mean values calculated will be used to obtain fuzzy and crisp weights using the following two equations:

$$\widetilde{w}_i = \tilde{r}_i \times (\tilde{r}_{i=1} + \tilde{r}_{i=2} + \cdots + \tilde{r}_{i=n})^{-1} = (lw_i, mw_i, uw_i) \quad (38)$$

$$G_i = \frac{lw_i + mw_i + uw_i}{3} \quad (39)$$

Table 4-4 shows the fuzzy and crisp weights calculated for criteria.

Table 4-4: Calculated Fuzzy and Crisp Weight Values for Criteria.

	$\tilde{r}_i$	$\tilde{w}_i = \tilde{r}_i \times$ (Total $\tilde{r}_i$)$^{-1}$	Crisp Weight
C1	(1.57, 1.86, 2.11)	(0.284, 0.388, 0.518)	0.397
C2	(0.47, 0.54, 0.64)	(0.085, 0.112, 0.156)	0.118
C3	(0.47, 0.54, 0.64)	(0.085, 0.112, 0.156)	0.118
C4	(1.57, 1.86, 2.11)	(0.284, 0.388, 0.518)	0.397

The exact above procedure is repeated to obtain the crisp weight values for sub-criteria. Tables 4-5, 4-6, 4-7, and 4-8 represent the decision matrices obtained for each criteria category with corresponding non-normalized crisp weight values.

Table 4-5: Production Criteria Decision Matrix.

	C11	C12	C13	Crisp Weight	Rank
C11	(1, 1, 1)	(3, 4, 5)	(0.17, 0.20, 0.25)	0.22	2
C12	(0.20, 0.25, 0.33)	(1, 1, 1)	(0.17, 0.20, 0.25)	0.09	3
C13	(4, 5, 6)	(4, 5, 6)	(1, 1, 1)	0.70	1

Table 4-6: Environmental Criteria Decision Matrix.

	C21	C22	C23	Crisp Weight	Rank
C21	(1, 1, 1)	(0.11, 0.13, 0.14)	(0.25, 0.33, 0.50)	0.078	3
C22	(7, 8, 9)	(1, 1, 1)	(4, 5, 6)	0.75	1
C23	(2, 3, 4)	(0.17, 0.20, 0.25)	(1, 1, 1)	0.18	2

Table 4-7: Social Criteria Decision Matrix.

	C31	C32	Crisp Weight	Rank
C31	(1, 1, 1)	(7, 8, 9)	0.89	1
C32	(0.11, 0.13, 0.14)	(1, 1, 1)	0.11	2

Table 4-8: Economic Criteria Decision Matrix.

	C41	C42	Crisp Weight	Rank
C41	(1, 1, 1)	(0.13, 0.14, 0.17)	0.12	2
C42	(6, 7, 8)	(1, 1, 1)	0.88	1

Table 4-9 tabulates the finalized local and global crisp weight values calculated for the criteria and sub-criteria available in this model. Furthermore, Figure 4-3 shows the overall global weights calculated for each sub-criteria. Figure 4-4 (a)-(d) illustrates the normalized local weights obtained for sub-criteria under the production, environmental, social, and economic criteria, respectively.

Table 4-9: Finalized Calculated Local and Global Weights.

Code	Criteria Name	Normalized and Rounded Weights	Code	Sub-Criteria Name	Normalized and Rounded Local Weights	Global Weight	Rank
C1	Production	0.39	C11	Rework Ratio	0.221	0.08619	4
			C12	Setup Ratio	0.089	0.03471	7
			C13	Production Process Ratio	0.690	0.2691	2
C2	Environmental	0.11	C21	Direct (Scope 1) GHG Emissions	0.077	0.00847	10
			C22	Energy Consumption within Organization	0.739	0.08129	5
			C23	Material used by Weight or Volume	0.184	0.02024	8
C3	Social	0.11	C31	Work-Related Injuries	0.888	0.09768	3
			C32	Hazard Identification, Risk Assessment, and Incident Investigation	0.112	0.01232	9
C4	Economic	0.39	C41	Price Earnings Ratio	0.126	0.04914	6
			C42	Return on Assets	0.874	0.34086	1

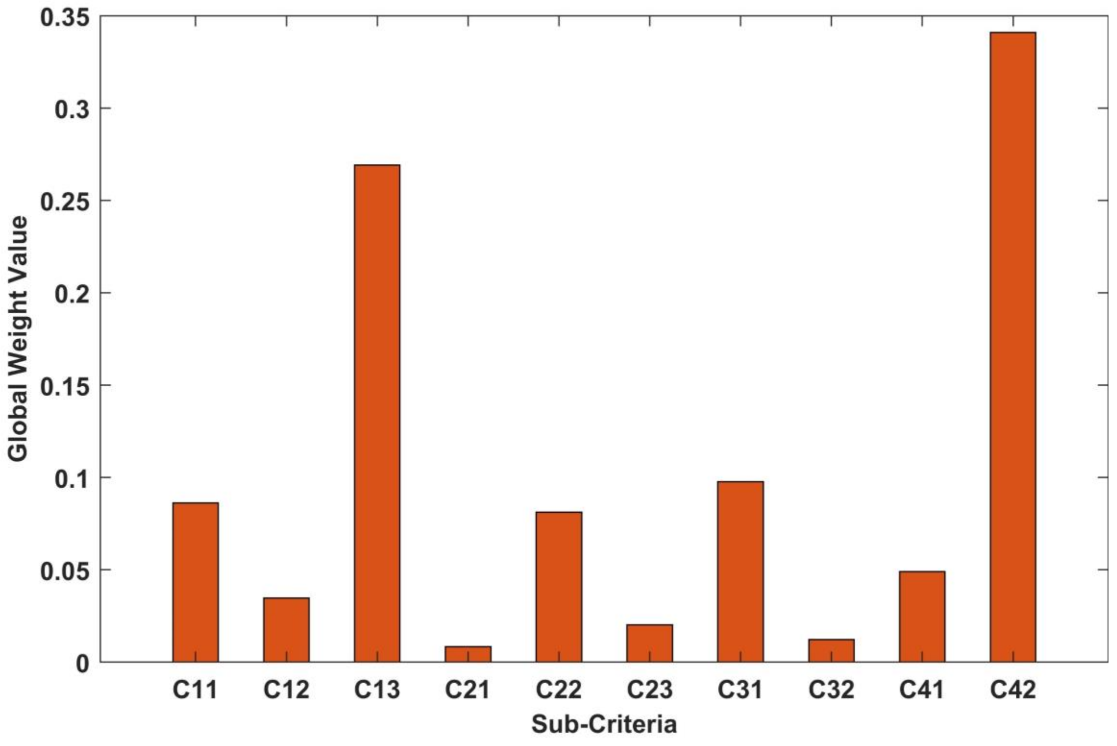


Figure 4-3: Sub-Criteria Global Weights Bar Chart.

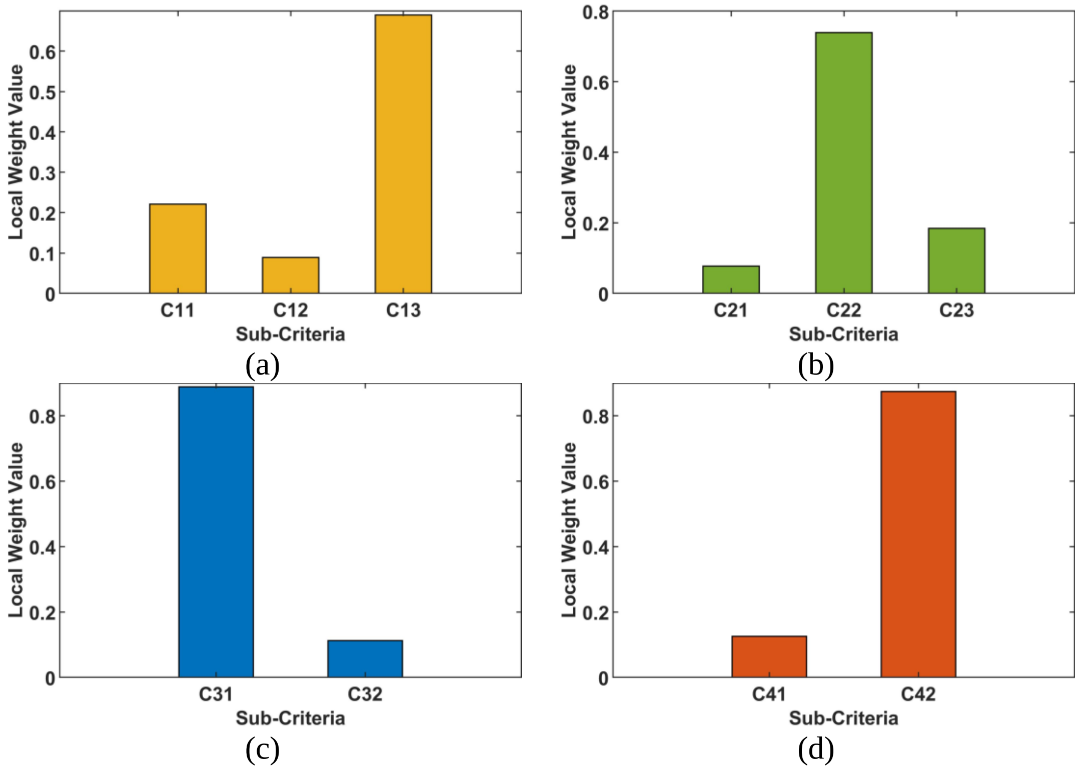


Figure 4-4: Normalized Local Weights Obtained for (a) Production (b) Environmental (c) Social and (d) Economic Dimensions.

4.1.3. Fuzzy TOPSIS for aggregating results and ranking technologies

After obtaining crisp weight values from fuzzy AHP method, fuzzy TOPSIS is used to obtain the rankings of technologies. Similar to fuzzy AHP, linguistic variables are used in fuzzy TOPSIS to measure the degree of impact of each technology on the given criteria/sub-criteria. Table 4-10 presents the membership functions defined to be used in fuzzy TOPSIS procedure. The steps for fuzzy TOPSIS method will be discussed in this sub-section [89-91].

Table 4-10: Membership Functions Defined for Fuzzy TOPSIS Method [91].

Linguistic Term	Notation	Fuzzy Value
Very Low Impact	VLI	(1, 1, 3)
Low Impact	LI	(1, 3, 5)
Medium Impact	MI	(3, 5, 7)
High Impact	HI	(5, 7, 9)
Very High Impact	VHI	(7, 9, 9)

The very first step in fuzzy TOPSIS is creating a fuzzy decision matrix where each input to the matrix is a fuzzy number as shown below:

$$\tilde{X} = [\tilde{x}_{ij}] = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{40}$$

The decision matrix obtained based on survey results from the firm of interest is represented in Table 4-11 and Table 4-12.

Table 4-11: Fuzzy TOPSIS Decision Matrix (Linguistic Values).

	C11	**C12**	**C13**	**C21**	**C22**	**C23**	**C31**	**C32**	**C41**	**C42**
T1	HI	MI	VHI	MI	VHI	HI	HI	LI	MI	HI
T2	MI	LI	MI	MI	MI	LI	LI	LI	LI	LI
T3	VHI	HI	VHI	MI	HI	MI	VHI	MI	MI	HI
T4	LI	LI	LI	LI	LI	VLI	VLI	VLI	VLI	VLI
T5	LI	LI	HI	MI	MI	MI	LI	LI	VLI	VLI
T6	MI	LI	VLI	LI	LI	VLI	MI	MI	LI	LI
T7	HI	HI	HI	MI	LI	HI	VHI	VHI	LI	LI
T8	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI

Table 4-12: Fuzzy TOPSIS Decision Matrix (Fuzzy Numerical Values).

	C11	**C12**	**::**	**::**	**C41**	**C42**
T1	(5, 7, 9)	(3, 5, 7)	….	….	(3, 5, 7)	(5, 7, 9)
T2	(3, 5, 7)	(1, 3, 5)	….	….	(1, 3, 5)	(1, 3, 5)
::	….	….	….	….	….	….
::	….	….	….	….	….	….
T7	(5, 7, 9)	(5, 7, 9)	….	….	(1, 3, 5)	(1, 3, 5)
T8	(1, 1, 3)	(1, 1, 3)	….	….	(1, 1, 3)	(1, 1, 3)

If multiple of experts are considered in fuzzy TOPSIS, below equation can be used to obtain the aggregated fuzzy decision matrix:

$$a_{ij} = min_k(a_{ijk}), \qquad b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ijk}, \qquad c_{ij} = max_k(c_{ijk}) \tag{41}$$

where k corresponds to the decision maker and K is the total number of decision makers.

The normalized fuzzy decision matrix and the weighted normalized fuzzy decision matrix are then obtained using following equations:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \qquad ; \qquad c_j^* = max_i(c_{ij}) \tag{42}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \qquad ; \qquad a_j^- = min_i(a_{ij}) \tag{43}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times w_j \tag{44}$$

Equation (42) is used when dealing with benefit criterion and equation (43) is used when dealing with cost criterion. Table 4-13 represent the normalized fuzzy decision matrix, and Table 4-14 represents the weighted normalized fuzzy decision matrix obtained.

Table 4-13: Normalized Fuzzy Decision Matrix.

	C11	**C12**	**::**	**::**	**C41**	**C42**
T1	(0.55, 0.77, 1)	(0.33, 0.55, 0.77)	….	….	(0.43, 0.71, 1)	(0.55, 0.77, 1)
T2	(0.33, 0.55, 0.77)	(0.11, 0.33, 0.55)	….	….	(0.14, 0.43, 0.71)	(0.11, 0.33, 0.55)
::	….	….	….	….	….	….
::	….	….	….	….	….	….
T7	(0.55, 0.77, 1)	(0.55, 0.77, 1)	….	….	(0.14, 0.43, 0.71)	(0.11, 0.33, 0.55)
T8	(0.11, 0.11, 0.33)	(0.11, 0.11, 0.33)	….	….	(0.14, 0.14, 0.43)	(0.11, 0.11, 0.33)

Table 4-14: Weighted Normalized Fuzzy Decision Matrix.

	C11	**C12**	**::**	**::**	**C41**	**C42**
T1	(0.047, 0.067, 0.086)	(0.011, 0.019, 0.027)	….	….	(0.021, 0.035, 0.049)	(0.189, 0.265, 0.340)
T2	(0.028, 0.047, 0.067)	(0.003, 0.011, 0.019)	….	….	(0.007, 0.021, 0.035)	(0.037, 0.113, 0.189)
::	….	….	….	….	….	….
::	….	….	….	….	….	….
T7	(0.047, 0.067, 0.086)	(0.019, 0.027, 0.034)	….	….	(0.007, 0.021, 0.035)	(0.037, 0.113, 0.189)
T8	(0.009, 0.009, 0.028)	(0.003, 0.003, 0.011)	….	….	(0.007, 0.007, 0.021)	(0.037, 0.037, 0.113)

The Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) values are next calculated to help in calculating the distance of each alternative from ideal solutions.

$$FPIS = A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \ldots., \tilde{v}_n^*) \quad ; \quad \tilde{v}_j^* = max_i(v_{ij3}) \tag{45}$$

$$FNIS = A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots., \tilde{v}_n^-) \quad ; \quad \tilde{v}_j^- = min_i(v_{ij1}) \tag{46}$$

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*) \tag{47}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{48}$$

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}((a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2)} \tag{49}$$

Table 4-15 showcases the calculated values for FPIS and FNIS.

Table 4-15: Calculated FPIS and FNIS Values.

	FPIS (A^*)	**FNIS (A^-)**
C11	(0.06704, 0.08619, 0.08619)	(0.00958, 0.00958, 0.02873)
C12	(0.01928, 0.027, 0.03471)	(0.00386, 0.00386, 0.01157)
C13	(0.2093, 0.2691, 0.2691)	(0.0299, 0.0299, 0.0897)
C21	(0.00363, 0.00605, 0.00847)	(0.00121, 0.00121, 0.00363)
C22	(0.06322, 0.08129, 0.08129)	(0.00903, 0.00903, 0.0271)
C23	(0.01124, 0.01574, 0.02024)	(0.0022, 0.00225, 0.00675)
C31	(0.07597, 0.09768, 0.09768)	(0.01085, 0.01085, 0.03256)
C32	(0.00958, 0.01232, 0.01232)	(0.00137, 0.00137, 0.00411)
C41	(0.02106, 0.0351, 0.04914)	(0.00702, 0.00702, 0.02106)
C42	(0.1893, 0.2651, 0.34086)	(0.03787, 0.03787, 0.11362)

Lastly the Closeness Coefficient (CC_i) values are calculated to rank the technologies using equation:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \tag{50}$$

Closeness coefficient calculations and obtained rankings are presented in Table 4-16 and Figure 4-5.

Table 4-16: Obtained Rankings for the Technologies.

Code	**Technology Name**	***D****	***D-***	***CC$_i$***	**Rank**
T1	Big Data Analytics	0.04849	0.63418	0.92897	2
T2	Cloud Computing	0.42419	0.27547	0.39372	4
T3	Cyber Physical Systems	0.02399	0.65484	0.96466	1
T4	Internet of Things	0.60449	0.08748	0.12643	7
T5	Computer Simulations	0.44754	0.24710	0.35573	5
T6	Blockchain	0.52131	0.17184	0.24792	6
T7	Autonomous/Industrial Robots	0.27892	0.42141	0.60174	3
T8	Additive Manufacturing	0.67560	0	0	8

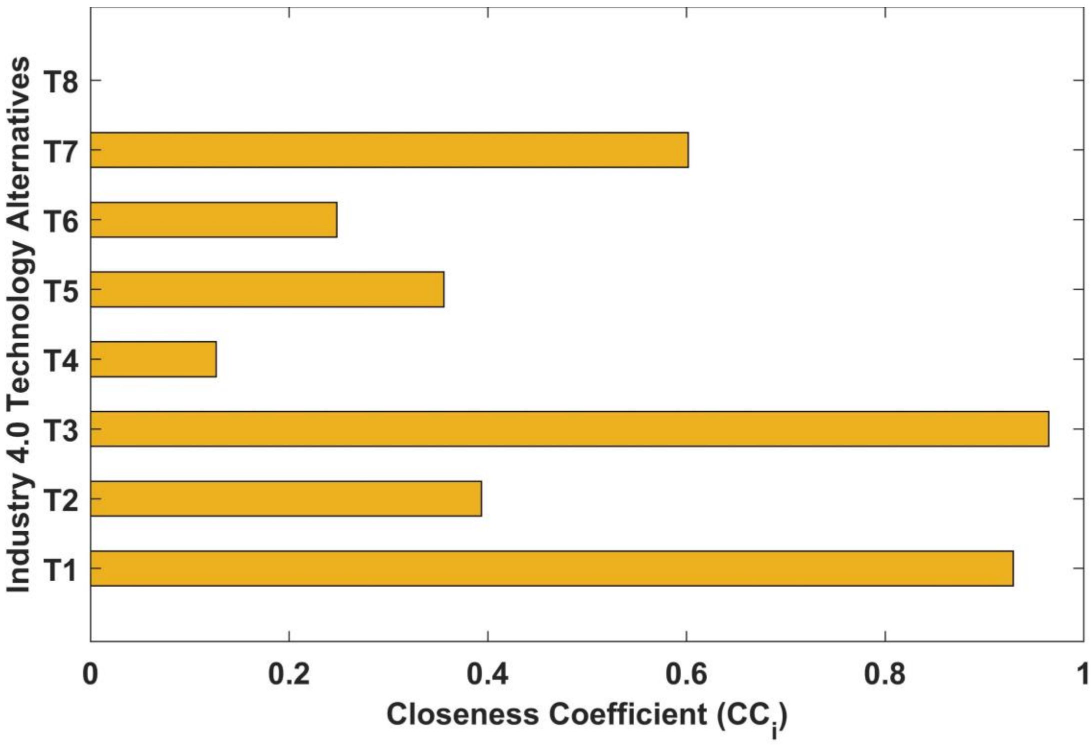


Figure 4-5: Industry 4.0 Technologies Rankings.

The results obtained can help the firm to understand which technologies are the most suitable to be implemented based on the given criteria.

4.1.4. Sensitivity analysis

Sensitivity analysis is also performed in this model to measure the sensitivity of the developed model to the changes in criteria/sub-criteria weightings. Two sets of experiments have been considered. In the first experiment, in each trial, one sub-criteria weight is assigned to be as 0.64 while other weights are the same and equal to 0.04. In the second experiment, at each trial, one sub-criteria weight will be 0.37 while other sub-criteria will have the same weight equal to 0.07. Table 4-17 and Table 4-18 tabulate sensitivity results from experiments 1 and 2, respectively

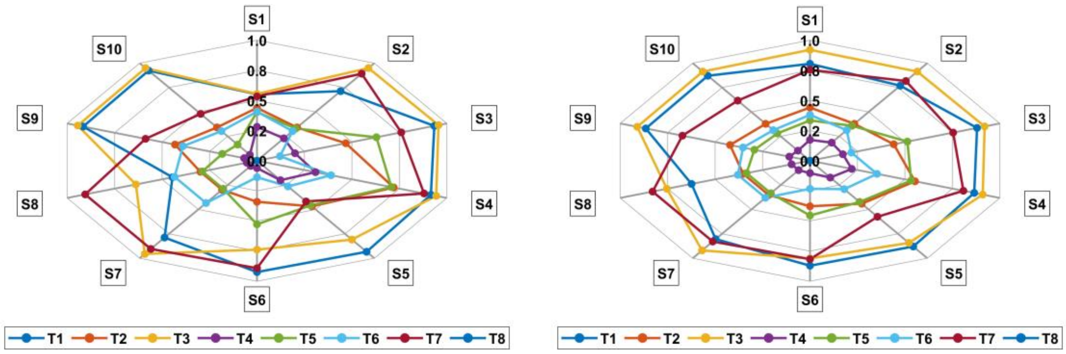
Table 4-17: Experiment 1 Sensitivity Analysis Results.

	S1 (W11=0.64)	**S2 (W12=0.64)**	**S3 (W13=0.64)**	**::**	**S8 (W32=0.64)**	**S9 (W41=0.64)**	**S10 (W42=0.64)**
T1	0.551	0.713	0.934	….	0.445	0.916	0.924
T2	0.438	0.341	0.468	….	0.298	0.432	0.341
T3	0.554	0.95	0.956	….	0.638	0.944	0.95
::	….	….	….	….	….	….	….
T6	0.407	0.303	0.121	….	0.434	0.39	0.303
T7	0.533	0.892	0.76	….	0.905	0.587	0.48
T8	0	0	0	….	0	0	0

Table 4-18: Experiment 2 Sensitivity Analysis Results.

	S1 (W11=0.37)	S2 (W12=0.37)	S3 (W13=0.37)	::	S8 (W32=0.37)	S9 (W41=0.37)	S10 (W42=0.37)
T1	0.804	0.769	0.88	….	0.624	0.865	0.871
T2	0.441	0.378	0.441	….	0.352	0.421	0.378
T3	0.92	0.914	0.92	….	0.754	0.91	0.914
::	….	….	….	….	….	….	….
T6	0.38	0.313	0.218	….	0.38	0.353	0.313
T7	0.754	0.817	0.754	….	0.829	0.672	0.616
T8	0	0	0	….	0	0	0

Figure 4-6 (a) illustrate the radar chart obtained for experiment 1, and Figure 4-6 (b) illustrate the radar chart obtained for experiment 2.



(a) (b)

Figure 4-6: Sensitivity Results for (a) Experiment 1 and (b) Experiment 2.

The radar chart for experiment 1 showcases high degree of sensitivity of developed model to changes in the criteria weight. On the other hand, radar chart for experiment 2 showcases low sensitivity of the model to changes in criteria weights. This conclusion is apparent since the shape of lines in experiment 2 are more circular than experiment 1. From Figure 4-6 it can be concluded that the technology selection model is relatively sensitive to the sub-criterion weights. This result is expected since this technology selection model should depend on firm’s requirements and goals.

4.2. Industry 4.0 Readiness Assessment Methodology and Implementation

Most of the readiness models found in literature are complex which make them not suitable for decision makers that are recently exposed to the idea of Industry 4.0. Hence, a simple readiness model is created in this section that includes discrete questions which can be replied by simple “yes” or “no” answers. For every “yes” answer, the firm obtain a single point whereas for every “no” answer, no points will be allocated to the firm [46]. According to the Industry 4.0 framework developed in this thesis, the readiness assessment section comes after the technology selection section. The reason for this is to exclude the technologies that are not suitable for the firm from readiness assessment. In previous section, it has been concluded that additive manufacturing technology is the least important technology to the firm. Hence, this specific technology can be omitted from the readiness assessment. In here, since the readiness assessment was performed prior to technology selection section in the thesis timeline, additive manufacturing is also included as one of the technologies.

4.2.1. Developed questions for the Industry 4.0 readiness assessment

Questions developed in the readiness model cover four main technology areas named as: Cyber Physical Systems, Additive Manufacturing, Internet of Things, and Industrial/Autonomous Robots. The category of CPS technologies itself includes other technologies like: Computer Simulations, Big Data Analytics, Blockchain, and Cloud Computing [46]. For the CPS category, questions asked follow four main dimensions of data acquisition, security, connectivity, and infrastructure. Questions asked for this category of technology are shown in Figure 4-7.

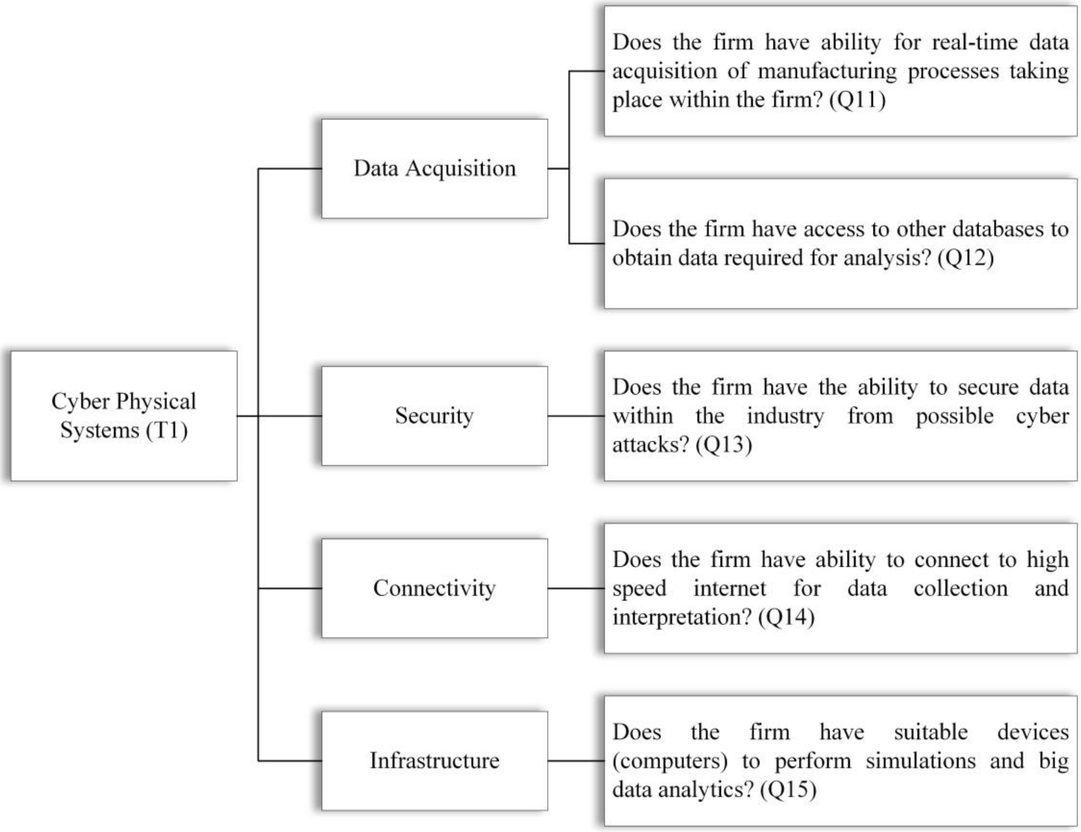


Figure 4-7: CPS Technology Readiness Questions.

Next category of technology is the Additive Manufacturing. Availability of 3D printers and 3D modeling software, availability of skilled workers that are familiar with 3D printing concepts, and availability of infrastructure in terms of post treatment equipment and raw material supply are counted as most important areas that the questions asked for this category tackle. Figure 4-8 represents the questions asked for the Additive Manufacturing technology.

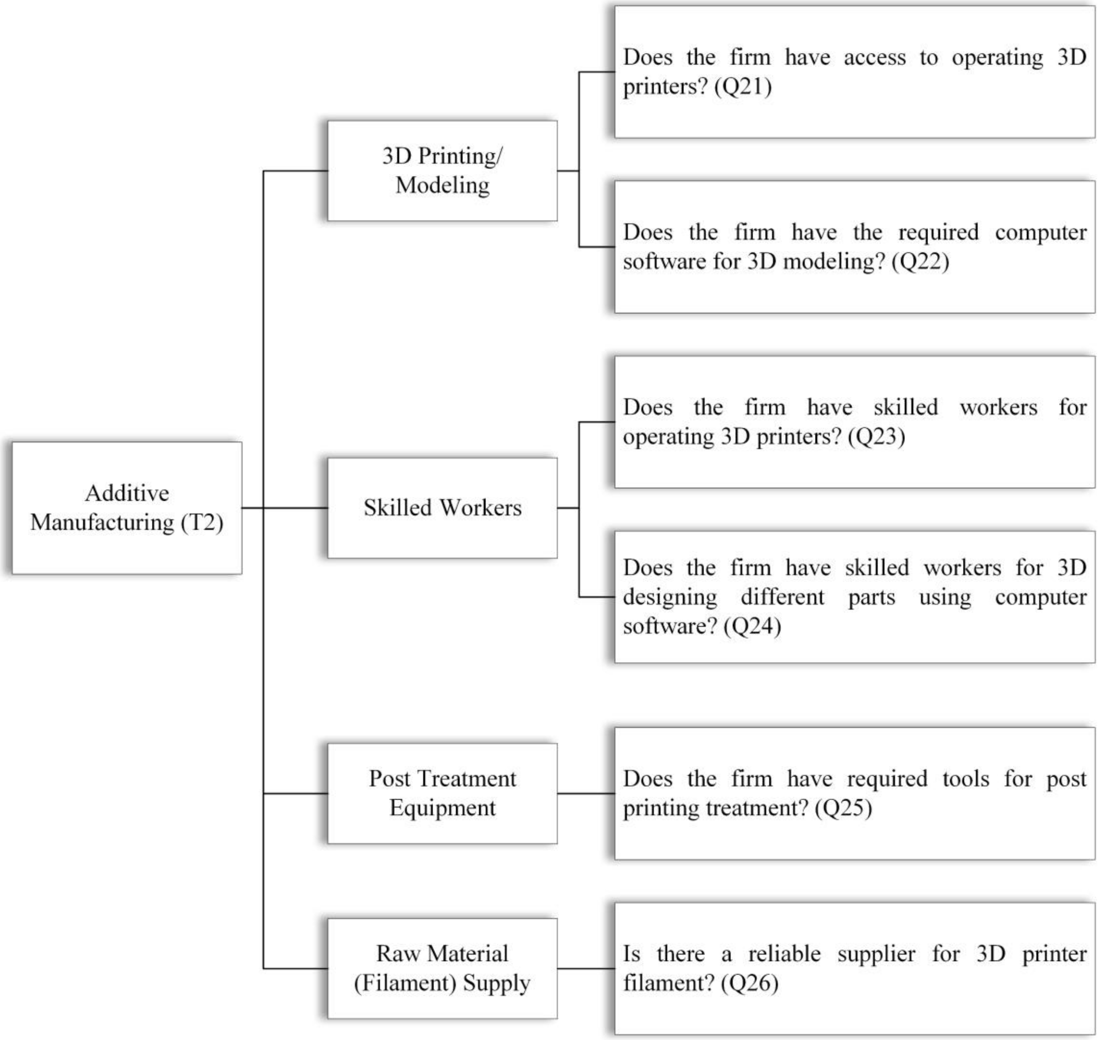


Figure 4-8: Additive Manufacturing Technology Readiness Questions.

The IoT category includes RFID and WSN technologies [46]. Three categories of questions have been assigned for the IoT technologies. Infrastructure, data monitoring, and skilled workers are the categories of questions. Questions for the IoT readiness assessment are shown in the Figure 4-9.

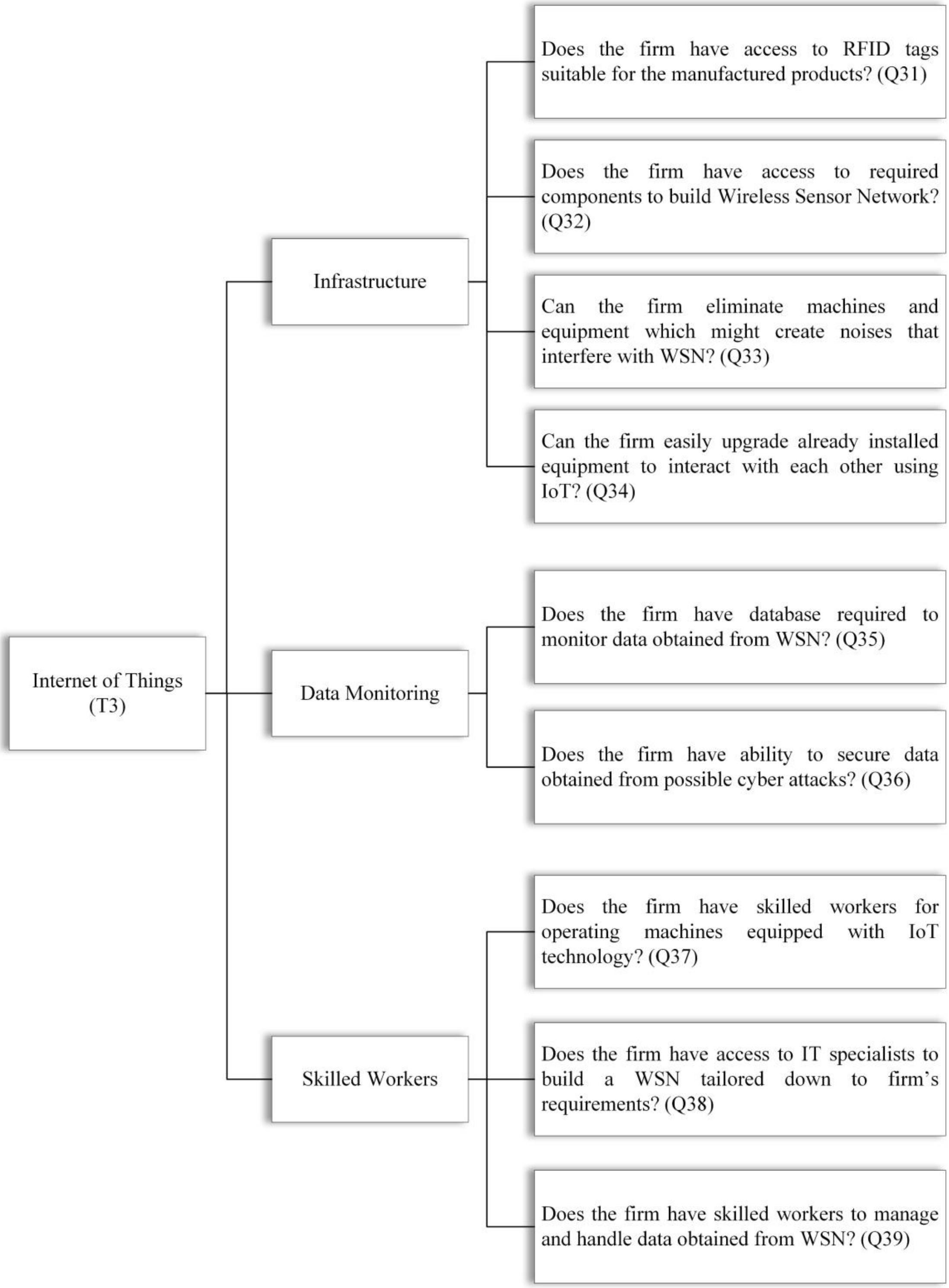


Figure 4-9: IoT Technology Readiness Questions.

The last category of technologies is the Industrial/Autonomous Robots category which includes following asked questions as shown in the Figure 4-10.

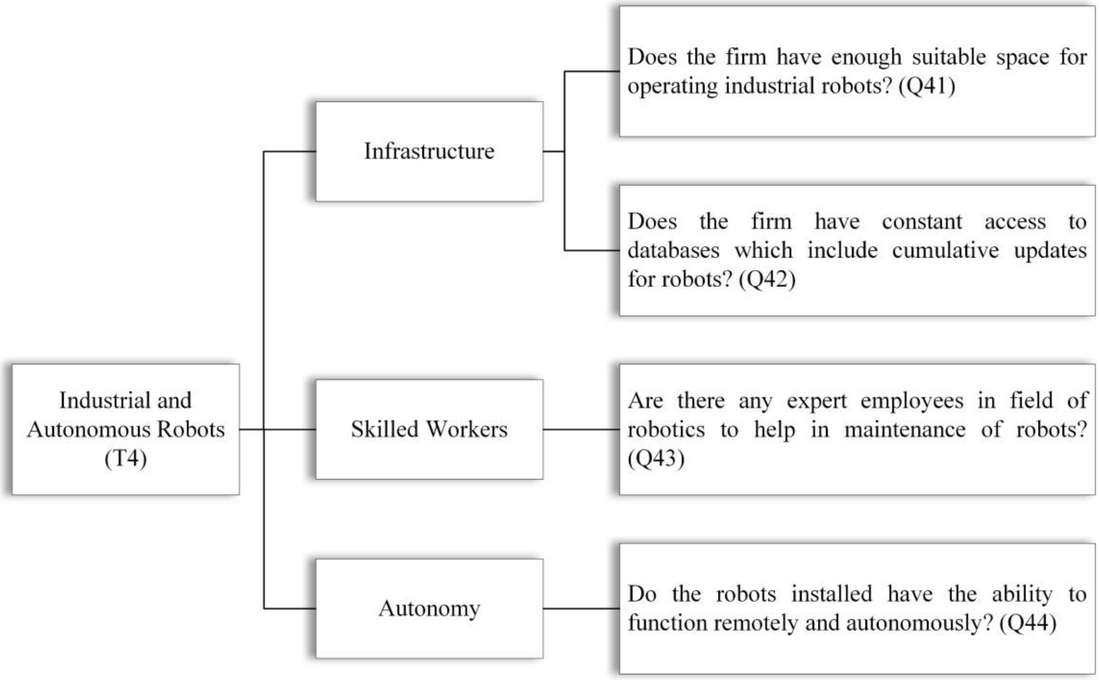


Figure 4-10: Industrial/Autonomous Robots Technology Readiness Questions.

4.2.2. Analysis and results obtained

After the firm has answered all the corresponding questions for each category of technology, below equations are used to calculate the readiness and weighted readiness score for each technology [46].

$$R_n = \frac{\sum_{i=1}^{m} Q_{ni}}{Z_n} \tag{51}$$

$$WR_n = W_n \times \frac{\sum_{i=1}^{m} Q_{ni}}{Z_n} \tag{52}$$

Q_{ni} is the point obtained from answering the question for technology 'n'. Z_n is the maximum score possible for the technology 'n'. R_n is the readiness score of the technology 'n'. m is the total number of questions available for each technology. Lastly, W_n and WR_n relate to weight assigned and weighted readiness score for the technology 'n'.

Table 4-19 tabulates the results obtained from the survey response done by the expert from an aluminum extrusion factory in Jordan.

Table 4-19: Readiness Assessment Results Obtained [46].

	Cyber Physical System	Additive Manufacturing	Internet of Things	Industrial and Autonomous Robots
Z_n	5	6	9	4
Q_{ni}	2	3	4	2
W_n	0.3 (30%)	0.1 (10%)	0.2 (20%)	0.4 (40%)
R_n	0.4	0.5	0.44	0.5
WR_n	0.12	0.05	0.088	0.2

The calculated readiness score for each technology show that the firm is more prepared toward implementation of Additive Manufacturing and Industrial/Autonomous Robots in comparison to other two categories of technologies due to higher degree of readiness obtained. Figure 4-11 provides a comparison between readiness scores obtained for each technology.

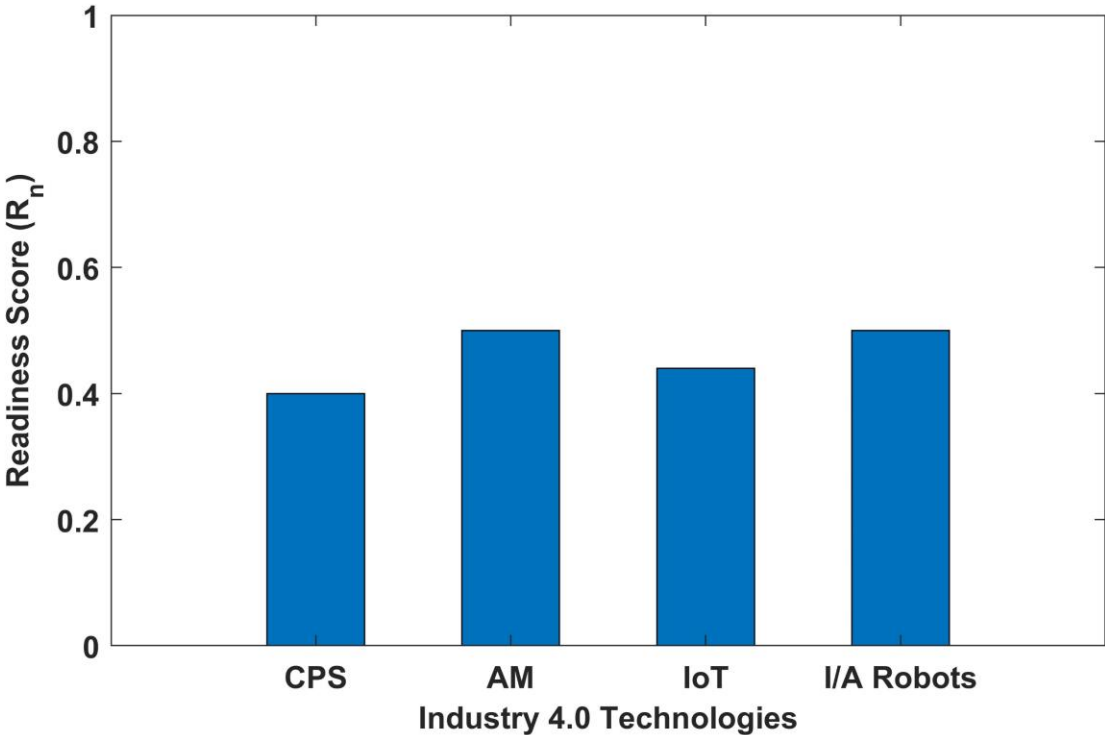


Figure 4-11: Calculated Readiness Scores for each Technology.

Next, the total readiness percentage for the firm can be calculated using equations below where k is the total number of technologies considered in the model:

$$R_t = \sum_{n=1}^{k} WR_n \tag{53}$$

$$\%R_t = R_t \times 100 \tag{54}$$

After obtaining the total degree of readiness percentage, firm owners can refer to Table 4-20 and Figure 4-12 to understand the current readiness level of their industry.

Table 4-20: Readiness Level Index [46].

Readiness Level	**Category**	**Evaluation**	**Percentage Readiness Range**
0	Not Prepared	The firm has high shortage in infrastructure and skilled workers.	$0<R_t\%<20$
1	Primary	There is an indication of limited availability of infrastructure and skilled workers within the firm.	$20<R_t\%<40$
2	Intermediate	The firm is correctly working toward Industry 4.0 technologies execution.	$40<R_t\%<60$
3	Progressive	The firm has improved knowledge and infrastructure but requires few modifications and investments.	$60<R_t\%<80$
4	Prepared	The firm is fully prepared to convert to Industry 4.0.	$80<R_t\%<100$

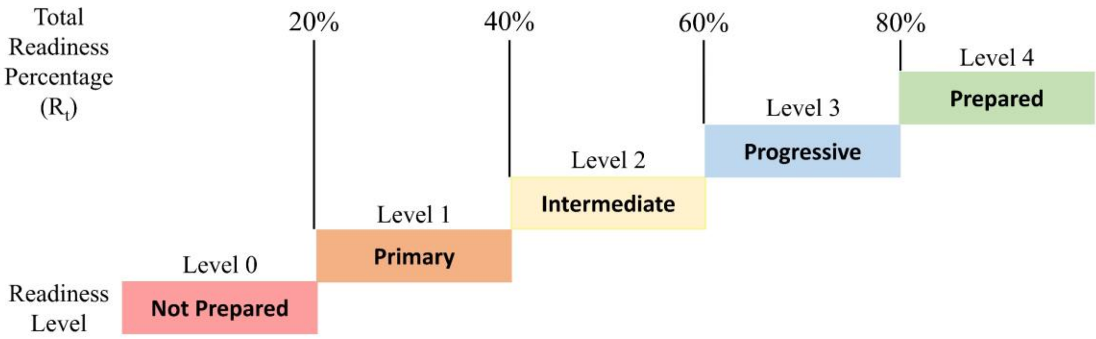


Figure 4-12: Schematic Representation of Readiness Level Index.

Based on obtained answers for the questions, the total degree of readiness for the firm is calculated as:

$$R_t = \sum_{n=1}^{k} WR_n = 0.12 + 0.05 + 0.088 + 0.2 = 0.458$$

$$\%R_t = R_t \times 100 = 0.458 \times 100 = 45.8\ \%$$

Total readiness percentage of 45.8 indicates that the firm is currently at the intermediate level in the developed scale. Hence, it can be understood that the firm is moving correctly toward implementation of Industry 4.0 technologies but also needs more investment and knowledge in this field.

Chapter 5. Conclusion and Future Work

In this thesis, a decision model for implementation of Industry 4.0 technologies on manufacturing firms have been developed. Different aspects in Industry 4.0 such as technology selection, readiness assessment, and reference architecture selection have been combined to create this comprehensive framework. This thesis work also introduces new decision models for Industry 4.0 technology selection and readiness assessment. Due to limited availability of funds in implementing the full framework on a manufacturing firm, only the technology selection and readiness assessment stages of the framework have been implemented on a case study. Cyber-Physical Systems, Big Data Analytics, and Autonomous/Industrial Robots were the top three rated technologies with closeness coefficient scores of 0.964, 0.928, and 0.601, respectively. The firm achieved a readiness score of 45.8% after implementing the readiness assessment model showing that the firm is at an intermediate readiness level.

As for the future work, a decision model for Industry 4.0 reference architecture selection can be developed to further clarify the reference architecture selection stage for the decision makers. Furthermore, the framework can be expanded so that it also includes the costs associated with implementation of each technology.

References

[1] N. Carvalho, O. Chaim, E. Cazarini, and M. Gerolamo, "Manufacturing in the fourth industrial revolution: A positive prospect in Sustainable Manufacturing," *Procedia Manufacturing*, vol. 21, pp. 671-678, 2018/01/01/ 2018, doi: https://doi.org/10.1016/j.promfg.2018.02.170.

[2] K. Schwab, The Fourth Industrial Revolution. Switzerland: World Economic Forum, 2016, p. 172.

[3] E. O. B. Nara et al., "Expected impact of industry 4.0 technologies on sustainable development: A study in the context of Brazil's plastic industry," *Sustainable Production and Consumption*, vol. 25, pp. 102-122, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.spc.2020.07.018.

[4] O. Chaim, B. Muschard, E. Cazarini, and H. Rozenfeld, "Insertion of sustainability performance indicators in an industry 4.0 virtual learning environment," *Procedia Manufacturing*, vol. 21, pp. 446-453, 2018/01/01/ 2018, doi: https://doi.org/10.1016/j.promfg.2018.02.143.

[5] K. Thomas, S. Kannan, M. Nazzal, S. Pervaiz, and R. Karthikeyan, "A Numerical Simulation of Machining 6061 Syntactic Foams Reinforced with Hollow Al2O3 Shells," *Metals*, vol. 12, no. 4, p. 596, 2022, doi: 10.3390/met12040596.

[6] A. Alhourani, M. Awad, M. A. Nazzal, and B. M. Darras, "Optimization of friction stir back extrusion mechanical properties and productivity of magnesium AZ31-B seamless tubes," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 235, no. 13, pp. 2143-2154, 2022/04/27 2021, doi: 10.1177/09544054211014465.

[7] A. A. Ahmed, M. A. Nazzal, and B. M. Darras, "Cyber-Physical Systems as an Enabler of Circular Economy to Achieve Sustainable Development Goals: A Comprehensive Review," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 9, pp. 955-975, 2021, doi: 10.1007/s40684-021-00398-5.

[8] O. M. Jarrah, M. A. Nazzal, and B. M. Darras, "Numerical modeling and experiments of Friction Stir Back Extrusion of seamless tubes," *CIRP Journal of Manufacturing Science and Technology*, vol. 31, pp. 165-177, 2020, doi: https://doi.org/10.1016/j.cirpj.2020.11.001.

[9] M. H. Saad, O. M. Jarrah, M. A. Nazzal, B. M. Darras, and H. A. Kishawy, "Sustainability-based evaluation of Friction Stir Back Extrusion of seamless tubular shapes," *Journal of Cleaner Production*, vol. 267, p. 121972, 2020, doi: https://doi.org/10.1016/j.jclepro.2020.121972.

[10] M. H. Saad, B. M. Darras, and M. A. Nazzal, "Evaluation of Welding Processes Based on Multi-dimensional Sustainability Assessment Model," *International*

Journal of Precision Engineering and Manufacturing-Green Technology, vol. 8, no. 1, pp. 57-75, 2021, doi: 10.1007/s40684-019-00184-4.

[11] M. Alkhader, M. Nazzal, and K. Louca, "Design of bending dominated lattice architectures with improved stiffness using hierarchy," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 233, no. 11, pp. 3976-3993, 2022/04/27 2018, doi: 10.1177/0954406218810298.

[12] M. H. Saad, M. A. Nazzal, and B. M. Darras, "A general framework for sustainability assessment of manufacturing processes," *Ecological Indicators*, vol. 97, pp. 211-224, 2019, doi: https://doi.org/10.1016/j.ecolind.2018.09.062.

[13] M. A. Nazzal, "Stability analysis and finite element simulations of superplastic forming in the presence of hydrostatic pressure," *AIP Conference Proceedings*, vol. 1957, no. 1, p. 050006, 2022/04/27 2018, doi: 10.1063/1.5034336.

[14] M. A. Nazzal and A. G. Al Sabouni, "The effects of pressure control technique on hot gas blow forming of Mg AZ31 sheets," *International Journal of Material Forming*, vol. 12, no. 4, pp. 519-533, 2019, doi: 10.1007/s12289-018-1432-5.

[15] F. S. Jarrar and M. A. Nazzal, "Inclination angle effect on the thickness distribution in a superplastic formed long rectangular pan," *Materials Science Forum*, vol. 735, pp. 155-161, 2012.

[16] M. Nazzal, F. Abu-Farha, and R. Curtis, "Finite Element Simulations for Investigating the Effects of Specimen Geometry in Superplastic Tensile Tests," *Journal of Materials Engineering and Performance*, vol. 20, no. 6, pp. 865-876, 2011, doi: 10.1007/s11665-010-9727-9.

[17] F. Abu-Farha, M. Nazzal, and R. Curtis, "Optimum Specimen Geometry for Accurate Tensile Testing of Superplastic Metallic Materials," *Experimental Mechanics*, vol. 51, no. 6, pp. 903-917, 2011, doi: 10.1007/s11340-010-9396-5.

[18] M. A. Nazzal, F. K. A. Farha, and F. Jarrar, "The Effects of Hydrostatic Pressure on Superplastic Deformation Stability in the Presence of Cavitation," *10th Int. Conf. on Technology of Plasiticity-2011*, pp. 1061-1065.

[19] F. Abu-Farha and M. Nazzal, "Advancing elevated temperature hydro/pneumatic sheet metal forming operations through reverse bulging," Transactions of the NAMRI/SME, vol. 38, pp. 601-608, 2010.

[20] F. K. Abu-Farha, M. A. Nazzal, O. Rawashdeh, and R. Michael, "Contact Sensors for Accurate Monitoring and Prediction of Sheet Deformation during Hydro/Pneumatic Forming Operations," *Key Engineering Materials*, vol. 433, pp. 125-132, 2010.

[21] F. K. Abu-Farha, M. A. Nazzal, and R. Curtis, "The effects of specimen geometry on the accuracy of tensile testing of metallic superplastic materials," *Key Engineering Materials*, vol. 433, pp. 325-331, 2010.

[22] M. A. Nazzal and F. K. Abu-Farha, "Finite element modeling of superplastic forming of tubular shapes," *Key Engineering Materials*, vol. 433, pp. 179-184, 2010.

[23] F. K. Abu-Farha, L. G. Hector, and M. A. Nazzal, "On the development of viable cruciform-shaped specimens: towards accurate elevated temperature biaxial testing of lightweight materials," *Key Engineering Materials*, vol. 433, pp. 93-101, 2010.

[24] M. A. Nazzal and M. K. Khraisheh, "Impact of Selective Grain Refinement on Superplastic Deformation: Finite Element Analysis," *Journal of Materials Engineering and Performance*, vol. 17, no. 2, pp. 163-167, 2008, doi: 10.1007/s11665-007-9180-6.

[25] M. A. Nazzal, M. K. Khraisheh, and F. K. Abu-Farha, "The effect of strain rate sensitivity evolution on deformation stability during superplastic forming," *Journal of Materials Processing Technology*, vol. 191, no. 1, pp. 189-192, 2007, doi: https://doi.org/10.1016/j.jmatprotec.2007.03.097.

[26] F. K. Abu-Farha, M. A. Nazzal, and M. K. Khraisheh, "An Experimental Study on the Stability of Superplastic Deformation of AZ31 Mg Alloy," *AIP Conference Proceedings*, vol. 907, no. 1, pp. 1289-1294, 2022/04/27 2007, doi: 10.1063/1.2729692.

[27] M. A. Nazzal and M. K. Khraisheh, "The Effects of Stress State and Cavitation on Deformation Stability During Superplastic Forming," *Journal of Materials Engineering and Performance*, vol. 16, no. 2, pp. 200-207, 2007, doi: 10.1007/s11665-007-9032-4.

[28] M. Nazzal and M. K. Khraisheh, "On The Stability of Superplastic Deformation Using Nonlinear Wavelength Analysis," *Key Engineering Materials*, vol. 344, pp. 47-54, 2007.

[29] N. V. Thuramalla, M. A. Nazzal, and M. K. Khraisheh, "Variable Strain Rate Forming Technique to Optimize Superplastic Forming of AA 5083 Using Multiscale Stability Analysis," *International Journal of Forming Processes*, vol. 10, no. 1, p. 45, 2007.

[30] M. Nazzal and M. K. Khraisheh, "Finite element modeling of superplastic forming in the presence of back pressure," *Materials Science Forum*, vol. 551-552, pp. 257-262, 2007.

[31] M. K. Khraisheh, F. K. Abu-Farha, M. A. Nazzal, and K. J. Weinmann, "Combined Mechanics-Materials Based Optimization of Superplastic Forming of Magnesium AZ31 Alloy," *CIRP Annals*, vol. 55, no. 1, pp. 233-236, 2006, doi: https://doi.org/10.1016/S0007-8506(07)60405-3.

[32] M. Nazzal, "Finite Element Modeling and Optimization of Superplastic Forming," Ph.D dissertation, University of Kentucky, 2005.

[33] M. A. Nazzal and M. K. Khraisheh, "Finite Element Simulation of Superplastic Forming using a Microstructure Based Constitutive Model." *ABAQUS Users Conference*. 2005

[34] M. A. Nazzal, M. K. Khraisheh, and B. M. Darras, "Finite element modeling and optimization of superplastic forming using variable strain rate approach," *Journal of Materials Engineering and Performance*, vol. 13, no. 6, pp. 691-699, 2004, doi: 10.1361/10599490421321.

[35] H. Singh, "Big data, industry 4.0 and cyber-physical systems integration: A smart industry context," *Materials Today: Proceedings*, vol. 46, pp. 157-162, 2021, doi: https://doi.org/10.1016/j.matpr.2020.07.170.

[36] E. R. da Silva, A. C. Shinohara, C. P. Nielsen, E. P. de Lima, and J. Angelis, "Operating Digital Manufacturing in Industry 4.0: the role of advanced manufacturing technologies," *Procedia CIRP*, vol. 93, pp. 174-179, 2020/01/01/ 2020, doi: https://doi.org/10.1016/j.procir.2020.04.063.

[37] X. Xu, "From cloud computing to cloud manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 28, no. 1, pp. 75-86, 2012/02/01/ 2012, doi: https://doi.org/10.1016/j.rcim.2011.07.002.

[38] M. A. Pisching, M. A. O. Pessoa, F. Junqueira, D. J. dos Santos Filho, and P. E. Miyagi, "An architecture based on RAMI 4.0 to discover equipment to process operations required by products," *Computers & Industrial Engineering*, vol. 125, pp. 574-591, 2018, doi: https://doi.org/10.1016/j.cie.2017.12.029.

[39] C. Greer, M. Burns, D. Wollman, and E. Griffor, "Cyber-Physical Systems and Internet of Things," NIST Special Publication 1900-202, 2019, doi: https://doi.org/10.6028/NIST.SP.1900-202.

[40] C. Bai, P. Dallasega, G. Orzes, and J. Sarkis, "Industry 4.0 technologies assessment: A sustainability perspective," *International Journal of Production Economics*, vol. 229, p. 107776, 2020/11/01/ 2020, doi: https://doi.org/10.1016/j.ijpe.2020.107776.

[41] J. Leng et al., "Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey," *Renewable and Sustainable Energy Reviews*, vol. 132, p. 110112, 2020/10/01/ 2020, doi: https://doi.org/10.1016/j.rser.2020.110112.

[42] J. Lohmer and R. Lasch, "Blockchain in operations management and manufacturing: Potential and barriers," *Computers & Industrial Engineering*, vol. 149, p. 106789, 2020/11/01/ 2020, doi: https://doi.org/10.1016/j.cie.2020.106789.

[43] H. Liu and L. Wang, "Remote human–robot collaboration: A cyber–physical system application for hazard manufacturing environment," *Journal of Manufacturing Systems*, vol. 54, pp. 24-34, 2020/01/01/ 2020, doi: https://doi.org/10.1016/j.jmsy.2019.11.001.

[44] A. Kumar Srivastava, N. Kumar, and A. Rai Dixit, "Friction stir additive manufacturing – An innovative tool to enhance mechanical and microstructural properties," *Materials Science and Engineering: B*, vol. 263, p. 114832, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.mseb.2020.114832.

[45] M. K. Thompson et al., "Design for Additive Manufacturing: Trends, opportunities, considerations, and constraints," *CIRP Annals*, vol. 65, no. 2, pp. 737-760, 2016/01/01/ 2016, doi: https://doi.org/10.1016/j.cirp.2016.05.004.

[46] P. Dadash Pour, M. A. Nazzal, and B. M. Darras, "The role of industry 4.0 technologies in overcoming pandemic challenges for the manufacturing sector," *Concurrent Engineering*, vol. 0, no. 0, pp. 1-16, 2022, doi: 10.1177/1063293X221082681.

[47] UNICEF. "Supply assessment and outlook on non-specific COVID-19 supplies." UNICEF. https://www.unicef.org/supply/covid-19-impact-assessment-supplies-and-logistics-sourced-unicef-supply-division (accessed 12th Nov, 2020).

[48] J. Kilpatrick and L. Barter, "COVID-19, Managing supply chain risk and disruption," Deloitte, 2020. [Online]. Available: https://www2.deloitte.com/global/en/pages/risk/articles/covid-19-managing-supply-chain-risk-and-disruption.html (accessed 13th Dec, 2020).

[49] M. Pu and Y. Zhong, "Rising concerns over agricultural production as COVID-19 spreads: Lessons from China," *Global Food Security*, vol. 26, p. 100409, 2020/09/01/ 2020, doi: https://doi.org/10.1016/j.gfs.2020.100409.

[50] A. Majumdar, M. Shaw, and S. K. Sinha, "COVID-19 debunks the myth of socially sustainable supply chain: A case of the clothing industry in South Asian countries," *Sustainable Production and Consumption*, vol. 24, pp. 150-155, 2020/10/01/ 2020, doi: https://doi.org/10.1016/j.spc.2020.07.001.

[51] M. Shafi, J. Liu, and W. Ren, "Impact of COVID-19 pandemic on micro, small, and medium-sized Enterprises operating in Pakistan," *Research in Globalization*, vol. 2, p. 100018, 2020/12/01/ 2020, doi: https://doi.org/10.1016/j.resglo.2020.100018.

[52] N. J. Rowan and J. G. Laffey, "Challenges and solutions for addressing critical shortage of supply chain for personal and protective equipment (PPE) arising from Coronavirus disease (COVID19) pandemic – Case study from the Republic of Ireland," *Science of The Total Environment*, vol. 725, p. 138532, 2020/07/10/ 2020, doi: https://doi.org/10.1016/j.scitotenv.2020.138532.

[53] M. S. Tareq, T. Rahman, M. Hossain, and P. Dorrington, "Additive manufacturing and the COVID-19 challenges: An in-depth study," *Journal of Manufacturing Systems*, vol. 60, pp. 787-798, 2021, doi: https://doi.org/10.1016/j.jmsy.2020.12.021.

[54] A. Belhadi, K. Zkik, A. Cherrafi, S. r. M. Yusof, and S. El fezazi, "Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies," *Computers & Industrial Engineering*, vol. 137, p. 106099, 2019, doi: https://doi.org/10.1016/j.cie.2019.106099.

[55] R. Hamzeh, R. Zhong, X. W. Xu, E. Kajáti, and I. Zolotova, "A Technology Selection Framework for Manufacturing Companies in the Context of Industry 4.0," in *2018 World Symposium on Digital Intelligence for Systems and*

Machines (DISA), 23-25 Aug. 2018 2018, pp. 267-276, doi: 10.1109/DISA.2018.8490606.

[56] L. Evans, N. Lohse, and M. Summers, "A fuzzy-decision-tree approach for manufacturing technology selection exploiting experience-based information," *Expert Systems with Applications*, vol. 40, no. 16, pp. 6412-6426, 2013, doi: https://doi.org/10.1016/j.eswa.2013.05.047.

[57] M. Yurdakul, "Selection of computer-integrated manufacturing technologies using a combined analytic hierarchy process and goal programming model," *Robotics and Computer-Integrated Manufacturing*, vol. 20, no. 4, pp. 329-340, 2004, doi: https://doi.org/10.1016/j.rcim.2003.11.002.

[58] Y. T. İç, "An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies," *Robotics and Computer-Integrated Manufacturing*, vol. 28, no. 2, pp. 245-256, 2012, doi: https://doi.org/10.1016/j.rcim.2011.09.005.

[59] A. Schumacher, S. Erol, and W. Sihn, "A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises," *Procedia CIRP*, vol. 52, pp. 161-166, 2016, doi: https://doi.org/10.1016/j.procir.2016.07.040.

[60] A. P. T. Pacchini, W. C. Lucato, F. Facchini, and G. Mummolo, "The degree of readiness for the implementation of Industry 4.0," *Computers in Industry*, vol. 113, p. 103125, 2019, doi: https://doi.org/10.1016/j.compind.2019.103125.

[61] L. D. Rafael, G. E. Jaione, L. Cristina, and S. L. Ibon, "An Industry 4.0 maturity model for machine tool companies," *Technological Forecasting and Social Change*, vol. 159, p. 120203, 2020, doi: https://doi.org/10.1016/j.techfore.2020.120203.

[62] R. G. G. Caiado, L. F. Scavarda, L. O. Gavião, P. Ivson, D. L. d. M. Nascimento, and J. A. Garza-Reyes, "A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management," *International Journal of Production Economics*, vol. 231, p. 107883, 2021, doi: https://doi.org/10.1016/j.ijpe.2020.107883.

[63] A. Bastos, M. L. S. C. D. Andrade, R. T. Yoshino, and M. M. D. Santos, "Industry 4.0 Readiness Assessment Method Based on RAMI 4.0 Standards," *IEEE Access*, vol. 9, pp. 119778-119799, 2021, doi: 10.1109/ACCESS.2021.3105456.

[64] E. Y. Nakagawa, P. O. Antonino, F. Schnicke, R. Capilla, T. Kuhn, and P. Liggesmeyer, "Industry 4.0 reference architectures: State of the art and future trends," *Computers & Industrial Engineering*, vol. 156, p. 107241, 2021, doi: https://doi.org/10.1016/j.cie.2021.107241.

[65] I. V. C. Initiative. "Industrial Value Chain Reference Architecture." IVRA. https://docs.iv-i.org/doc_161208_Industrial_Value_Chain_Reference_Architecture.pdf (accessed 10th Oct, 2021).

[66] J. Butt, "A Strategic Roadmap for the Manufacturing Industry to Implement Industry 4.0," *Designs*, vol. 4, no. 2, p. 11, 2020, doi: 10.3390/designs4020011.

[67] M. Ghobakhloo, "The future of manufacturing industry: a strategic roadmap toward Industry 4.0," *Journal of Manufacturing Technology Management*, vol. 29, no. 6, pp. 910-936, 2018.

[68] J. Qin, Y. Liu, and R. Grosvenor, "A Categorical Framework of Manufacturing for Industry 4.0 and Beyond," *Procedia CIRP*, vol. 52, pp. 173-178, 2016, doi: https://doi.org/10.1016/j.procir.2016.08.005.

[69] A. Cotrino, M. A. Sebastián, and C. González-Gaya, "Industry 4.0 Roadmap: Implementation for Small and Medium-Sized Enterprises," *Applied Sciences*, vol. 10, no. 23, p. 8566, 2020, doi: 10.3390/app10238566.

[70] M. Jayawickrama, A. Kulatunga, and S. Mathavan, "Fuzzy AHP based Plant Sustainability Evaluation Method," *Procedia Manufacturing*, vol. 8, pp. 571-578, 2016, doi: 10.1016/j.promfg.2017.02.073.

[71] M. Overall. "How to make your materiality assessment worth the effort." Greenbiz. https://www.greenbiz.com/article/how-make-your-materiality-assessment-worth-effort (accessed 25th Oct, 2021).

[72] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, no. 1, pp. 9-26, 1990, doi: https://doi.org/10.1016/0377-2217(90)90057-I.

[73] P. Niemcewicz, "The use of the multi-criteria AHP method to select a cloud computing provider," *Procedia Computer Science*, vol. 192, pp. 2558-2567, 2021, doi: https://doi.org/10.1016/j.procs.2021.09.025.

[74] H. R. Zafarani, A. Hassani, and E. Bagherpour, "Achieving a desirable combination of strength and workability in Al/SiC composites by AHP selection method," *Journal of Alloys and Compounds*, vol. 589, pp. 295-300, 2014, doi: https://doi.org/10.1016/j.jallcom.2013.11.181.

[75] J. Li, Y. Chen, X. Yao, and A. Chen, "Risk Management Priority Assessment of heritage sites in China Based on Entropy Weight and TOPSIS," *Journal of Cultural Heritage*, vol. 49, pp. 10-18, 2021, doi: https://doi.org/10.1016/j.culher.2021.04.001.

[76] C. Oluah, E. T. Akinlabi, and H. O. Njoku, "Selection of phase change material for improved performance of Trombe wall systems using the entropy weight and TOPSIS methodology," *Energy and Buildings*, vol. 217, p. 109967, 2020, doi: https://doi.org/10.1016/j.enbuild.2020.109967.

[77] P. Wang, Z. Zhu, and Y. Wang, "A novel hybrid MCDM model combining the SAW, TOPSIS and GRA methods based on experimental design," *Information Sciences*, vol. 345, pp. 27-45, 2016, doi: https://doi.org/10.1016/j.ins.2016.01.076.

[78] S. H. Mousavi-Nasab and A. Sotoudeh-Anvari, "A new multi-criteria decision making approach for sustainable material selection problem: A critical study on

rank reversal problem," *Journal of Cleaner Production*, vol. 182, pp. 466-484, 2018, doi: https://doi.org/10.1016/j.jclepro.2018.02.062.

[79] J. Yang, "Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis," *Environmental Modelling & Software*, vol. 26, no. 4, pp. 444-457, 2011, doi: https://doi.org/10.1016/j.envsoft.2010.10.007.

[80] D. M. Hamby, "A review of techniques for parameter sensitivity analysis of environmental models," *Environmental monitoring and assessment*, vol. 32, no. 2, pp. 135-154, 1994.

[81] N. Kang, C. Zhao, J. Li, and J. A. Horst, "A Hierarchical structure of key performance indicators for operation management and continuous improvement in production systems," *International Journal of Production Research*, vol. 54, no. 21, pp. 6333-6350, 2016, doi: 10.1080/00207543.2015.1136082.

[82] N. Yalcin, A. Bayrakdaroglu, and C. Kahraman, "Application of fuzzy multi-criteria decision making methods for financial performance evaluation of Turkish manufacturing industries," *Expert Systems with Applications*, vol. 39, no. 1, pp. 350-364, 2012, doi: https://doi.org/10.1016/j.eswa.2011.07.024.

[83] C. Johnsson, "Key Performance Indicators Used as Measurement Parameter for Plant-Wide Feedback Loops," Berlin, Heidelberg, 2014: Springer Berlin Heidelberg, pp. 91-99.

[84] "Consolidated Set of the GRI Standards 2021." GRI Standards. https://www.globalreporting.org/how-to-use-the-gri-standards/gri-standards-english-language/ (accessed 25th Feb, 2022).

[85] J. J. Buckley, "Fuzzy hierarchical analysis," *Fuzzy Sets and Systems*, vol. 17, no. 3, pp. 233-247, 1985, doi: https://doi.org/10.1016/0165-0114(85)90090-9.

[86] R. Chandna, S. Saini, and S. Kumar, "Fuzzy AHP based performance evaluation of massive online courses provider for online learners," *Materials Today: Proceedings*, vol. 46, pp. 11103-11112, 2021, doi: https://doi.org/10.1016/j.matpr.2021.02.255.

[87] A. H. Afolayan, B. A. Ojokoh, and A. O. Adetunmbi, "Performance analysis of fuzzy analytic hierarchy process multi-criteria decision support models for contractor selection," *Scientific African*, vol. 9, p. e00471, 2020, doi: https://doi.org/10.1016/j.sciaf.2020.e00471.

[88] S. Ali Sadat, M. Vakilalroaya Fini, H. Hashemi-Dezaki, and M. Nazififard, "Barrier analysis of solar PV energy development in the context of Iran using fuzzy AHP-TOPSIS method," *Sustainable Energy Technologies and Assessments*, vol. 47, p. 101549, 2021, doi: https://doi.org/10.1016/j.seta.2021.101549.

[89] R. J. Kuo, C. W. Hsu, and Y. L. Chen, "Integration of fuzzy ANP and fuzzy TOPSIS for evaluating carbon performance of suppliers," *International Journal of Environmental Science and Technology*, vol. 12, no. 12, pp. 3863-3876, 2015, doi: 10.1007/s13762-015-0819-9.

[90] C.-T. Chen, "Extensions of the TOPSIS for group decision-making under fuzzy environment," *Fuzzy Sets and Systems*, vol. 114, no. 1, pp. 1-9, 2000, doi: https://doi.org/10.1016/S0165-0114(97)00377-1.

[91] S. Kumar and A. G. Barman, "Fuzzy TOPSIS and fuzzy VIKOR in selecting green suppliers for sponge iron and steel manufacturing," *Soft Computing*, vol. 25, no. 8, pp. 6505-6525, 2021, doi: 10.1007/s00500-021-05644-1.

Vita

Parham Dadash Pour was born in 1998, in Tehran, Iran. He received his B.Sc. degree in Mechanical Engineering from the American University of Sharjah in June 2020. In September 2020, he joined the Mechanical Engineering master's program in the American University of Sharjah as a Graduate Teaching Assistant. During his master's study, he co-authored multiple journal and conference papers covering different areas in the field of Mechanical Engineering. His research interests are in Industry 4.0, sustainable manufacturing, MCDM analysis, and fuzzy inference systems.