DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF BUSINESS ADMINISTRATION (ENGLISH)
BUSINESS ADMINISTRATION PROGRAM

DOCTORAL THESIS

Doctor of Philosophy (PhD)

INDUSTRY 4.0 AND SUSTAINABILITY IMPLICATIONS

Elif ÇİRKİN

Supervisor
Assoc. Prof. Aşkın ÖZDAĞOĞLU

İZMİR - 2021

DOCTORAL THESIS

APPROVAL PAGE

University	: Dokuz Eylul University
Graduate	: Graduate School of Social Sciences
Name and Surname	: Elif ÇİRKİN
Title of the Thesis	: Industry 4.0 and Sustainability Implications
Defence Date	: 29/12/2021
Supervisor	: Doç.Dr. Aşkın ÖZDAĞOĞLU

EXAMINING COMMITTE MEMBERS

Title,Name and Surname	**University**	**Signature**
Doç.Dr. Aşkın ÖZDAĞOĞLU	- Dokuz Eylül Üniversitesi	....
Doç.Dr. Banu DEMİREL	- Dokuz Eylül Üniversitesi	....
Prof.Dr. Mehmet Emre GÜLER	- İzmir Katip Çelebi Üniversitesi	....
Doç.Dr. Alptekin ULUTAŞ	- Sivas Cumhuriyet Üniversitesi	....
Doç.Dr. Zeliha TEKİN	- Muş Alparslan Üniversitesi	....

Unanimity ( )

Majority of votes ( )

The thesis titled as "**Industry 4.0 and Sustainability Implications** " prepared and presented by Elif ÇİRKİN is accepted and approved.

Prof. Dr. Asuman ALTAY
Müdür

DECLARATION

I hereby declare that this master's thesis titled as "Industry 4.0 and Sustainability Implications" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honour.

Date

29/12/2021

Elif ÇİRKİN

ABSTRACT

Doctoral Thesis

Doctor of Philosophy (PhD)

Industry 4.0 and Sustainability Implications

Elif ÇİRKİN

Dokuz Eylül University

Graduate School of Social Sciences

Department of Business Administration (English)

Business Administration Doctorate Program

The potential of the production ecosystems shaped in the light of technological developments and innovative approaches to provide opportunities in creating social, economic, and environmental sustainability is a remarkable phenomenon in today's competitive global world where resources are rapidly depleted, social concerns are experienced, and the vitality of financial stability are accumulating. Within the scope of this study, it is aimed to analyze the role of Industry 4.0 technologies, which is a holistic production paradigm, in creating a sustainable production ecosystem. In line with the data obtained from the sample consisting of decision-makers being employed in various sectors such as petrochemical, metal production industry, automotive, textile, and food, the main and sub-criteria of the sustainability dimensions are weighted with fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory), which is one of the multi-criteria decision-making methods, and with fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) the ranking and selection of the Industry 4.0 technology that best meets these determined criteria are revealed. In this context, it has been concluded that although weights of sustainability sub-criteria dissociate on a sectoral basis, there were similarities in the selection of the most appropriate Industry 4.0 technology alternative. The results of the analysis were also enriched with the findings obtained from the in-depth interviews and the creation of word clouds that are benefitted as a data visualization tool. This study differs from the theoretical studies in the literature,

as it deals with all three dimensions of sustainability and Industry 4.0 together. Furthermore, mathematically revealing the values that Industry 4.0 technologies and applications will create in terms of economic, social and environmental sustainability reflects the original value of the study. As a result, this study provides contributions to the organizations planning to blend the concept of sustainability in their production systems with managerial and practical implications as well as to the relevant literature.

Keywords: Industry 4.0, Sustainable Production Ecosystems, Social sustainability, Economic Sustainability, Environmental Sustainability, Sustainable Development.

ÖZET

Doktora Tezi

Endüstri 4.0 ve Sürdürülebilirlik Uygulamaları

Elif ÇİRKİN

Dokuz Eylül Üniversitesi

Sosyal Bilimler Enstitüsü

İngilizce İşletme Anabilim Dalı

İngilizce İşletme Yönetimi Doktora Programı

Teknolojik gelişmeler ve inovatif yaklaşımlar ışığında şekillenen üretim ekosistemlerinin sosyal, ekonomik ve çevresel sürdürülebilirlik yaratmada fırsatlar sağlama potansiyeli kaynakların hızla tükendiği, sosyal kaygıların yaşandığı, finansal istikrarın gerekliliğinin giderek arttığı günümüz rekabetçi küresel dünyasında dikkat çeken bir olgudur. Bu çalışma kapsamında bütüncül bir üretim paradigması olan Endüstri 4.0 teknolojilerinin sürdürülebilir bir üretim ekosistemi yaratmadaki rolünün analiz edilmesini amaçlanmaktadır. Petrokimya, metal üretim endüstrisi, otomotiv, tekstil ve gıda gibi farklı sektörlerde çalışan karar vericilerden oluşan örneklemden elde edilen veriler doğrultusunda çok kriterli karar verme yöntemlerinden olan bulanık DEMATEL (Karar Verme Deneme ve Değerlendirme Laboratuvarı) sürdürülebilirlik boyutlarının alt kriterleri ağırlıklandırılmış ve bulanık TOPSIS (İdeal Çözüme Benzerlik Yoluyla Sıralama Tercihi Tekniği) yöntemiyle de belirlenen kriterler ağırlıkları baz alınarak bu kriterleri en iyi karşılayan Endüstri 4.0 teknolojisinin sıralama ve seçimi yapılmıştır. Bu bağlamda, sürdürülebilirlik alt kriterlerinin sektörel bazda farklılaştığı ancak en uygun Endüstri 4.0 teknoloji seçim alternatiflerinde benzerlikler olduğu sonuçlarına varılmıştır. Analiz sonuçları yapılan derinlemesine görüşmelerden elde edilen bulgular ile birlikte veri görselleştirme araçlarından olan kelime bulutları ile de zenginleştirilmiştir. Endüstri 4.0 ve sürdürülebilirliğin üç boyutunu da birlikte uygulamaya yönelik ele aldığı için bu çalışma literatürde yapılan kuramsal çalışmalardan farklılık göstermektedir. Bununla birlikte Endüstri 4.0

teknolojileri ve uygulamalarının ekonomik, sosyal ve çevresel sürdürülebilirlik açısından yaratacağı değerlerin matematiksel olarak ortaya konması çalışmanın özgün değerini yansıtmaktatır. Sonuç olarak bu çalışma çıktılarıyla, hem ilgili literatüre hem de sürdürülebilirlik kavramını üretim sistemleri ile birlikte harmanlamayı planlayan organizasyonlara yönetimsel ve uygulamaya yönelik katkılar sağlamaktadır.

Anahtar Kelimeler: Endüstri 4.0, Sürdürülebilir Üretim Ekosistemleri, Sosyal Sürdürülebilirlik, Ekonomik Sürdürülebilirlik, Çevresel Sürdürülebilirlik, Sürdürülebilir Kalkınma.

INDUSTRY 4.0 AND SUSTAINABILITY IMPLICATIONS

CONTENTS

CHAPTER TWO

SCOPE AND DISCUSSIONS OF SUSTAINABILITY AND CONVERGENCE OF INDUSTRY 4.0 TECHNOLOGIES WITH SUSTAINABILITY DIMENSIONS

CHAPTER THREE

INDUSTRY 4.0 TECHNOLOGY ALTERNATIVES` SELECTION BASED ON SOCIAL, ENVIRONMENTAL, ECONOMIC SUSTAINABILITY CRITERIA: A CASE STUDY WITHIN VARIOUS INDUSTRIES

ABBREVIATIONS

3D	Three-Dimensional
AHP	Analytic Hierachy Process
ANP	Analytic Network Process
AR	Augmented Reality
AV	Augmented Virtuality
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing
CNC	Computer Numerical Controller
CPS	Cyber-Physical System
DaaS	Data as a Service
DEMATEL	Decision-Making Trial and Evaluation Laboratory
ERP	Enterprise Resource Planning
GRI	Global Reporting Initiative
HDM	Head-Mounted Displays
HVAC	Heating, Ventilating, And Air Conditioning
IaaS	Infrastructure as a Service
ID	Identification Card
IoT	Internet of Things
IT	Information Technology
ITU	International Telecommunication Union
JIT	Just-In-Time
MADM	Multi-Attribute Decision-Making
MAUT	Multi-Attribute Utility Theory
MCDA	Multiple-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making Methods
MES	Manufacturing Execution Systems
MRP	Material Requirement Planning
PaaS	Platform as a Service
PB	Petabytes
QoS	Quality of Service

R&D	Research and Development
RFID	Radio Frequency Identification
SaaS	Software as a Service
SME	Small-Medium Enterprise
TB	Terabytes
TBL	Triple Bottom Line
TCP/IP	Transmission Control Protocol/Internet Protocol
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TQM	Total Quality Management
TÜSİAD	Turkish Industry and Business Association
UGV	Unmanned Ground Vehicle

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

INTRODUCTION

Generating solutions with palliative and sustainable approaches to human, economic, and environmental requirements, demands, and needs which are in a continuous cycle of change and development forms the basis of the struggle for life that humanity has been facing since its existence. Meeting these requirements, demands, and needs of the continuously increasing world population as well as ensuring growth and liveliness in the economy have been ensured with the integration of technological innovations and developments that have been put forward in centuries into production systems.

The periods, which deeply affected industrial productivity, hence economies took place in the literature as industrial revolutions. The first industrial revolution began to show its effects between 1760 and 1830 with the mechanization of weaving looms using water and steam power. With the first industrial revolution handicraft production has been replaced by mechanical production, hence the basics of factory systems as well as the first steps of productivity in production have been taken. Then, with the invention of electricity, the second industrial revolution came to the agenda at the beginning of the 20th century and manufacturing processes started to adapt to mass production. Thereafter, in virtue of the contributions of electronic, information, and communication technologies to production, the concept of the third industrial revolution has been formed so automation and digitalization have been involved in the production. However, Industry 4.0 is rather a complex and widely discussed system with various technologies such as artificial intelligence cyber-physical systems, smart factory, autonomous robots, horizontal and vertical system integration, simulation, internet of things, cybersecurity, cloud computing, embedded systems, additive generation, augmented reality, sensors, data mining, big data, and machine learning.

The scope and application areas of the Industry 4.0 concept predominantly focus on a technical perspective, however, differently in this study, Industry 4.0 and its applications will be analyzed whether it produces solutions for issues such as elimination of environmental problems, the loss of non-renewable resources, climate change, biological diversity loss, and waste.

The starting point of this study relies on such threats as intense globalization, differentiation strategies that increase the competitiveness of companies each day, lack of resources and even depletion, changing demographic features, and intergenerational differences like different requirements of generations X, Y, and Z worldwide. That is to say, coping with the target group with high awareness of social and environmental responsibility for being a global information society forces organizations to create sustainable industrial value. Therefore, taking into social, environmental, and economic dimensions into consideration while producing and/or serving is of great importance for today's business environments.

Within the scope of achieving sustainable development goals and providing opportunities for sustainability with the integration of Industry 4.0 technologies and applications such as augmented reality, cyber-physical systems, real-time monitoring and data collection, additive generation, new business models, on-demand production/consumption, big data and analytics, blockchain technology, rapid prototyping into organizations processes with organizations' strategic goals open a new window in the literature. Thus, in this study, Industry 4.0 and its technologies will be evaluated under the framework of sustainability pillars including social, environmental, and economic. The principal research question of this study is that "Do Industry 4.0 technologies and applications play a role in creating a sustainable working environment?". To answer this research question, first of all, with the help of a systematic literature review Industry 4.0 technologies and their convergence with the sustainability dimensions along with the effects of Industry 4.0 technologies on sustainable dimensions will be highlighted. Next, with an application, which technology of Industry 4.0 is the most suitable for meeting the sustainability dimensions will be attempted to reveal. To do so, there will be brainstorming regarding the concepts of Industry 4.0 technologies, sustainability dimensions as well as the convergence of Industry 4.0 with sustainability dimensions. This brainstorming will be among personnel from various sectors. After creating a mind map based on this brainstorming, environmental, social, and economic sustainability criteria and alternatives of Industry 4.0 technologies of the selected organizations operating in the textile, metal production, petrochemical, automotive, and food industries will be determined through a focus group study and feedbacks from some academics with various backgrounds. For the analysis, multi-criteria decision-making methods will be used because analyzing and solving problems having both qualitative and quantitative data sets would not be feasible with two and/or three-dimensional matrices, thereby mathematical models treated beneath multi-criteria decision-making methods are preferred. Thus, in this thesis, for the selection problem of Industry 4.0 technology alternatives based on social, economic, and environmental sustainability criteria multi-criteria decision-making methods will be benefitted. Firstly, the determined criteria will be sorted using Fuzzy-DEMATEL (Decision-Making Trial and Evaluation Laboratory) method. Then, the Industry 4.0 technology that matches the criteria the best will be ranked and selected using the Fuzzy-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method. By doing this it will be found if there is a specific technology providing sustainability dimensions. In this way, Industry 4.0 technologies will be analyzed through real organizations' data to see which of these technologies are presumed to have effects on creating a sustainable manufacturing ecosystem.

The study is designated in such an order, in the first chapter, the background information regarding the previous industrial revolutions and then emergence, structure, dimensions, potential opportunities, and challenges of the fourth industrial revolution will be given. Then the fundamental technology trends and extensions of Industry 4.0 including additive manufacturing, augmented reality, autonomous, big data and analytics, cloud systems, cyber-physical systems, internet of things, system integration and simulation, and smart factory will be explained. In the second chapter, the scope and discussions of sustainability and its dimensions including social, environmental, and economic will be given in a detailed manner. Furthermore, a systematic literature review regarding the convergence of Industry 4.0 technologies with sustainability dimensions will be demonstrated with the help of various views of the researchers. In the last chapter, a case study within various industries with the help of multi-criteria decision-making methods will be depicted.

The first two chapters constitute the roof of this study with the support of a literature review whilst the last chapter is an application stage of this study and include the aim and objective of the study, conceptual background, methodology, questionnaire design, sample and data collection, data analysis and measurement as well as the empirical findings. Finally, in the conclusion part discussions regarding the study, the limitations of this study, and further research suggestions will be given.

CHAPTER ONE
AN OVERVIEW OF HISTORICAL INDUSTRIAL REVOLUTIONS

This chapter embodies the theoretical framework of the study and explains pre-industrial revolutions as well as the latest industrial revolution and its technologies.

1.1.PRE-INDUSTRIAL REVOLUTIONS ON THE WAY TO INDUSTRY 4.0

Throughout history, technological leaps and breakthrough innovations have led to paradigm shifts and deeply affected economic and social structures, hence revolutions. The term industrial revolution can be broadly described as a rapid, widespread, secular, and abrupt change in the business manners' of individuals and/or organizations. Although there are various aspects towards the dawn of the industrial revolution, the first industrial revolution has been emerged out of the mechanization of weaving looms using water and steam power between the years of 1750–1776 in Great Britain that lasted between 1820 and 1840. The reason why Great Britain was leading the first industrial revolution is that the country was holding a huge amount of coal and iron reserves and was also stable both economically and politically. Having considered as one of the significant technological advances, the steam engine was commenced by Thomas Newcomen in 1712. Subsequently, Scottish mechanical engineer James Watt, enlarged the steam engine in 1776, which triggered large amounts of coal-powered energy in an efficient and economical way (Usher, 1920; Jacob, 1997; Allen, 2009). With these developments, an early modern industrial era worldwide has been originated and handicraft production has been replaced by mechanical production hence, the basics of factory systems and the first steps in productivity have been taken.

In 1776, Adam Smith proposed the division of labor that is narrowing down a job and each of them executed by a separate worker, hence specialization of the workers at those tasks. Afterwards, in 1790, Eli Whitney introduced the interchangeable parts creating a pathway to manufacture firearms, clocks, watches, sewing machines, and other goods to evolve customized, on an individual basis production into volume production of standardized parts (Russel and Taylor III, 2003).

This turning point in production systems has led to a diverse range of social and economic consequences including the integration of contemporary science and empirical knowledge together with manufacturing processes, an invention of new types of machinery, tools, and technologies, increased economic activities owing to manufacturing for national and international markets rather than parochially individual and/or family use, improved efficiency in the textile industry, mines, steam-powered railroads, steam-powered ocean freighters, iron and steel production, chemical industry, and other areas of economic activities, enlargement of production capabilities and capacities, developments in agricultural productivity, and the emanation of new social and job-related classes (Deane and Deane, 1979: 1; Daunton, 1995).

Although it is evident that the first industrial revolution has been generated positive contributions related to socio-economic environments, it has been led to some unfavorable results consisting of an increase of unskilled workers, labor exploitation, a huge gap between social classes, the rise of the number of women and child labor in an unhygienic and risky situation, and the emergence of environment pollution (Galbi, 1994; Griffin, 2010).

The second industrial revolution was, in many ways, the continuation of the first industrial revolution and dated back to the years between 1870-1914, mainly in the United Kingdom and the United States, and spread throughout Western Europe and Japan. A large number of such new technologies and inventions as the widespread use of the iron and steel, internal combustion engine, chemical industries, use of petroleum, the beginning of electrification together with electrical communication technologies created potentials for perpetual innovation in processes therein an existing plant to work up overall production efficiency and volumes in production, however manufacturing plants needed to be redesigned to adopt these new developments and innovations (Jevons, 1931; Mokyr, 1998; Atkeson and Kehoe, 2001).

Frederick W. Taylor put forward an approach on management of work-oriented as a science and determined the best suitable method while performing the job based on various observations, measurements, and analysis, namely scientific management in the early 1900s. After that, all workers' procedures were standardized, and financial incentives were put in place to encourage workers to pursue the standards. Henry Ford applied scientific management to the production of the T model in 1913 and developed an assembly-line approach driving down the time required to assemble a car from over 728 hours to 1 ½ hour. Therefore, laying the foundations of mass production and benefitting from managerial and technical expertise, manufacturers in the United States have dominated the production ecosystems worldwide. However, lower costs, higher quality with such quality revolutions as Just-In-Time (JIT), Total Quality Management (TQM), and mindset of lean production generated by Japanese culture challenged the superiority of manufacturers in the United States (Russel and Taylor III, 2003).

The growth of the steel industry and oil refining industry in the second industrial revolution era both in cost advantage and quality affected many industries including the construction of sophisticated machinery, ships, railroad tracks, and buildings. Moreover, improvements in transportation systems and a decline in transportation costs have led organizations to distribute their products to long distances of regional and/or national markets, thus the development of global import and export markets (Chandler, 1993).

The use of chemicals like nitrates, potassium, and phosphates as fertilizers in the agriculture sector that was the crop of the combination of scientific knowledge with production techniques have amplified the soil productivity as well as supply of food and raw materials. Especially, in Germany, government-initiated institutions subsidized agricultural research and the outcomes eventually bred to drastically increased yields (Mokyr, 1998).

Working conditions in the second industrial revolution era resembled the first industrial revolution era. Long working hours, low wages, dangerous and risky working environments have been remained a problem, thus ensuing labor unions, labor strikes so as to publicize these problems and improve their working conditions (Kim, 2007).

Existing manufacturing methods of the first industrial revolution era were widely improved with the transition to mass production enabling faster and cheaper production in high volumes, so mass consumer culture emerged. Additionally, inventions including elevators, electric machinery, harvesting machine, sewing machine, and other various consumer appliances have provided comfort into daily lives of individuals; such modes of transportation as a motorcar, truck, and airplane have made transport facilities easier and more comfortable; constructing of highways and supermarkets has made everyday lives smooth and quality, thereby improving social, and economic welfare as well as living standards (Gordon, 2012).

Despite embodying many positive contributions, the second industrial revolution also created such global challenges as air pollution, water pollution, global warming, climate change, and habitat destruction. Furthermore, the wage gap between man and woman, and th issu of working under unfavorable conditions have yet remained a deadlock (Mohajan, 2013).

The third industrial revolution that is also known as automation and digitization of production has been started around the 1940s and lasted until 2010. The period between 1914 and 1918 witnessed the First World War and later years between 1939 and 1945 Second World War took place and the pace in terms of economical, industrial, and social developments have been slowed down compared to previous periods. Nonetheless, unlike the previous industrial revolutions, the third industrial revolution has caused radical changes in not only the way businesses operate but also the mindsets and every facet of life (Finkelstein and Newman, 1984; Fitzsimmons, 1994).

It is evident that the diverse use of fossil fuels in manufacturing and logistics frameworks profoundly changed the technological, social, and economical conditions, however, the impact of fossil fuels on the ecology has become deteriorating and issues on climate change, global warming, and environmental pollution have pervaded. Such adverse impacts of fossil fuels on the environment in addition to the scarcity of oil, hence surging prices forced politicians and academics to focus on innovations on renewable energies and eco-efficient technologies. Therefore, the term third industrial revolution was also labeled as a “green industrial revolution”, “efficiency revolution”, and “green capitalism” (Rifkin, 2011; Rifkin 2012, Schmidheiny and Timberlake, 1992; Fisher, 2015).

In 1947, the production of the first transistor as well as the introduction of semiconductors and integrated circuits have formed the basic structure of contemporary computers and digital solutions. Later in 1952, Computer Numerical Controller (CNC) machines have been revealed and product variety and efficiency have increased. The introduction of the Advanced Research Projects Agency Network, which was the first network to implement the Transmission Control Protocol/Internet Protocol (TCP/IP) in 1969 triggered the use of computers, computer-aided design and computer-aided manufacturing (CAD/CAM), development of the internet, and information age (Özdoğan, 2017). Moreover, manufacturing shifted from mass to lean manufacturing techniques as the manufacturers located in the United States and Europe began to adopt Japanese production approaches (Eden, 2018).

Furthermore, information technologies and software systems like Material Requirement Planning (MRP) and Enterprise Resource Planning (ERP) together with supporting hardware systems that have appeared in the third industrial era enabled automation and digitalization in production, which in turn led to positive contributions in management and control of resources, processes, financial analyses, production rates, efficiency, flexible manufacturing systems, and costs related to managerial activities and manufacturing processes. With the third industrial era, such innovations as microchips, microelectronics, fibre optics, lasers, nanotechnology, biotechnology, high-speed railway systems, mobile telecommunications, new materials, renewable raw materials, cleaner technology, intelligent systems, robotics, and three-dimensional (3D) printing have introduced and offered significant changes in the manufacturing processes, the management and control of systems, logistics, new product design and development processes, and life-cycle use of materials and also affected various sectors including medical, defense, agriculture, construction, government services, knowledge, education, advanced manufacturing, financial, and administrative (Cooper and Kaplinsky, 2005: 19; Karvonen, 2001: 10).

The globalization process, supported by the collapse of the Eastern Block and the end of the Cold War together with the convenience of communication and transportation using the internet has transformed the world into a single market and created a functional basis for a competitive environment within the scope of global markets (Jänicke and Jacob, 2009). Moreover, some large companies have shifted their production centers to China, where the labor force was abundant and cheap. This situation made China a serious competitor in global markets and negatively affected the manufacturing industries in many countries. This is the primary cause for the transition to a new industrial revolution process led by a series of technologies, enabling cheap, efficient, and fast manufacturing systems. The term sustainability was first coined in this era and renewable energy technologies including wind generation, solar generation systems, biomass, and geothermal together with green business practices and strategies were introduced in an effort to combat global warming, climate change, and environmental pollution (Clark II and Cooke, 2014). In the table below, a summary of the industrial revolutions is represented.

Table 1: Summary of Industrial Revolutions with key points

Industrial Revolutions	Summary
First Industrial Revolution (Industry 1.0)	The first industrial revolution happened at the end of the 18th century, from 1760 and 1840. Machines were introduced into the manufacturing process to reduce human effort. This first revolution leads to some improvements, particularly in the textile and agriculture industries.
Second Industrial Revolution (Industry 2.0)	This industrial revolution, which lasted from 1870 to 1914, was the first time the industry used a mass-production system. Although it boosted production speed, it limited design and manufacturing flexibility.
Third Industrial Revolution (Industry 3.0)	After 1950, the third industrial revolution began. Through the employment of robots and programmed flexible automation, this revolution brought quality, speed, and manufacturing flexibility. It introduced digital technology into production systems, as well as machines such as 3D printers, CNC machines, and robots that can be monitored via a computer. It resulted in substantial advancements in the fields of computer, communication, and information technology (IT). The transition from analogue to digital mechanical systems was ushered in by this revolution. With the application of various production methods, this revolution in automation offered a new degree of flexibility and customization in manufacturing. It improved the computer-integrated design and production system, which greatly helped product development and design.
Fourth Industrial Revolution (Industry 4.0)	This latest revolution offers disruptive technologies like machine learning, artificial intelligence, and robotics. Its goal is to inject major creativity into the manufacturing, design, development, research, business model, and supply chain industries. This new manufacturing approach will maximize the utilization of cutting-edge manufacturing technology.

Source: Bahrin et al., 2016; Morrar et al., 2017; Zhong et al., 2017; Wichmann et al., 2019; Kusmin, 2018.

Within the scope of this section, background information regarding previous industrial revolutions on the way to the latest industrial revolution so-called Industry 4.0, reasons for their emergence, development processes, technologies and innovations brought with them, and their impacts on production systems, economies, and societies have been handled thoroughly.

In the following section, structure, dimensions, revolving technologies around the fourth industrial revolution as well as potential opportunities, and challenges of the fourth industrial revolution shall be discussed.

1.2.THE FOURTH INDUSTRIAL REVOLUTION: THE EMERGENCE, STRUCTURE, DIMENSIONS, POTENTIAL OPPORTUNITIES, AND CHALLENGES OF INDUSTRY 4.0

A convergence of information technologies and operational technologies throughout the industrial revolutions' history originated with the first industrial revolution leading to the basics of factory systems, and handicraft production has been replaced by mechanical production, then with the invention of electricity, the second industrial revolution fostered the mass production, and later with the contributions of electronic, information and communication technologies to production, the concept of the third industrial revolution eventuated automation and digitalization in the production. However, the concept, structure, dimensions, potential opportunities, and challenges of "Industry 4.0", which has been pioneered as a differentiation strategy in 2011 in Hannover Fair in Germany to handle such issues as the increasing global competition, threat of cheap labor force, and unstoppable rising of Chinese's economy, are much more than all these revolutions (Almada-Lobo, 2015).

Industry 4.0 is a rapidly emerging concept that is known by various names such as "Smart Manufacturing" and "Intelligent Manufacturing", "Made in China 2025", and "Future of Manufacturing" in such different countries as the USA, China, and the United Kingdom respectively (Kagermann et al., 2013). In Turkey, TÜSİAD (Turkish Industry and Business Association) published a report, namely "Industry 4.0 in Turkey as An Imperative for Global Competitiveness-an Emerging Market Perspective" in 2016 (TÜSİAD, 2016). No matter how the concept is entitled in different cultures and countries, it is evident that this concept is used for better decision-making, improved productivity, flexible, automated, and customized manufacturing systems.

Enabling smart machines, smart devices, smart systems, smart factories, shortly “smart” phenomenon renders virtual and physical manufacturing systems to flexibly collaborate in a global environment. Nevertheless, the fourth industrial revolution is not merely concerning smart and connected machines and systems, it spreads over various fields such as gene sequencing, nanotechnologies, renewable energies, quantum data processing. Therefore, the factor that makes the fourth industrial revolution fundamentally discriminating from previous industrial revolutions is the intertwining of these technologies and their interaction in physical, digital, and biological fields (Schwab, 2016: 17). Other factors that differentiate Industry 4.0 from previous industrial revolutions are: sensors transforming physical and chemical signals into data fit for data selection and sorting, information that artificial intelligence filters and contemplates, and lastly the data processing that decision-makers use for an instant, better, and reliable decision-making processes (Strandhagen et al., 2017; Nagasawa et al., 2017). Furthermore, Industry 4.0 creates faster, more flexible, and more efficient production processes. Therefore, Industry 4.0 is expected to influence the workflows radically by altering the structure of business models, to increase competitiveness, to enhance the quality of operations, to meet individual customer requirements, to optimize decision making, to supply effective and efficient use of resources, and to create value opportunities through new products and services (Agostini and Filippini, 2019; Gümüşoğlu, 2018).

Within the scope of all these technological advances and developments, innovations in production systems and processes, it is an organization that needs to pursue the transformation processes and be able to adapt to the ever-changing demands and needs in a globally competitive environment. As a matter of fact, while Industry 4.0 applications overcome the challenges such as global competition, decreasing product life cycles, high-quality customized products also provide opportunities such as low-cost industrial value creation, productivity, revenue growth, and competitiveness (Ardito et al., 2019; Burritt and Christ, 2016). Despite the growing interest in Industry 4.0 and the technologies it brings, there is no definite consensus on the application areas and results of this new manufacturing paradigm. Moreover, most companies are not yet aware of the challenges they might face when they adopt Industry 4.0. Unlike previous industrial revolutions, the rate of technological development in Industry 4.0 is exponential, and therefore, it poses numerous challenges, as well as numerous benefits and opportunities. As it is expected, Industry 4.0 will significantly change the operations carried out from the design phase to the production processes and from the procurement of products and services to the operations that are carried out until and after reaching the end customer (Yu et al., 2015; Lee et al., 2015). Moreover, Industry 4.0 technologies bring out such opportunities as creating changing and developing business and market models that affect the product life cycle, providing a new way in production systems and workflows, improving processes and increasing the organizations' competitiveness whilst it requires high-cost investments, encounters problems with the size of data and their processing and analysis as well as the difficulty of cybersecurity and data management (Li et al., 2017; Zhang et al., 2017). Furthermore, In the 1770s, the philosophy of Luddism erupted against the advent of machinery and mechanization that arose as a consequence of the first industrial revolution. Luddism was indeed triggered by the employees that are unwilling to change and faced the threat of unemployment, hence these employees showed resistance to change and protested by breaking machines (Dinwiddy, 1979). As various authors claimed, with the spread of Industry 4.0 technologies in a manufacturing environment, a huge loss of employment is anticipated, so the resistance to change is inevitable and this transition from muscle power to brain power poses some ethical and social threats and challenges. However, new job opportunities including robot engineering, industrial computer engineering, network development engineering, 3D printer engineering, big data expertise, data security analyst, data analyst and e-commerce and social media expertise, artificial intelligence, and machine learning experts are emerging (Prause, 2015; Cohen et al., 2019) and numerous benefits of Industry 4.0 technologies should not be ignored as monotonous, dangerous, mentally, and physically straining task are replaced by these technologies. Therefore, adaptation processes should be meticulously managed and maintained and employees should be prepared for this change in their working environments accordingly (Holmström et al., 2016).

Many of the nine technological advancements that build the foundation for Industry 4.0 have been already used in manufacturing, however with Industry 4.0, they are expected to alter production into more isolated, fully integrated, and automated systems and this will result in the optimized production flow, greater efficiencies and change traditional manufacturing paradigms among producers, suppliers, and customers as well as human and machine (Rüßmann et al., 2015).

Intelligent factories that enable horizontal and vertical integration with artificial intelligence-based self-optimizing, self-configuring, constantly interactive industrial robots and machines, real-time data flow, advanced automation and digitalization in the supply chain and production line, cyber-physical systems, internet of things, additive manufacturing, augmented reality, simulation, and cloud systems constituting the key factors of the Industry 4.0 concept, provide grounds for more productive, flexible, high quality, superior cost-effectiveness, versatile, safer and collaborative ecosystems (Martín et al., 2017).

Furthermore, under Industry 4.0 technologies, products can be designed to include a product-specific electronic identification card (ID) for tracking life cycles; with the data collected in this way, businesses can distinguish themselves from their competitors in understanding their consumption patterns, improving their products, new product developments, managing and controlling their operations such as maintenance and repair services. In addition, through links between machines, devices, and supply chain layers, and real-time shared information, opportunities such as flexibly changing order priorities, monitoring and controlling production performance and production lines, and improving logistics routes through production and purchasing arising from customer needs and maintenance requirements can also be created (de Man and Strandhagen, 2017).

Therefore, in general, it is evident that various benefits and challenges are expecting the business environment with the introduction of Industry 4.0. In the next stage, the fundamental technology trends and extensions of Industry 4.0 in a detailed manner.

1.2.1. Fundamental Technology Trends and Extensions of Industry 4.0 under the Umbrella of Sustainability Pillars

This part encapsulates the fundamental technology trends and extensions of Industry 4.0 including additive manufacturing, augmented reality, autonomous robots, big data and analytics, cloud systems, cyber-physical systems, internet of things, system integration, simulation, and smart factory.

1.2.1.1. Additive Manufacturing

A wide variety of such factors as cost, quality, flexibility, and production rate are considered in the selection of a manufacturing approach for a given product and/or service. An increase in both direct and indirect costs of manufacturing operations is a paramount obstacle within the organizations. Therefore, organizations pursue the elimination of waste, effective utilization of resources, stabilization of the production process, and tightening productivity standards so as to obtain a cost-effective position. Moreover, quality issues including minimizing defect rates and/or conforming to design specifications are broadly involved in production activities to compete on quality. The propensity to accord with changes in product mix, production volume, and/or design, which is regarded as flexibility, and production rate/time to market are also essential sources through the perspectives of competition in manufacturing (Watson and Taminger, 2018; Russel and Taylor III, 2003: 19).

Within the scope of Industry 4.0, apart from other transformative technologies, additive manufacturing is directly associated with manufacturing operations. Concordantly, additive manufacturing appears to be one of the backbones of Industry 4.0 that are developed as a counterpart of conventional techniques such as lathe and/or milling and can automatically adapt the physical models specifically from 3D prototypes of CAD. That is to say, additive manufacturing processes also known as 3D printing or rapid prototyping have a digital data flow transforming the various raw materials into homogeneous and heterogeneous final products with highly complex geometries in a time and cost-effective manner. So, the challenges of increasing the individualization of products, decreasing product life cycles, and reducing time to market can be tackled by additive manufacturing technologies (Vaidya et al., 2018).

Additive manufacturing is based upon building up of feedstock onto a substrate to produce a final product and/or work-in-process product, namely layer-by-layer manufacturing technology, whereas an operating logic of the conventional production paradigm, also known as subtractive manufacturing, hinges upon the removal of material in an (x-y) plane two-dimensionally to generate a final product and/or work in process product with such processes as lathing, drilling, turning, and milling. C.W. Hull introduced Stereolithography in 1983, providing the basis for the technologies that later would become additive manufacturing including direct laser powder fed processes, laser powder bed processes, and direct electron beam wire fed processes. Furthermore, various additive manufacturing techniques have been launched according to the structure of raw materials; for liquids Fused Deposition Modelling, for discrete particles Selective Laser Sintering, and for solid sheets Laminated Object Modelling (Watson and Taminger, 2015; Ahuett-Garza and Kurfess, 2018; Gibson et al., 2010; Ceruti et al., 2019).

Even though additive manufacturing technologies are opening new opportunities in terms of design, manufacturing, and distribution to end-users, subtractive manufacturing appears to be more favorable in situations where material removal processes are less, thereby creating opportunities such as lower cost, faster and less energy consumption whereas, in other situations, additive manufacturing fulfills the aforementioned promises. According to Mehrpouya et al. (2019), one of the pitfalls of subtractive processes is that the amount of material waste is considerably high and there is a lack of control systems continuously modifying the processes. Therefore, shortcomings and positive aspects throughout the process are to take into consideration in selecting a suitable manufacturing approach (Watson and Taminger, 2015).

Having compared to traditional manufacturing approaches, additive manufacturing technologies provide several advantages. Additive manufacturing technologies can manufacture geometries that are extremely challenging or in some cases impossible to manufacture any other way. As the physical model can be developed rapidly through CAD representations, some tests such as functionality, reliability, usability, maintainability can be done before the design cycle. Potential failures owing to misinterpretation of the design could be reduced. With additive manufacturing technology, raw materials are used efficiently by building parts layer by layer. Therefore, leftover materials can often be reused with minimum processing. Additive manufacturing is amicably established in specific applications characterized by a high level of customization and low volume production. Additive manufacturing provides decentralized production methods, flexibility in design for creating complex components, highly customizable products, efficient waste minimization, and time and material saving. Additive manufacturing equipment is economical in small batch production. The quality of the parts relies on the process rather than operator skills. The issue of fulfilling constantly changing customer demands and requirements could be coped with additive manufacturing since production can be synchronized with customer demand. Moreover, problems of line balancing and production bottlenecks can be virtually and promptly eliminated (Prakash et al. 2018; Ngo et al. 2018; Rüßmann et al., 2015; Mehrpouya et al., 2019).

Additive manufacturing processes can be applied to a series of industries such as aerospace, automotive, bio-medical including custom medical implants in dentistry, artificial organs, and medical devices, transportation, machine-tool production, art, and architecture. Ingredients of aerospace generally are composed of highly complex structures and/or geometries and such advanced materials as titanium alloys, special steels, and/or ultra-high-temperature ceramics that are hard, costly, and time-consuming to manufacture. Hence, using additive manufacturing technologies in aerospace applications is notably appropriate (Prakash et al. 2018). Additionally, in the automotive sector, using additive manufacturing technologies could diminish the cycles of design and development of automotive parts, hence a reduction in manufacturing costs. Additive manufacturing processes can be also used to obtain small quantities of structural and functional parts, such as engine exhausts, driveshafts, and gearbox components. However, in the automotive and aerospace sectors, the product quality and reliability of 3D prototypes are yet a concern. Additionally, strength in materials, limited printing volumes, and process velocity are being obstacles for additive manufacturing technologies (Garza and Kurfess, 2018).

Although additive manufacturing technologies demonstrate significant application potential and benefits in the aerospace, automotive, biomedical, energy, transportation, machine-tool production, dental care, art, and architecture, through the production of low-volume, customized products with cluttered geometries and advanced material features in a cost-effective and timely manner, some challenges in the implementation of additive manufacturing exist including building scalability, strength in materials, material heterogeneity, structural reliability, skills shortage, intellectual property issues, particularly regarding copyright, and development and standardization of new materials (Gao et al., 2015). Furthermore, despite some drawbacks such as manufacturing speed, accuracy, repeatability, and cost, conventional manufacturing approaches might be selected rather than additive manufacturing, particularly for the mass production of regular parts. Nevertheless, additive manufacturing technologies predominate conventional manufacturing approaches in the manufacturing of low-volume, customized products with cluttered geometries (Dilberoglu et al., 2017). Consequently, there are some situations in which conventional manufacturing tools and techniques are more appropriate, thus to compensate for the balance of drawbacks and advantages of these two manufacturing approaches, emerging hybrid manufacturing infrastructure might be developed further.

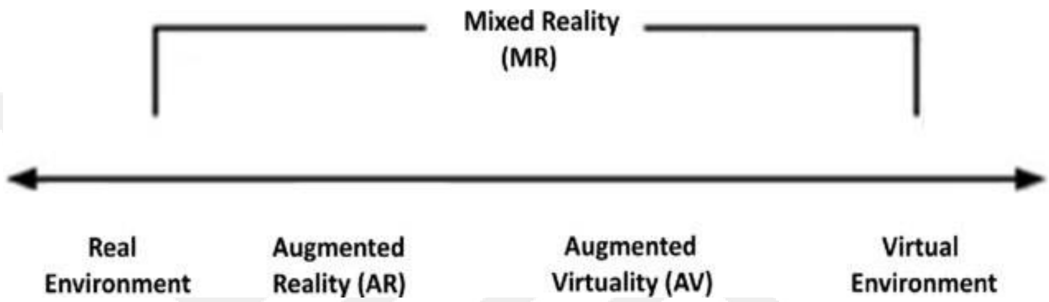
1.2.1.2. Augmented Reality

Having gathered various reviews on the occurrence of augmented reality, it can be deduced that it was not until Sutherland's work in the 1960s. A pioneer of computer graphics Ivan Sutherland and his students exploited a see-through head-mounted display (Azuma et al., 2001; Fraga-Lamas et al., 2018; Bottani and Vignali, 2019).

Scientists, then employed at the Boeing Corporation coined the term "augmented reality" while helping workers assemble wires and cable for an aircraft to increase the visual field of the workers with information regarding the task, thus simplifying the manufacturing processes of the air company (Caudell and David, 1992).

Later in 1994, a proposed model for augmented reality has been revealed by Paul Milgram and Fumio Kishino. As designed by Milgram and Kishino (1994), Milgram's Reality-Virtuality Continuum spans between the real environment and the virtual environment and embodies Augmented Reality (AR) and Augmented Virtuality (AV) in between, where AR is closer to the real environment and AV is closer to a purely virtual environment, as seen in Figure 1 below.

Figure 1: Milgram's Reality-Virtuality Continuum



Source: Milgram and Kishino, 1994.

Since the late-1990s, augmented reality has been a specific field of research, several conferences on augmented reality have been held including the International Workshop and Symposium on Augmented Reality, the International Symposium on Mixed Reality, and the Designing Augmented Reality Environments Workshop. Moreover, with such projects and organizations as mixed reality systems lab in Japan and the Arvika consortium in Germany, industrial augmented reality technologies and applications have been developed. However, the technical obstacle of augmented reality systems and applications was the lack of cost-affordable devices. With the widespread adoption of such mobile devices as smartphones and tablets having required sensors and processing units for the development and deployment of augmented reality applications, this limitation seems to be handled and augmented reality solutions, technologies, and applications have been boosted in several industries (Azuma et al., 2001; Fraga-Lamas et al., 2018).

According to Berryman (2012) augmented reality is used to enhance the experience, perception, interaction, and understanding of the user by blending a digital environment with the real-world, thus facilitating the user’s life. Augmented reality also differs from virtual reality, in virtual reality, a wholly digital environment is created, thus resulting in a digital, or simulation of reality and users immerse in an artificial world without seeing the real world, whereas, in augmented reality, there is a real-time combination of digital information and a physical real-world environment. Augmented reality enhances the real world with digital features, providing new patterns of environmental perceptions through virtual computer-generated information and interacting the users with these patterns (Schneider, 2019). Augmented reality systems and technologies have the following features:

- merges real and virtual items in a real environment,
- provide flexible real-time information,
- coordinates real and virtual items with each other,
- enables users to close the space between the physical and digital environment, and
- promote a human-centric industrial environment (Azuma et al., 2001).

Although a large variety of extensions of augmented reality systems and technologies are obtainable, there are several requirements and dimensions in the natural structure of an entire augmented reality system including displays, input devices, tracking, and computers. To put it simply, a display is required to provide a perception of reality and digital information. There exist three models of displays in augmented reality: head-mounted displays (HDM), handheld displays, and spatial displays. Even though HDMs offer synchronization of the virtual and real environment, it requires users to wear cameras on his/her head, leading to jittering of the virtual image. Handheld displays, on the other hand, are more portable and powerful but more expensive and heavy. Spatial displays foster a more natural perception of the real environment however do not support mobile systems. An input device is an indispensable pointing tool to convey and process information, that digital information is to be appropriately harmonized with what the user has been seeing via a tracking dimension. Last, a computer system is required to control, manage, and enhance what has been shown. Furthermore, based on an application being developed how the aforementioned requirements and dimensions of an augmented system are being assembled and operated varies (Carmigniani et al., 2011).

A wide range of applications of augmented reality exists changing from visualization of prototypes to interactive workshops for operators in risky industries. Applications of augmented reality have been broadly deployed in personal information and/or personal assistance, media, medical visualization, robot path planning, gaming, entertainment, fashion, real estate, retail, architecture, construction, education through innovative learning approaches, military, and tourism in an attempt to cultivate the experience of users and provide additional information regarding an object and/or a display (Berryman, 2012).

Moreover, augmented systems and technologies are being utilized both in marketing to engage potential customers across the product design and development processes and advertising while launching new products: augmented brand experience and augmented advertisement, respectively (Zhao et al.,2019; Salah et al., 2019).

Potentially, augmented reality systems and technologies can also be implemented to other senses comprising smell, touch, and hearing. Therefore, augmented reality systems and technologies can pamper individuals with poor visions and/or even blind and deaf ones by augmenting and substituting missing senses with such sensory substitutions as audio and visual cues (Carmigniani et al., 2011).

According to a research paper by Bottani and Vignali (2019) classifying and analyzing the augmented reality literature based on sectors that deploy it, aerospace, automotive, electronics, food industry, footwear, manufacturing, machine tool, warehousing, nuclear/power plants are the most encountered industrial sectors.

Owing to the proliferation of smart tools and devices, augmented reality technologies are anticipated to become widespread, however, there are some challenges of implementing augmented reality. The challenges encompass lack of interoperability as each device and platform depend on unique, individual development. Further, augmented reality documentation authoring is regarded as a time-consuming and complicated task due to the fact that 3D modeling, computer graphics/animation skills, programming, and know-how to registration and tracking are required (Gattullo et al., 2019).

Moreover, privacy and ethical issues in displaying the information apart from the user and such user issues as ergonomic, aesthetic, and design-related hesitations, as well as the rate of the user acceptance of technology are vulnerable points of augmented reality (Berryman, 2012).

Some studies claim that the user adaptation to augmented reality equipment can negatively affect performance, another study shows that the augmented reality displays that could not provide the requirements of ergonomics might cause fatigue, eye strain, and concentration issues for long-term use (Biocca and Rolland, 1998; Ellis et al., 1997). Such human-related factors are to be investigated to eliminate the drawbacks and enrich the experience throughout augmented reality technologies. Other hurdles include hardware and software issues, data transfer, integration and security issues, content authoring, adaptive instructions, marker tracking reliability and cost (Masood and Egger, 2019).

Comprehensively, being one of the enabling technologies of Industry 4.0, applications and systems of augmented reality are rapidly nourishing that provide flexible and innovative business models in the manufacturing environment intertwined with technology, improve the industrial productivity, reliability, performance, and safety, and unveil discrepancies precisely. As the user experience is the most important factor for expanding the applicable business models and the pervasiveness of augmented reality, organizations should play an arbiter role in the development of augmented reality solutions and applications.

1.2.1.3. Autonomous Robots

Autonomy encapsulates the systems that are inclined to operate in the real-world environment deprived of external control for extended periods. Autonomous systems, thus are assumed they could survive in a dynamic environment, cultivate their internal structures and processes, demonstrate a variety of behaviors, and even within limits, adapt to environmental changes whereas automatic systems include devices and tools that operate on their own, self-managing or moved mechanically with the information from the sensor. In automatic systems, there are repetitive mechanical and/or electronic operations, there is neither instant decision power nor machine learning as such an automatic washing machine (Yılmaz, 2018).

Thereafter the emergence of digital control electronics in the 1970s, an intensive focus on automated perception and the advent of artificial intelligence along with reductions in the cost of sensors, actuators, and processors, autonomous systems and robots have developed enormously, yet been developing and found in a variety of applications (Watson and Scheidt, 2005).

A myriad of tasks is performed through approaches of manual instructions or in a semi-autonomous way. Even though these approaches facilitate reliability in tackling unpredictable environments through the integration of human cognitive decision-making processes and robotics, efficiency is of immediate concern as human effort requires to grasp sensory data remotely and lead the robot accordingly. In this manner, there is a developing requirement for more prominent degrees of intelligence and autonomy to permit these physical systems to perform ideally inside brutal situations. Various approaches have started to rise as conceivably viable solutions including human-robot collaboration effort and machine learning for more generalized autonomy (Wong et al., 2018).

Industrial robot manipulators formerly had lacked sensing and/or reasoning features, and merely were pre-programmed to execute certain tasks. That is to say, although robots have already been used in manufacturing environments, the functions and structures were quite limited. However, with the introduction of Industry 4.0 and its enabling technologies, mass customization alongside advanced manufacturing approaches autonomous robots and systems have occupied the agenda more than ever and become much more flexible, cooperative, self-configuring and the deployment of autonomous robots and systems have accelerated in manufacturing, assembling, maintenance, and logistics, warehousing, material handling, office management controlled via human-robot cooperation (Rüßmann et al., 2015: 3). Currently, such robots with different characteristics, functions, and designs as wheeled mobile vehicles, snake robots, legged robots, humanoids, household robots, industrial robots, and mobile robots are evolving hinged on the magnitude of autonomy, intelligence, dexterity, and mobility to carry out various tasks in dynamic, uncertain, complex, and unpredictable environments (Bekey, 2005: 2).

The development of artificial intelligence, reduction in implementation costs of autonomous systems along with improvements in performance, punctuality, versatility, flexibility, and endowments have enabled autonomous robots and systems to be deployed in various facets of life. There are several applications of mobile robots in manufacturing environments such as environmental monitoring and inspection processes including control of Heating, Ventilating, and Air Conditioning (HVAC), air quality, radiation rate, and detection of hazardous environmental changes. The flexible, intelligent, and autonomous robotic systems are also anticipated to affect incorporate information out of sensors with the operational and technical capabilities and to standardize communication interfaces with other factory-automation components, thus integration into an industrial computer integrated manufacturing environment (Freund and Rossmann, 1994). Furthermore, household chores applications, military, security, surveillance, and detection of intrusion are amidst the application of autonomous robots, namely mobile robots (Fahimi, 2009: 7).

The harsh environment encompasses circumstances that are compelling to execute a task in a cluttered, dynamic, unstructured, and unpredictable environment and are hazardous by virtue of the high levels of radiation, explosive risk, extreme temperatures, and lack of oxygen (Fahrner et al., 2001). Therefore, in such industries as oil and gas inspection, space exploration, deep-sea operations, deployment of autonomous robots and systems are broadly deemed to handle health, safety, and environment issues (Wong et al., 2018). Autonomous robots yielding safety, reliability, productivity, and efficiency are also utilized in such manufacturing industries as automotive, electronics, transportation, metal, machinery, chemical, rubber, plastics, and food to deal with tasks in dynamic, uncertain, complex, and unpredictable environments that are not practically handled by a man-power, thereby achieving a manufacturing optimization (Watson and Scheidt, 2005). Furthermore, unmanned ground vehicles, namely UGVs, have been ushered in diverse fields such as search and rescue missions, labor automation, environment exploration, and map building tasks. Moreover, autonomous vehicles, generally deemed as self-driving cars and specifically developed for personal use, have been steadily developing and are ensuring augmented safety and mobility for individuals who are unable and/or unwilling to drive as well as providing sustainability benefits such as enhanced vehicle utilization, decreased demand for urban parking infrastructure, and reduced pollution (Bausys et al., 2019; Mitchell et al., 2010).

However, there are several challenges regarding autonomous systems and robots. Primarily, laws, legal systems, and regulations should be redesignated in order to cope with accountability issues and obligations and answer the question of whether autonomous robots have similar rights and responsibilities as humans (Schwab, 2016: 165). Security issues and cyber-attacks are other consequences of embracing such autonomous systems and robots, therefore regardless of their size, organizations should be aware of these challenges and take precautions.

1.2.1.4. Big Data and Analytics

The rapid growth and advancements in technologies, notably in IoT (Internet of Things), wireless tools and sensors, mobile devices, and smart applications along with the kaleidoscopic manufacturing dynamics in line with operations' dimensions and structures have spread big data and big data analytics out, both constructive and compelling phenomena in today's information era. Having considered the recent data flow, scope, and spread, it can be deduced that enormous amounts of data are currently attainable for managerial and operational decision-making processes. Moreover, capture, storage, and collection of data capabilities have become apparently much more economical and effortless, however, dealing with such magnitude of data is of vast hassle and inefficient with conventional tools and techniques. Therefore, big data analytics evolving from business intelligence and decision support systems are benefitted in order to extract insights, patterns, and knowledge over diversified, rapidly changing and surging big data ranging from operational logs and connected devices to customer interactions and social network data (Perner, 2014).

The framework of big data hinges upon constantly piling exponential data sets stretching from terabytes (TB) to petabytes (PB) that surpass the features of traditionally used software tools and techniques to capture, store, search, manage, share, visualize, and process the data (Kubick, 2012). Hence, dealing with such amount of heterogeneous, unstructured, and complex data so as to unveil the relevant information, correlations, trends, facts, and insights behind it is merely feasible with big data analytics applying advanced analytic techniques on big data sets.

Nevertheless, it can be deduced that the larger the dataset, the more burdensome it is to handle yet provide a more accurate statistical analysis (Russom, 2011).

Big data can be outlined under the three V`s including volume, variety, and velocity. Basically, the volume of the data accounts for the size of the data, the velocity of the data is the rate with which data is varying, and the variety consists of the various formats and types of data, along with the numerous sorts of uses and the ways of analyzing the data (Elgendy and Elragal, 2014). Furthermore, the volume of the data is the fundamental attribute of big data: it can be quantified in proportion to its size in TBs or PBs and also according to the number of records, transactions, and files. The issue of what makes big data that big could be enlightened by considering the immense variety of sources than ever before including clickstreams, cloud platforms, and social media. Having these sources for analytics integrates common structured data with unstructured data drawn out of the text, audio, video, human language, and other devices and such semi-structured data as eXtensible Markup Language or Rich Site Summary feeds, hence the variety of big data is as big as its volume. Additionally, the velocity of big data ascribing to the frequency of data generation is among the leading edge of big data as it is piled up in real-time capacity (Elgendy and Elragal, 2014).

Although many resources and researchers put forward the term three V`s for revealing the big data characteristics, some researchers are discussing the additional dimensions, namely veracity, value, and volatility. Veracity explains the quality of the data and relies on the data consistency, completeness, accuracy, context, availability, latency, deception, and approximations (Mills et al., 2012). As for value, it reveals improvements so as to back up big data analytics and establishes standards and norms to enlighten and demonstrate big data needs and competencies (Moyne and Iskandar, 2017: 3). Volatility encapsulates storage capacity and retention of data as the volume and velocity of data increases enormously the storage and security of such amount of data become crucial (Belhadi et al., 2019: 2). Apart from these, such notions as validity, variability, venue, vocabulary, and vagueness are also used while explaining the big data features (Tsai et al., 2015: 2).

With the emergence of big data analytics, data management and its techniques have started to shift from structured data into unstructured data, and from a stable environment to a ubiquitous cloud-based environment (Wang et al., 2018). In big data analytics, data can be generated out of separate sources and in various forms as the reflection of its variety attribution. For instance, data could emerge from the web, logs, clickstreams, ERP systems, cloud systems, and social media applications in unstructured formats including image, audio, video, text, and graphics, hence the processing of such data is a basic task of big data analytics, or even more explicitly tasks of web analytics, social analytics, multimedia analytics, and so forth (Choi et al., 2018). That is to say, regardless of the form of data that could be structured, semi-structured, and/or unstructured, big data analytics technologies and tools aimed at transforming them into more understandable, analyzable, and processable data format so as to enhance business operations.

However, there are some obstacles to big data analytics. These obstacles are not only limited to the existence of massive amounts of unstructured and complex data but also the hardship of capturing, storing, managing, analyzing, and processing the data with conventional tools and techniques. To handle the aforementioned obstacles of big data analytics such strategies as suggested by Choi and others (2018) including divide and conquer, distributed and parallel processing, incremental learning using unfamiliar situations, statistical inference, addressing uncertainty with learning, scalability, and heuristics can be implemented. Furthermore, statistics, machine learning, artificial intelligence, natural language processing, optimization, data mining, social network analysis, sequence pattern mining, decision trees, clustering algorithm analysis, data envelopment analysis, and visualization analysis are among the commonly used techniques for big data analytics. There are also different analytics tools like descriptive, inquisitive, predictive, exploratory, and golden path analysis. In descriptive analytics, dashboards, scorecards, and data visualization have been used to deduce a general assumption from the data. Inquisitive analytics interrogates the root causes and are nourished by the descriptive analytics outputs to discover the data characteristics, similarities, and correlations existing in data with clustering analytics, sequence pattern mining, and query tools. In predictive analytics, regression analysis, machine learning, and neural networks have been selected to make feasible forecasting regarding future events. Similarly, exploratory analytics have been focusing on the relationships in big data and creating further opportunities for understanding facts, insights, and associations. Golden path analysis is a developed form of predictive and exploratory analytics and analyzes a large amount of behavioral data to divulge the hidden patterns, trends, and behaviors of events and activities in a more efficient way (Watson, 2014: 6). Moreover, based on the requirements of real-time analytics, off-line analytics, business intelligence level analytics, and memory-level analytics are used to handle a huge amount of datasets within a feasible amount of time (Marjani et al, 2017: 3).

According to Clemons et al. (2014), personal privacy violations and online invasions are among the biggest handicaps of big data analytics. For instance, spam advertising, pop-ups, and sponsored sites while browsing the internet might seem harmless though disturbing and annoying. However, fraudulent e-commerce transactions and identity theft are much more serious threats. Additionally, the term "personal profiling" that is related to gathering personal information can be used for commercial benefits without your knowledge and/or intention. Furthermore, an inadequately skilled workforce, difficulties in architecting big data analytics systems, data security and cyber-attacks, cost-related issues, data storage, and standardization are among the obstacles of big data analytics. Therefore, organizations that are inclined to adopt big data analytics within their business operations are required to be aware of both benefits and challenges of big data analytics and select the most suitable tools, techniques, and trends of big data analytics that match their organizational requirements.

1.2.1.5. Cloud Systems

Owing to the constantly accumulating data storage and computation requirements, cloud computing has become prominently crucial. Cloud computing reveals data storage potential as well as dynamic and scalable computing resources including infrastructure, software, and services through the network and real-time adaptations (Xu et al., 2009: 244; Dell et al., 2014). A broad definition of cloud computing is that it includes any pay-as-you-go or subscription-based services via the internet and is deprived of investing in new infrastructure or licensing new software (Knorr and Gruman, 2008: 1). Wang et al. (2010: 3) described cloud computing as "a set of network-enabled services, providing scalable, QoS (Quality of Service) guaranteed, normally personalized, inexpensive computing infrastructures on demand, which could be accessed in a simple and pervasive way." Another definition of cloud computing is that "cloud computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." (Mell and Grance, 2009: 6). The basic characteristics of cloud computing are being "service-based, massively scalable and elastic, shared, consumption-based billing, and delivered via internet technologies" (Voss, 2010: 7).

The emergence of cloud computing dates back to 2007, however with the implications of Industry 4.0, the cloud computing paradigm has been conceptually evolving and contributing to both lives of individuals and business environments with growing data sharing, developed system performance, and reduced costs over online systems (Liu and Xu, 2017: 4). Basically, cloud computing encompasses five layers as clients, applications, platform, infrastructure, and servers (Gong et al., 2010: 1). Moreover, there are four sorts of clouds public cloud, private cloud, community cloud, and hybrid cloud based on the accessibility and requirements of the user. The public cloud is established for any users having an internet connection, whereas in the private cloud there is a bunch of users and the access to the private cloud is merely limited with them. The community cloud is a shared cloud system among two or more organizations with similar cloud needs. As for the hybrid cloud, it encompasses the combination of at least two clouds as in the mixture of public and private or public, private, and community (Huth and Cebula, 2011: 2). Therefore, users could opt for any sort of cloud system based on their requirements and demands.

Furthermore, the functional aspects of cloud computing rely on flexible and convenient access to hardware, software, and data resources and there exist three deployment models of cloud computing including Infrastructure-as-a-Service (IaaS), Software as a Service (SaaS), and Platform-as-a-Service (PaaS). IaaS such as International Business Machines Corporation's Blue Cloud project offers its users IT hardware solutions and an entire data center that is controllable, progressive, and versatile. SaaS provides access to software and/or an application via internet connection without installation such as Microsoft's "Software + Service". PaaS like

Microsoft's Azure Services Platform is fundamentally a variation of SaaS that constitutes a link between hardware and an application and supports users to develop a set of applications and cloud services (Dillon et al., 2010: 2). Another deployment model of cloud computing is that file hosting services including Microsoft OneDrive, Amazon Simple Storage Service, and Google Docs and they are among the Data as a Service (DaaS) helping users to access, store, retrieve, and manage their data through network services. What differs cloud computing from other computing models like grid, global, and internet computing is lying behind its aspects of having user-centric interfaces, autonomous systems, adaptability to user's requirements, and providing on-demand service and virtualization (Wang et al., 2010).

As cloud computing creates real-time access to various hardware, software, and data resources, this leads to agile and flexible on-demand services, improvements in development and emanation of new products and/or services as well as reductions in time to market thus enabling competitive advantages for many enterprises (Marston et al., 2011: 178). Additionally, the management and organization of hardware, software, and data resources are much more effortless, timely, and viable in the cloud environment. Apart from abrupt and unexpected outages, cloud computing caters for uninterrupted services to the users. More importantly, damages to the environment owing to broad-spectrum use of traditional systems in the enterprises could be diminished to some extent through the use of cloud computing as in the reduction of e-waste (Jadeja and Modi, 2012: 3).

Although cloud systems address various solutions regarding hardware, software, and data usage of individuals and businesses, one of the main drawbacks of the system is the security owing to potential software bugs and crashes, increasing rate of hackers and malfeasance. As the users entrust their personal and private information to an external source, they are to be aware of such security measures as encryption methods of the service providers, methods of protection, and ways of the backups of the data (Huth and Cebula, 2011: 3). Other concerns regarding cloud computing are availability, standardization, privacy, support, interoperability, and compliance. The availability concern with cloud computing occurs when the cloud computing vendors are unable to deliver the service, namely outage, thereby in such circumstances, users should have contingency plans including keeping back-up storage and/or cloud, or rigorously not putting critical and vital data on the cloud. The compliance issue is merely affiliated with enterprises because they are obliged to sustain business-related legal documents and ensure their integrity to comply with relevant laws and regulations hence cloud computing vendors are to actualize appropriate technologies to provide with these compliance requirements (Kim, 2009: 4).

As a result, it is evident that there are some obstacles to adapting cloud computing systems into the enterprises' current managerial and operational processes, therefore proper management and control of such agile and innovative solutions are crucial to ensure the effectiveness of cloud systems within enterprises.

1.2.1.6. Cyber-Physical Systems

Through the developments of manufacturing technologies along with Industry 4.0 trends and extensions, production environments and paradigms have been revolutionizing, hence intellectualized, integrated, reliable, flexible, productive, efficient, and digitalized processes and systems have been emerging. Cyber-Physical System (CPS) is among the fundamental enabling technologies to actualize Industry 4.0. CPSs harmonize and manage cyber and physical systems simultaneously via the broad use of computation, communication, and control technologies (Zhang et al., 2017: 138). According to Rajkumar et al. (2010: 1), cyber-physical systems are "physical and engineered systems, whose operations are monitored, coordinated, controlled, and integrated by a computing and communicating core." CPSs in general pave the way for the intersection and/or integration of cyber and physical sources and enhance the capabilities of the physical environments. The features of cyber-physical systems are that having a cyber-aptitude in each physical item and integration among cyber and physical environments to train and adapt reactively along with being thoroughly networked, automated, dynamically reconfigurable for effective data-flows, self-organization, reliable operation of the systems, and enhanced outputs (Huang, 2008).

CPSs contain physical phenomena, cyber systems, and interfaces. The physical phenomena ascribe to the surrounding that is required to be monitored, managed, and controlled. The cyber systems are physically-aware next-generation sophisticated and embedded systems. Such innovative approaches as real-time computing techniques, visualization methods, embedded systems to provide system reliability, safety, and security have been developed. Similarly, through the interfaces including embedded systems, actuators, sensors, analogue-to-digital converters, digital-to-analogue converters, and wireless communication generating an adaptive, autonomous, smart feedback loops physical sources and processes could be monitored and managed, hence real-time, reliable, resilient, and dynamic collaboration between physical and cyber systems are provided. That is to say, these aforementioned interfaces are bridging the cyber systems with the physical world (Leitao et al., 2016: 1; Gunes et al., 2014: 3).

The term CPS could be intertwined with other technologies and tools of Industry 4.0 as in the IoT. However, cyber-physical systems differentiate from wireless sensor networks and the internet of things. That is to say, wireless sensor networks basically detect the signal and focus on the perception, collection, and processing of the data. As for IoT, it interconnects such tools as wireless sensors and Radio Frequency Identification (RFID) via wireless network and internet connections in order to provide reliable transmission and effective processing of information, so in general, the internet of things have merely the perception of the physical environment rather than the control. Cyber-physical systems, on the other hand, are manageable, reliable, and adaptable systems ensuring feedback loops distributed through embedded computing systems with the computation, communication, and control infrastructures and technologies. CPSs also have control of the physical environment and affect the functioning and route of the physical processes (Liu et. al, 2017). The establishment of cyber-physical systems yet inevitably requires such technologies as the IoT, cloud computing, augmented reality, big data, and machine-to-machine. In order to implement cyber-physical systems properly, a robust harmony providing real-time data acquisition out of the physical environment and information feedback out of the cyber environment along with agile data management and analytics are also necessary. Furthermore, a smart connection ensuring rigorous and reliable data out of machines, components, and equipment as well as an effective transformation from data to information creating a self-awareness attribute to machines, components, and equipment are required. A cyber-level acting as a pivotal information hub and creating a self-comparison attribute to machines, components, and equipment through wide-spread insights over the conditions, workflows, and schedules of them, a cognition level in which decisions are prioritized and optimized, and a configuration level operating as a feedback control mechanism out of the cyber environment to the physical environment and creating self-configuration and self-adaptiveness attributes to machines, components, and equipment are also among the functional requirements for the proper implementation of cyber-physical systems, hence acquiring better product quality, overall system and process reliability with smarter and agile production equipment (Lee et al., 2015).

Although cyber-physical systems furnish a considerable amount of benefits, improvements, and implications in smart manufacturing, health care and medicine systems, transportation and traffic management, robotics, protection and control of infrastructures such as water, electricity, gas, and oil, the implementation and design of cyber-physical systems bring about various challenges and various requirements including functional, reliability, and performance. Based on the study conducted by Gunes et al. (2014: 3):

- dependability that is the performance of the systems meeting the requirements of the processes and operations without disruptions,
- maintainability that is the ability to fix and repair in case of any failure within the system,
- availability referring to the accessibility even if the failure occurs,
- reliability ascribing to what extend the system provide factuality and validity while functioning,
- robustness that is the capacity to maintain the system coherence and handle any faults,
- predictability referring to the level of the forecast of systems' condition, pattern, and functionality,
- accuracy that is the degree to which a system's tracked outcome resembles its real one,
- compositionality that is the capability of digest the whole system by checking out any aspect of it,

- adaptability referring to adjustment of the system configuration based on the potential alterations,
- confidentiality referring to sharing vulnerable information merely with the authorized entities,
- interoperability that is the capability of the information exchange and collaboration of the systems and/ or items, and
- the heterogeneity that is the ability of a system to integrate a variety of interconnected and interacting components are among the challenges of cyber-physical systems.

Owing to the increasing number of IoT devices, vulnerability issues arise and cyber-physical systems might expose to cyber-attacks. Other barriers to these systems include a bunch of protocols and standards, safety, and security issues. Cyber-physical systems should ensure the issues of dependability, reliability, accuracy, availability, adaptability, effectiveness, predictability, interoperability, heterogeneity, and maintainability in the early design stage so as to prevent any disruptions within the processes and/or operations as well as the sensitive information leakage and malicious attacks. As a result, emerging technologies and mechanisms including human-centric sensing, wireless and quantum sensors, smart networked sensors could be developed in order to provide cyber-physical systems' security, reliability, and privacy requirements (Alguliyev, 2018: 1).

The term, cyber-physical systems generally collocate with cybersecurity and/or cyber security encompassing security issues related to information technology and/or operational technology environments. Cybersecurity handles the privacy, integrity, and availability of data and has no concern with an orchestration of physical and cyber sources and processes, on the other hand, it is often converged on computer security and information security (Walls et al., 2013). Some authors' approaches to cybersecurity are relying on the fact that this discipline is broadly treated as a sub-discipline of information security yet features including the nature, structure, implementation, and strategies behind these disciplines are to be distinguished. Overall, integrity and availability are highlighted in cybersecurity whilst information security's primary concern is confidentiality (Barzilay, 2013; Wamala, 2011). There exist such threats as "cyber-attacks" referring to harm and halt cyber systems and “cyber-exploitation” referring to the exploitation of cyber-infrastructure illegally and defilingly. In order to cope with these sorts of threats and violations, measures should be taken at individual, non-governmental, national, and international levels (Tonge et al., 2013: 2).

1.2.1.7. Internet of Things

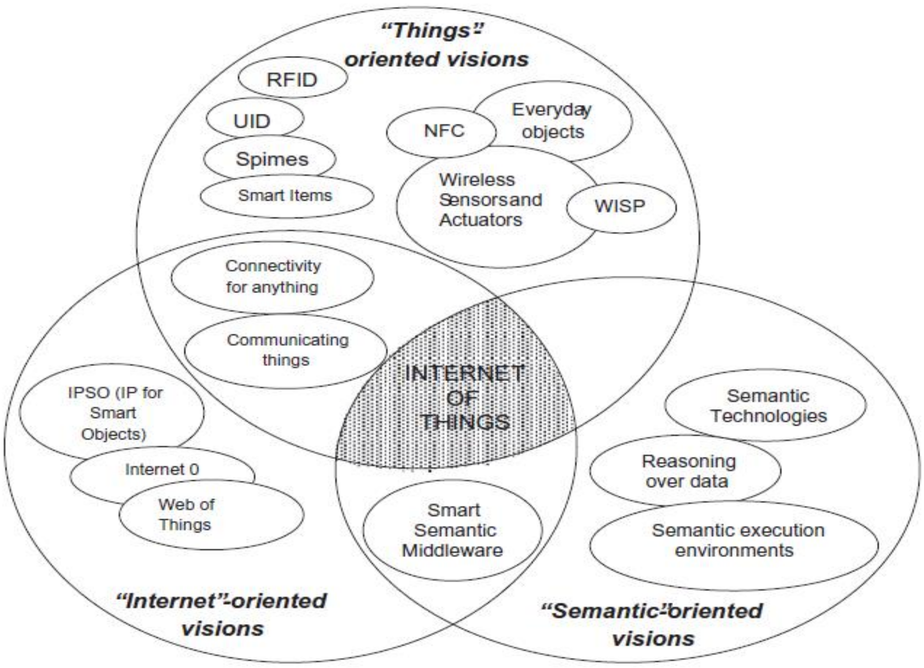
The notion of the Internet of Things (IoT) refers to a framework of the interconnection of everyday objects through the internet in which the connection of physical items to the virtual environment is provided incessantly along with the control of these items is ensured remotely owing to them operating as physical access points to internet services. The term IoT was first coined in 1999 by Kevin Ashton in the Auto-ID Laboratory of Massachusetts Institute of Technology in order to define a system providing the internet connection of objects in a physical world through sensors basically referring to RFID tags that are used in supply chains and logistics operations for counting and tracking down the commodities without the human interaction. Now, IoT is an emerging technology with its technical, social, and economic importance and variety of applications. According to predictions, it is anticipated that there will be at least 100 billion connected IoT devices along with its global economic impact of more than $11 trillion by 2025 (Rose et al., 2015).

The International Telecommunication Union (ITU) describes the IoT as a “global infrastructure for the Information Society, enabling advanced services by interconnecting (physical and virtual) things based on, existing and evolving, interoperable information and communication technologies” (ITU, 2012). Accordingly, the features of the IoT encompass communication and cooperation via wireless technologies, identification via RFID and barcode technologies, tracking, data collection, identification, sensing, actuation, embedded information processing, localization, and user interfaces through smart objects and things (Rose et al., 2015).

According to the authors, there are several definitions regarding the IoT including things-oriented, internet-oriented, and semantic-oriented. In the things-oriented definitions, the focus is on the things including, particularly RFID, wireless sensors and actuators, smart items, and emerging sensing technologies that become connected in the IoT. Even though these technologies and items constitute a fundamental component of the road to the IoT structure, the overall deployment of the IoT requires other components as well. In the internet-oriented definitions, the internet-related aspects of the IoT including internet protocols as the network technology have been buttressed. Moreover, it is evident that the merge of the terms “Internet” and “Things” creates a distinctive level of innovation in information and communications technology. IoT conceptually refers to ‘‘a worldwide network of interconnected heterogeneous objects (sensors, actuators, smart devices, smart objects, RFID, embedded computers, etc.) uniquely addressable, based on standard communication protocols.” (Fortino and Trunfio, 2014: 1).

Another definition of the IoT is semantic-oriented and concentrates on the challenges in the IoT associated with the storage, interconnection, search, and organization information generated by the IoT. The figure below shows how these various definitions, explanations, and technologies are converging and forming the term IoT together (Atzori et al., 2010).

Figure 2: ‘‘Internet of Things” Paradigm as a Result of the Convergence of Different Visions



Source: Atzori et al., 2010: 2789.

IoT is regarded as the combination of physical and digital components for creating new products and enabling novel business models. From a technical point of view, the implementation of an IoT technology requires three layers including the thing or device, the connectivity, and the IoT cloud. The device layer is composed of core hardware components along with such IoT components as sensors, actuators, or processors and embedded software operating the physical thing to control and run its functionality. The connectivity level provides communication through protocols between the individual thing and the cloud. Next, the device communication and management software is used at the IoT cloud layer to communicate with, plan, and control connected things, whilst an application platform is used to design and run IoT applications (Wortmann, and Flüchter, 2015). According to another definition of IoT, it encompasses the sensing layer, the access layer, the network layer, the middleware layer, and the application layer. In the sensing layer, the required information is captured through various sorts of sensors, and the access layer is used to transfer information from the sensing layer to the network layer via mobile, wireless, and/or satellite networks as well as wireless local areas networks. The network layer is then responsible for integrating the information resources of the network with the internet platform and the establishment of an efficient and reliable infrastructure platform. The middleware layer manages and controls the real-time network information. Last, the application layer builds the practical application of several industries including smart logistics, disaster observation, and remote medical care (Chen and Jin, 2012).

Based on a study conducted by Mukhopadhyay and Suryadevara (2014) business sectors including customer service/support, data management and analysis, supply chain management and logistics, energy management, asset management, technology infrastructure management are expected to be positively affected by the developments of IoT. However, due to lack of employee skills/knowledge, lack of top management commitment/knowledge, immaturity of industry standards around IoT, high costs of investment in IoT infrastructure, weaknesses in current technology infrastructure businesses are to deal with obstacles and challenges throughout the implementation of IoT. Other technological challenges include scalability, interoperability, software complexity, data volumes, security, privacy, computational ability, fault tolerance, power supply, short-range communication, and interaction (Nižetić et al., 2020).

As a result, the IoT is an emerging technology system that has significant potential and a wide range of application areas. Furthermore, the development of IoT is expected to enable the interconnectedness among objects anytime, anywhere hence converting these real-world objects into smart virtual objects however technical, operational and managerial challenges aforementioned should be handled effectively so as to make the most of the IoT technologies and applications.

1.2.1.8. System Integration

A holistic system integration horizon has emerged with the Industry 4.0 technologies and applications. Before Industry 4.0, organizations were barely integrated both horizontally and vertically. Nonetheless, there exist a considerable amount of organizations that are not yet wholly integrated. However, with the Industry 4.0 technologies and applications, organizations, departments within the organizations, and entire value chains are expected to convert into much more cohesive, coherent, harmonious, and fully integrated (Rüßmann et al., 2015). Industry 4.0 paves the way for various dimensions of integration including horizontal integration, vertical integration and network-based production systems, and end-to-end engineering across the entire product life cycle (Stock and Seliger, 2016: 537).

A horizontal integration refers to an accretion internally or externally through activities like mergers, strategic alliances, and acquisition hence the integration of companies that are at the same level is generated. With the horizontal integration economies of scale, elimination of competition, increase in market share and dominance, creation of win-win situation for the collaborators of the horizontally integrated structure, and new business opportunities could be achieved. However, a domino effect can be seen if one of the collaborators of the horizontal integration structure has a low-quality product and/or service or some delivery issues so the reputation of the other integrated parts could also fall into disrepute (Naik et al., 2010: 2; Yelis, 2021). Therefore, understanding, analyzing, and seizing both the limitations and opportunities are of great importance to work harmoniously in horizontal integration structures.

A vertical integration basically occurs when a company handles its operations including sourcing, manufacturing, distribution, and marketing within its supply chain at various levels and the direction of the integration could be either upstream or downstream. In this way, a vertically integrated company could avoid any supply interruptions or bullwhip effects as it holds the control across the entire supply chain and it also experiences a reduction in the costs and increases in the competitive advantages. Nonetheless, as the company attempts to vertically integrate with other operational bodies some issues including the managerial complexity and decrease in flexibility might happen (Amadeo, 2020).

As for the end-to-end integration, it encompasses the entire functions of the supply chain including demand and supply management, procurement, purchasing, sourcing, product and/or service design and development, scheduling, manufacturing, warehousing, delivery and transportation, after-sales services, reverse logistics, and recycling and it attempts to bring about a holistic view of the supply chain and gather abovementioned functions so as to drive down costs such as labor and material, provide efficiency, transparency, visibility across the entire value chain, hence providing customer satisfaction with much more customized products and services (Kremer, 2021).

1.2.1.9. Simulation

The basic definition of the simulation is that it is the replica, reproduction, reflection, and/or resemblance of a real-world process or system over time. Simulation fundamentally generates a simulated record of the process and/or system and through the observation of that simulated records functioning aspects of the represented real-world process and/or system can be apprehended and analyzed (Jahangirian et al., 2010. Simulation applications can be used in various fields including capacity planning, transportation management, forecasting, process design and improvement, production planning, inventory control, purchasing, resource allocation, logistics, scheduling, supply chain management, workforce planning, maintenance management, project management, financial management, quality management along with defence, healthcare, and public services for diagnosing real-world problems, indicating and then analyzing the behavior of the process and/or system, exploring opportunities and possibilities, asking “what if” questions regarding the represented environment and identifying the constraints and limitations within the represented environment. However, the implementation can be quite time-consuming and expensive and requires a skilled workforce. Moreover, an exposition and analysis of the represented environment can also be difficult (Banks, 1999).

Now being among the Industry 4.0 technologies, simulation collaborates with other Industry 4.0 related trends and extensions including cyber-physical systems, smart factories, and augmented reality for virtualization and optimization and has a significant impact on the designing, analyzing, and improving both the quality and efficiency of the manufacturing processes and other simulated functions (Gunal and Karatas, 2019). Furthermore, simulation provides various benefits such as reduced waste in time and resources, increased efficiency through the optimization and alteration of the routing conditions, machine processing times, and production speed along with increased revenue, productivity, and work safety (Gunal, 2019).

1.2.1.10. Smart Factories

The notion of “smart” encompasses individuals’ lives as in smartphones, smart appliances, smart home systems, even smart cities. Furthermore, the manufacturing approaches and systems have been penetrating smart technologies and smart devices, hence smart factories holistically (Radziwon et al., 2014).

Smart factories are consisting of flexible structures that can optimize their performance on their own, adapt to unexpected and/or new situations, learn simultaneously, and manage the production processes autonomously. Smart factories have fundamental features including connectivity, optimization, transparency, proactiveness, and agility (Burke et al., 2017).

Based on the horizon of Wang et al. (2016b) upon a smart factory, there exist distinct layers including physical resource, industrial network, cloud and intelligence, and control within a production plant. In a physical resource layer, various sorts of machines and equipment consisting of such as smart products, smart devices, and smart machines are located and operations are taking place as a reflection of a shop floor. The industrial network layer embodies the data flow process from machines to the cloud, and vice versa, in other words, it connects the physical resource layer with the cloud layer. The data is then captured, stored, in the cloud layer to further be processed via big data analytics. The last layer of the production plant is the control mechanism linking human force to the smart factory via enablers such as personal computers, tablets, and mobile phones. Moreover, smart factory encapsulates an integration of cyber-physical systems and such physical objects as machines, products with information systems as well as emerging technologies including Manufacturing Execution Systems (MES), ERP, IoT, big data, cloud computing, and embedded systems so as to adapt flexible and agile manufacturing environments (Wang et al., 2016a). As a result, smart factories are extremely intelligent organisms that can use automation in all processes within the organization, improve themselves, and exchange data so as to ensure the combination of the physical world and the virtual world. In traditional factory systems, there are limited and predetermined resources, through the fixed routing and schedules, manufacturing operations are carried out. Table 2 below demonstrates the difference between traditional factory systems and smart factory mechanisms.

Table 2: The difference between traditional factory systems and smart factory

The smart factory production mechanism	The traditional factory production mechanism
Various resources	Limited and predetermined resources
Flexible routing	Scheduled routing
Strong Co-ordination	Diverse Layers
Digitized processes and operations	Manual processes and operations
Complete data for faster decision-making processes and data-driven decision-making	Limited data for decision-making processes and process-driven decision making
Enhanced productivity, flexibility, and resource utilization, high interoperability, faster procurement, improved customer experience, motivated workforce, and more improvements	Reduced productivity, poor resource utilization, poor interoperability, slow procurement, poor customer experience, time-consuming, and fewer improvements

Technologies such as IoT, cloud computing, autonomous robots, additive manufacturing, big data and analytics are being involved in manufacturing systems	Limited technology involvement

Source: Wang et al., 2016b.

It is evident that the smart factory differs from the traditional factory with its operational and managerial approaches. While traditional factories include diverse layers including design, production, marketing, and other departments within the factory, departments in smart factories are deeply coordinated, cooperated, and collaborated. In smart factories, processes and operations are digitized, technology and data-driven, thus enhanced productivity, flexibility, and resource utilization, high interoperability, faster procurement, improved customer experience, motivated workforce, whereas in traditional factories processes and operations are manual, and there exist limited and poor data for decision-making processes, thus reduced productivity, poor resource utilization, poor interoperability, slow procurement, poor customer experience, time-consuming, and fewer improvements. Therefore, it is inevitable that traditional manufacturing systems and factories will be replaced by smart factories over time, as smart factories provide numerous positive outcomes and benefits. Accordingly, smart factories are shaping the future of manufacturing environments and Industry 4.0 technologies and extensions including cyber-physical systems, IoT, autonomous robots, augmented reality, big data and analytics, cloud computing, and artificial intelligence facilitate the smart factory implementation (Hozdić, 2015).

Although smart factories have many benefits and advantages over the traditionally operating factories there are some requirements and challenges in the implementation of a smart factory including an update of smart management systems, identification, status knowledge, support for different queries, integration of heterogeneous information. Assignment of virtual world information to real-world objects via various identification methods, tags, and sensors can be also seen as one of the basic challenges in creating a smart industrial ecosystem. To execute continuous improvements in processes and drive down lead times, localization, that is to say, information regarding the position of such objects as tools and/or materials along with the status and/or situation of the objects are required (Lucke et al., 2008). Additionally, implementation of the smart factory requires such factors as “modularity, interoperability, decentralization, virtualization, service orientation, and real-time capability” that should be taken into consideration. Challenges regarding the skilled workforce, technology, infrastructure, and investment are also required to be handled. As a large volume of real-time data, unstructured sensor data, machine logs are being piled up within the smart factory, storage, analysis, interpretation of these various sorts of data properly for conducting such functions and operations as quality control management and maintenance management are also regarded as complicated and complex tasks. Accordingly, the security and privacy of these data generated are of vital importance so factories demonstrating smart features and attributes are required to improve their data security and privacy systems (Hermann et al., 2015; Chen et al., 2017; Wang 2016a). Therefore, challenges in the implementation of the smart factory systems should be handled effectively in order to make the most out of these systems and applications.

CHAPTER TWO

SCOPE AND DISCUSSIONS OF SUSTAINABILITY AND CONVERGENCE OF INDUSTRY 4.0 TECHNOLOGIES WITH SUSTAINABILITY DIMENSIONS

The root of the sustainability and/or sustainable development hinges upon "the Brundtland report" (World Commission on Environment and Development, 1987). In the report, sustainable development is described as "meeting the needs of the present without compromising the ability of future generations to meet their own needs". The term development in the definition of sustainability appertains not only to economic growth but also to social progress and environmental protection. Another definition of sustainable development is that it includes economic and social development strategies that maintain and enhance the natural environment while also promoting social fairness (Diesendorf, 2000: 23). The author also stated that if the term sustainability would be regarded as a goal and/or an endpoint, sustainable development would then be considered as a process. To put it differently, sustainability embodies a bunch of today`s actions and plans that do not tether economic, social, and environmental opportunities for future generations (Elkington, 1997). An extension of these technical definitions is put forward by Veiderman (cited in Munier, 2005: 10) that is sustainability is a vision of the future that gives us a road map and helps us focus on a set of values, ethical and moral standards, by which we should lead our activities. Moreover, sustainability can be considered as a process of change and enhancement in behaviors, attitudes, consumption patterns, and habits involving individuals, institutions, and governments and is about a quality of life (Munier, 2005). According to Arowoshegbe and Emmanuel (2016: 91), sustainability can also be explained as:

> -*an overarching conceptual framework that describes a desirable, healthy, and dynamic balance between human and natural systems, -a system of policies, beliefs, and best practices that will protect the diversity and richness of the planet's ecosystems, foster economic vitality and opportunity, and increase quality of life levels for people and, -a vision describing a future that anyone would want to inhabit.*

Moreover, if we transform general sustainability definition into the business point of view, it can be gathered that sustainability is about filling the demands of a firm's direct and indirect stakeholders (such as shareholders, workers, clients, communities, and so on) without jeopardizing the firm's capacity to satisfy the needs of future stakeholders" (Dyllick and Hockerts, 2002: 131). Savitz (2013: 2) also suggested that a sustainable business makes profits for its shareholders while also safeguarding the environment and improving the lives of individuals it interacts with. In general, it can be concluded that sustainability stands out for societal, economic, and environmental evolution for a better future. The importance of sustainable development, hence the term sustainability has been rising as a result of the ever-increasing mobility of industrial activities since the dawn of the industrial revolutions and has been occupying the agenda of businesses, stakeholders, governments, and non-profit organizations to find viable and innovative solutions to problems of environment, society, and economy. In such, environmental problems include global warming, greenhouse effect, ozone depletion, lack of resources and even depletion of resources, pollution, loss of non-renewable resources, climate change, biological diversity loss, and waste; societal problems include high unemployment rates, poor working conditions, and social vulnerability; economic challenges include supply risk, the pressure of intense globalization, a need for differentiation strategies due to high levels of competition. Furthermore, changing demographic features, intergenerational differences like different requirements of generations X, Y, and Z worldwide, a need for coping with the target group with high awareness of social and environmental responsibility as a result of being a global information society also have pushed businesses to create towards sustainable industrial value in social, environmental and economic dimensions (Stock and Seliger 2016; Müller et al., 2018; Kiel et al., 2017).

Apart from the term sustainability, there is also another term called "corporate social sustainability" and it is associated with the terms including environmental management, sustainable development, and corporate sustainability. According to the authors, focusing on environmentally and socially responsible activities leads to a better public image, hence economic benefits (Christofi et al., 2012). This encouraged businesses to report their environmental and social activities willingly and to do so the United Nations Environment Programme and the Nonprofit Coalition for Environmentally Responsible Economies together introduced the first standards for sustainability reporting: The Global Reporting Initiative (GRI) (Brockett & Rezaee, 2012; Christofi et al., 2012). GRI sustainability reporting standards are developed for organizations that are willing to share their economic, environmental, and/or social impacts. The figure indicates the economic, environmental, and social standards designated by GRI in 2016.

Table 3: GRI's Topic Specific Standards

GRI 200: Economic
201: Economic Performance
202: Market Presence
203: Indirect Economic Impacts
204: Procurement Practices
205: Anti-corruption
206: Anti-competitive Behavior
GRI 300: Environmental
301: Materials
302: Energy
303: Water
304: Biodiversity
305: Emissions
306: Effluents and Waste
307: Environmental Compliance
308: Supplier Environmental Assessment
GRI 400: Social
401: Employment
402: Labor/Management Relations
403: Occupational Health and Safety
404: Training and Education
405: Diversity and Equal Opportunity
406: Non-discrimination
407: Freedom of Association and Collective Bargaining
408: Child Labor
409: Forced or Compulsory Labor
410: Security Practices
411: Rights of Indigenous Peoples
412: Human Rights Assessment
413: Local Communities
414: Supplier Social Assessment
415: Public Policy
416: Customer Health Safety
417: Marketing and Labeling
418: Customer Privacy
419: Socioeconomic Compliance

Source: GRI, 2016.

Apart from the GRI, International Integrated Reporting Council Framework, and the Sustainability Accounting Standards Board guidelines are considered to be among the most prevalent sustainability reporting frameworks (Calace, 2016, 2017). So, these reports in general provide some information regarding the economic indicators, environmental compliance, labor practices, human rights, society, and product responsibility.

Furthermore, in an attempt to raise awareness and globally emphasize sustainable development, the latest "United Nations Sustainable Development Summit" was held in September 2015 and seventeen sustainable development goals were determined, which are targeted to be accomplished by 2030. These goals are demonstrated in Figure 3 below.

Figure 3: United Nations Sustainable Development Goals

Source: UNDP, 2021.

As depicted in the figure above, the sustainable development goals are targeting at ending poverty, elimination of hunger, providing good health and well-being, offering quality education, adopting gender equality, supplying clean water and sanitation, creating affordable and clean energy, focusing on decent work and economic growth, industry, development of innovation, and infrastructure, reducing inequalities among individuals, tendering sustainable cities and communities, encouraging responsible consumption and production, taking climate actions, caring the life below water and on land, spreading the peace, justice and strong institutions, and partnering for the goals (UNDP, 2021). An urge to achieve these sustainable development goals is of great importance. Not only the businesses alone but also the non-profit organizations, governments, more importantly individuals should be a part of these actions and act upon them to achieve these goals by altering the direction of quantitative economic development towards a more qualitative and responsible way.

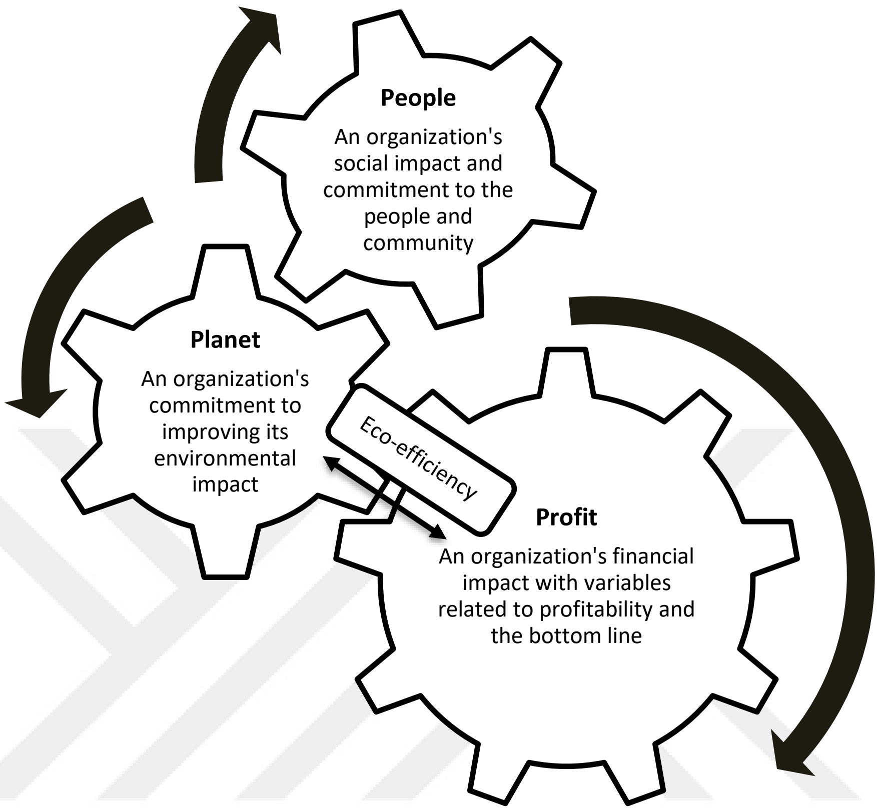
Among these seventeen sustainable development goals, the seventh goal, "accessible and clean energy", the eighth goal "decent work and economic growth", the ninth goal "industry, innovation and infrastructure", the twelfth goal "responsible consumption and production" and the thirteenth goal "climate action" are chosen while shaping this study due to their solid relations with the environment, production and industry (Bonilla, 2018). In detail, the seventh goal, the use of accessible and clean energy, benefits both organizations and the fight against climate change with increased efficiency, employment, cost advantages, and prevention of environmental pollution. The eighth goal, decent work and economic growth, promotes superior working conditions with regards to health and safety, reasonable working hours, equal rights both on wage systems and in the working environment, and social security. The ninth goal, industry, innovation and infrastructure, offers real-time control on the production systems, productivity, flexibility, transparency, mass customization with the latest technologies and innovations. The twelfth goal, responsible consumption and production, emphasizes green production technologies and business strategies like "Triple Bottom Line of Sustainability" (TBL) thus organizations increase their public images and achieve competitive advantages with the responsible and effective use of resources and energy as well as increased financial gains. Lastly, the thirteenth goal, climate action, focuses on the reduction of greenhouse gases and carbon footprint particularly along the value chains of businesses along with the energy and resource efficiency (Özdağoğlu and Yılmaz, 2020; Korkmaz, 2020; Yılmaz and Özdağoğlu, 2020; İpek and Hızarcı-Payne, 2020; Madran, 2020). Business strategies, government regulations, and legislation as well as the initiatives of non-profit organizations and individual approaches are expected to pave the way for executing social, environmental and economic sustainability as well as sustainable development goals globally, thereby ensuring a better life for future generations.

Based on the various views on sustainability, it is evident that sustainability covers the promise of societal, economic, and environmental evolution for a better future that refers to the “triple bottom line of sustainability", an extension of corporate social sustainability. The triple bottom (TBL) line was coined in 1994 and used by Elkington in 1997 and the author highlighted that the triple bottom line involves economic growth, environmental quality, and societal benefit simultaneously on the contrary to the traditional business accounting views focusing on the financial bottom line solely (Elkington, 1997). Moreover, TBL, also known as 3BL implies the necessity and importance of long-term social, environmental, and economic benefits instead of short-term financial gains because the success and/or failure of a business is thought not to be defined only by pecuniary return but also by its conformity with societal expectations and environmental impacts (Arowoshegbe and Emmanuel, 2016).

There are three main focuses of TBL: 3P (people, planet, profit) (Global Reporting Initiative, 2006). So, in general, it can be said that “people” is related to social performance, societal issues, and approaches, “planet” concerns ecological impacts and environmental performance, and “profit” refers to the financial stability and economic functions of the businesses.

The Venn diagram of the three pillars was first presented by Barbier (1987) and the author suggests that rather than conflicting these dimensions are reinforcing each other. In Figure 3 below a demonstration of TBL and brief explanations are given. While adapting the figure below, a gear wheel shape is preferred to highlight the fact that sustainability revolves around these three dimensions and that the disruption of one would affect the operation of the others.

Figure 4: Triple Bottom Line



Source: Gillis, 2021.

Next, all three dimensions under the umbrella of sustainability will be mentioned in a detailed manner.

2.1. SOCIAL SUSTAINABILITY

The notion of social sustainability concerns human and society-related issues and has not been in the spotlight and has been overshadowed by economic and environmental sustainability. This dimension is also regarded as the weakest pillar of sustainability and there is a lack of understanding and work on this dimension (Vallance et al., 2011). In Jacobs et al. (1987)'s definition of sustainable development, a satisfaction of basic human needs for jobs, food, energy, water, sanitation, and education, achievement of equity and social justice, procuration for social self-determination and cultural diversity cohere with the social dimension of the sustainability. Furthermore, social sustainability includes satisfying basic needs, reducing poverty, equity-enhancing, increasing useful goods and services, and social justice (Barbier, 1987).

According to the authors, the conceptual framework of social sustainability is composed of four concepts including safety, urban forms, equity, and eco-prosumption. Safety is the basic requirement of social sustainability and refers to not only having the right to be safe but also adopting security measures to prevent potential safety risks. Urban forms include socially desired urban and communal dimensions including compactness, diversity, clean energy, greening, sustainable transport, and utilization. Equity promotes equal policies and justice to deal with vulnerabilities and enhance the development of public involvement in sustainability projects. Eco-prosumption encourages individuals, hence society to consume, produce and gain values in and towards socially and environmentally responsible ways (Eizenberg and Jabareen, 2017). An industry-based definition of social sustainability can be found in the definition of Elkington (1987) that is the social dimension of the triple bottom line is regarded with the beneficial and fair business practices to the labor, human capital, and the community. Similarly, based on the empirical analysis done by the authors, the social part of sustainability covers such topics including protection of health and safety, education and free personal development, sustaining cultural and societal values, and juridical equality and certainty (Hansmann et al., 2012).

Moreover, Dyllick and Hockerts (2002: 134) define socially sustainable companies as companies that “add value to the communities within which they operate by increasing the human capital of individual partners as well as furthering the societal capital of these communities. They manage social capital in such a way that stakeholders can understand its motivations and can broadly agree with the company’s value system.”

In the context of this study, concerning the convergence of social sustainability with Industry 4.0, thanks to technologies such as autonomous robots, intelligent production infrastructures, intelligent factory systems, and advanced machine learning through human-machine interfaces, it is assumed that brainpower is used instead of the muscle power in order to perform monotonous and risky tasks for industrial workplaces (Koca, 2018). Therefore if these abovementioned technologies are used at a factory level within various departments such as production, transportation, and logistics this situation will create a better, safe and secure working environment from a social sustainability aspect. However, this situation also leads to a clash of ideas. Some authors think that especially blue-collar workers will be unemployed and replaced by robots. However, others think that various job definitions will emerge and these new job definitions will offer new opportunities. These job definitions include robot engineering, industrial computer engineering, network development engineering, 3D printer engineering, big data expertise, data security analyst, data analyst, e-commerce and social media expertise, and artificial intelligence and machine learning experts (Prause, 2015; Cohen et al., 2019). Both arguments should be tackled carefully because there is a fine line between utilizing and suffering from these new technologies. So, the biggest share of the worries falls on the top management of the enterprises in eliminating the worries of the workers who are afraid of losing their current works to smart systems or robots. Top management needs to answer the following questions before applying these technologies:

- What is the current status of the enterprise in terms of technological, worker capacity and workers' competence, managerial approaches of top management?
- How will the senior management of the business and workers approach these transformation processes?
- What is the road map to follow in the transformation or adaptation processes to Industry 4.0?

After analyzing the current situation in the transformation or adaptation processes to Industry 4.0, the top management should prepare a road map to follow in this transformation process.

As a result, based on the studies analyzed earlier Industry 4.0 technologies and applications not only will offer new job definitions in terms of social sustainability but also will offer such opportunities as workplace safety, enhanced employee welfare and health as well as the improvement and development of working standards and conditions of the working environment.

2.2. ENVIRONMENTAL SUSTAINABILITY

Although environmental and/or ecological sustainability has emerged due to social concerns, it is clearly distinguished from social sustainability. However economic sustainability and environmental sustainability overlap to some extent. In fact, the term industrial metabolism originated from the linkage between the industry and the ecosystem. Here, the industry is considered as a living organism that consumes energy and materials and creates both the desired output like a product/service and an undesired output like a waste. Unless the balance between this consumption and production can be provided efficiently ecologically unsustainable situation occurs (Ayres, 1989). There is also another term called "eco-development" describing the process of balancing social and economic goals with environmentally sound management in the interest of future generations (Mellos, 1988). Accordingly, a key to achieving economic sustainability is based on efficient use of materials and environmental sustainability basically focuses on the protection of the raw materials used, elimination of waste, and the use of renewable energy sources (Goodland, 1995). Another definition of the environmental dimension is in line with the general definition of sustainability and refers to the practices that do not jeopardize the environmental resources for future generations. It also focuses on the efficient use of energy recourses, reduction of greenhouse gas emissions, and minimization of the ecological footprint (Goel, 2010). According to Dyllick and Hockerts (2002: 133),

> *ecologically sustainable companies use only natural resources that are consumed at a rate below the natural reproduction, or a rate below the development of substitutes. They do not cause emissions that accumulate in the environment at a rate beyond the capacity of the natural system to absorb and assimilate these emissions. Finally, they do not engage in activity that degrades eco-system services.*

In order to survive in today's business environments and attract customers organizations apply green innovation strategies. These strategies are to create environmental sustainability and offer many opportunities including decreasing the impact of operations on the natural environment and using renewable energy while mitigating the use of chemicals and waste (Meseguer-Sánchez et al., 2021). Other opportunities for environmental sustainability include the protection of natural spaces and biodiversity, reduction of the use of nonrenewable resources, protection from environmental hazards, and reduction of ecological risks (Hansmann et al., 2012).

The environmental dimension of sustainability has gained importance due to factors such as the continuous increase in population growth, development of new products, high production levels and intensification of global industrialization with excessive consumption, contributing to economic development while causing environmental degradation of ecosystems (Carvalho et al., 2018; Koren et al., 2018).

Within this study, the relationship between environmental sustainability and Industry 4.0 along with the technologies it brings are analyzed. These technologies are expected to lead to such drivers including increasing transparency and traceability in both demand and processes, designing sustainable products and services, intelligent planning of processes, and hereby reducing energy and material consumption. In a factory, intelligent production systems offer flexible and open systems by creating horizontal and vertical integration of digital and production systems, and these systems are designed to immediately control and intervene in indicators such as excess emissions of carbon dioxide and greenhouse gases, wastes, environmental pollution, and resource consumption, and thus reduce environmental damages. Furthermore, the internet of things applications, one of Industry 4.0 technologies, can be used in planning environmental factors, uninterrupted monitoring of environmental changes, analysis and control of pollution sources (Yu et al., 2015). Additionally, cloud computing systems and automation optimize processes to predict and better manage water quality, air pollution, pollution caused by heavy metals or mercury (Zhang et al., 2017). Similarly, sensors and RFID technology embedded in internet-connected smart objects could enable efficient information collection and real-time control of environmental conditions and reveal the direct and indirect environmental impacts of the operations in sectors such as agriculture, transport, and manufacturing. In addition, the adoption of Industry 4.0 concepts and technologies, such as big data, can lead to improved environmental conditions, particularly in the quality of the soil where it is used (Yu et al., 2015).

Other potential environmental benefits that may arise with the inclusion of Industry 4.0 technologies in production processes are ensuring the accuracy, reliability, and comparability of the reported environmental accounting data through improved data quality, less management discretion about what is measured, how is measured and reported, and elimination of the concept of "Green Washing" as well as contribution to sharing more reliable information with the public (Burritt and Christ, 2016; Valdez et al., 2015; Posada et al., 2015).

As a result, Industry 4.0 technologies and applications are expected to provide benefits including reducing the negative environmental impacts, resource and energy efficiency, effective energy management, reduced amount of material used, increased share of reused, remanufactured, and recycled materials, reduced total amount of waste and pollution, improved use of renewable resources, less amount of greenhouse gas emissions in the fight against depletion of non-renewable resources, loss of biodiversity, climate change, waste, and pollution as well as the creation of a sustainable ecosystem.

2.3. ECONOMIC SUSTAINABILITY

In its simplest form, economic sustainability refers to the balance between financial costs and financial values (Popovic et al., 2013). Economic sustainability however does not only deal with the economic indicators but also considers manufacturing, circulation, and consumption of goods and services (Mohamed and Antia, 1998). Economic sustainability can be measured by life cycle costing and alleviation of both short-term and long-term environmental impacts of a product/service through its life cycle is of great importance to achieve economic sustainability (Six et al., 2016). Economic sustainability revolves around the management of financial capital like equity and debt, tangible capital like machinery and inventory along with intangible capital like reputation, brand image, customer satisfaction, know-how, and organizational routines. If an organization is economically sustainable then that organization ensures cash flow adequate to assure liquidity at all times while providing shareholders with a consistently above-average return (Dyllick and Hockerts, 2002). The economic pillar of sustainability "focuses on the economic value provided by the organization to the surrounding system in a way that prospers it and promotes for its capability to support future generations" (Arowoshegbe and Emmanuel, 2016: 104). Furthermore, economic sustainability, hence sustainable growth forms a basis for both social and environmental sustainability and is mainly wheeled by the pursuit of economic growth, economic objectives, and profit-driven strategies (Purvis et al., 2019). On the contrary, Elliott (2005) believed that a primary focus of economic sustainability should be on efficiency rather than equity along with a trade-off between current and future consumption. By providing economic sustainability, a firm can achieve such opportunities include creating revenue and employment, strengthening human and social capital, promoting the economy's innovative power, market consideration of externalities, and future generations' economic status (Hansmann et al., 2012).

Technological developments in manufacturing have played a vital role in supporting economic growth and generating social benefits for decades. Sustainable factories of the future form the basis of industrial growth and economic and social well-being. Globalization has significantly changed the consumption habits of society so that the manufacturing processes of the products produced in line with customer demands have changed significantly in this period, which in turn has caused sustainability concerns. New technologies emerging with Industry 4.0, providing faster and cheaper research and development (R&D) processes, such as 3D printing, simulation, and concurrent engineering can significantly reduce product launch time and provide a competitive advantage as being the first supplier in the market. Furthermore, the applications such as smart production technologies and blockchain brought by Industry 4.0 increase the competitive power of a company with such opportunities as efficiency, flexibility, transparency, traceability, optimization of quality problems and resource utilization, minimization of waste, and early detection of errors, thus increase profitability (de Man and Strandhagen, 2017). It is also likely to optimize processes and use of resources based on speed and efficiency and to reduce material costs by using cyber-physical systems that provide real-time monitoring. Moreover, thanks to Industry 4.0-based technologies, it is possible to reduce machine downtimes or replacement times with early detection of possible machine-related faults through continuous and remote monitoring of machine conditions. Costs can be reduced and production efficiency can be improved as a result of preventing and correcting errors. It has been supported by studies that Industry 4.0 applications have potentials such as reduced energy and resource use, optimization of material and waste flows, and reduction of production waste (Kamble et al., 2018; Stock et al., 2018). In logistics systems as well as in production systems, it is also possible to diminish the number of transportation processes, wrong deliveries, unnecessary waiting times, and damaged goods throughout the entire supply chain and prevent unnecessary material flows (Blunck & Werthmann, 2017). Additionally, the issue of the efficient management of inventories as too much inventory results in huge capital costs can be addressed with Industry 4.0 applications. This is because with Industry 4.0 technologies and applications such as real-time supply chain optimization and advanced analytical demand planning, excessive stock-keeping can be prevented and this makes it possible to meet customer needs completely and accurately (Bakkari and Khatory, 2017). Therefore, it can be concluded that Industry 4.0 technologies and applications are assumed to provide numerous economic benefits including cost reduction, optimization, increased productivity, enhanced quality, and elimination of waste.

Having taken sustainability dimensions separately into consideration, next the convergence of Industry 4.0 technologies with the sustainability dimensions based on a systematic literature review will be given in the following headings.

2.4. ADDITIVE MANUFACTURING FROM SUSTAINABILITY PERSPECTIVES

Recently, the sustainability concept has been incorporated vigorously into manufacturing environments. Therefore, organizations are perpetually in the tendency to embrace path-breaking and innovative trends that are adaptable with their existing equipment and technologies in order not to lag in the market. Accordingly, the emergence of Industry 4.0 and its enabling technologies like additive manufacturing systems are assumed to provide organizations with an opportunity to fully integrated, automated, and optimized production flow, thus leading to sustainability potentials (Prakash et al. 2018). Table 4 demonstrates an overview of convergence of additive manufacturing and sustainability dimensions based on various studies.

Table 4: An Overview of a Convergence of Additive Manufacturing with Sustainability Dimensions

Authors	Reviews
(Morrow et al., 2007; Reeves, 2009)	Additive manufacturing processes enable material and resource efficiency, and flexibility in production, hence providing economic sustainability.
(Watson and Taminger, 2015).	There exist some potential advantages of additive manufacturing processes for enabling more environmentally sustainable manufacturing through reduced consumption of energy and materials.
(Butt, 2020).	Additive manufacturing plays a significant role in economic sustainability with increased customization options and allows manufacturers to print on-site promptly reducing shipping costs, diminishing waste and time to market.
(Dilberoglu et al., 2017).	Additive manufacturing may have an important effect in diminishing waste resources and reducing energy consumption by employing just-in-time production.
(Paris et al., 2016).	Based on a combined indicator for environmental impact ratio and volume of material removal ratio, additive manufacturing appears to be environmentally friendly.
(Huang et al., 2015).	Additive manufacturing procures opportunities in promoting materials efficiency, reducing life cycle impacts, less requirement for special tooling in part fabrication, rapid tooling production, and diminishing material waste.
(Peng et. al, 2018).	Three aspects of environmental impact including resource consumption, waste management, and pollution control in the context of sustainable additive manufacturing have been studied. The results showed additive manufacturing has the potentials to diminish the amount of raw material required in the supply chain, reduce the need for energy-intensive, wasteful, and polluting manufacturing processes, and enable more efficient and flexible product design.
(Ford and Despeisse, 2016).	On the social sustainability side, when compared to traditional production techniques, additive manufacturing provides health advantages by allowing workers to avoid long-term exposure to demanding and possibly dangerous work situations. Furthermore, additive manufacturing has various environmental benefits, including the capacity to generate less waste during manufacture, the ability to optimize geometries and make lightweight components, all of which minimize material and energy consumption.
(Haleem and Javaid, 2019).	Positive outcomes of additive manufacturing can be summarised under the following: customization, virtual inventory, prototyping, flexibility in design and development, waste, risk, and cost reductions, improvements in customer satisfaction, speed, accuracy, productivity, profitability, and supply chain performance.
(Chen et al., 2015; Mani et al., 2014).	Additive manufacturing brings along numerous sustainable benefits including less raw material consumption, waste material, and pollution, higher resource efficiency and flexibility in production processes, reduced number of transportation processes and carbon footprint, decentralized and close-to-consumer manufacturing, extended product life through novel technical methods such as remanufacturing, reusing, repairing, refurbishing, and sustainable socio-economic production.

As a result, it appears that additive manufacturing technologies could be embedded into manufacturing processes in order to enhance flexibility and efficiency in the mass personalization of complex materials, hence providing potentials for a working sustainable environment (Kobryn et al., 2006; Kohtala, 2015).

2.5. AUGMENTED REALITY FROM SUSTAINABILITY PERSPECTIVES

Incessantly accelerating developments and advancements in manufacturing environments, processes, and technologies along with volatile market circumstances and ever-challenging core requirements regarding precise quality, customer demands, and improvements in cost and time issues have led organizations to push their capabilities and keep up with Industry 4.0 and its enabling technologies. Proven to be amidst the Industry 4.0 technologies, augmented reality is a set of systems and technologies that provide the visual and aural understanding and reasoning of cyber-physical production systems in a context-sensitive manner (Grieves, 2014).

Industry applications of augmented reality systems can be dispersed into process monitoring and control, real-time evaluation of plant layout, plant and building construction, online guidance systems for operators, decision-making processes combining the physical experience along with the display of information extracted in real-time from databases, material management, enhancing industrial safety, and human resources through recruitment, hiring, and training. Augmented reality can be also used in quality assurance and inspections since the variety and complexity of products increase the inspection task becomes even harder not to mention owing to the cognitive limitations of human inspection processes are less effective. So, with augmented reality systems providing a direct comparison between the real object and an ideal model, the performance and effectiveness of quality assurance and inspections surge. Additionally, augmented reality could be applied to product design, facility inspection and management, assembly, and repair processes and provide improvements and acceleration in product and process development, reduction in costs and performance enhancements in plant and machinery maintenance through textual, visual, or auditory information. Hence, repetitive and prone to human error tasks are to be handled by augmented reality systems as augmented reality systems are expected to cause less cognitive load and body fatigues and reduce the number of errors per employee as well as the time it takes to accomplish a task (Fite-Georgel, 2011; Zhu et al., 2014; Masood and Egger, 2019; Zubizarreta et al., 2019).

Table 5 below shows the various views of the authors regarding the convergence of augmented reality and sustainability dimensions.

Table 5: An Overview of a Convergence of Augmented Reality with Sustainability Dimensions

Authors	Reviews
(Fite-Georgel, 2011; Zhu et al., 2014; Masood and Egger, 2019; Zubizarreta et al., 2019).	Augmented reality enables less cognitive load and body fatigues, decreasing both the number of errors and the time required to complete a given task. These advantages could lead to material and resource efficiency, and flexibility in production, thus both social and economic sustainability.
(De Pace et al., 2018).	Some economic benefits of augmented reality applications are improvements in product design and product development, early determination and elimination of any design-related errors and/or discrepancies, reduction in the number of physical prototypes and helping and facilitating employees' workloads.
(Azuma et al., 2001).	Additive manufacturing plays an important role in the improvement of industrial productivity, reliability, performance, and safety, thus referring to social and economic sustainability.

Industry applications of augmented reality systems can be dispersed into process monitoring and control, real-time evaluation of plant layout, plant and building construction, online guidance systems for operators, decision-making processes combining the physical experience along with the display of information extracted in real-time from databases, material management, enhancing industrial safety, and human resources through recruitment, hiring, and training. Augmented reality can be also used in quality assurance and inspections since the variety and complexity of products increase the inspection task becomes even harder not to mention owing to the cognitive limitations of human inspection processes are less effective. So, with augmented reality systems providing a direct comparison between the real object and an ideal model, the performance and effectiveness of quality assurance and inspections surge. Additionally, augmented reality could be applied to product design, facility inspection and management, assembly, and repair processes and provide improvements and acceleration in product and process development, reduction in costs and performance enhancements in plant and machinery maintenance through textual, visual, or auditory information. Hence, repetitive and prone to human error tasks are to be handled by augmented reality systems as augmented reality systems are expected to cause less cognitive load and body fatigues and reduce the number of errors per employee as well as the time it takes to accomplish a task (Fite-Georgel, 2011; Zhu et al., 2014; Masood and Egger, 2019; Zubizarreta et al., 2019).

Having taken applications and solutions of augmented reality in various fields into account, it can be deduced that augmented reality should not be comprehended as a tool replacing the labor force, but rather as a tool helping and facilitating their workloads. Moreover, with augmented reality, tasks are anticipated to be performed promptly and efficiently, resulting in optimization in the core operating business processes. As a result, augmented reality supports mainly the economic and social pillar of sustainability as it encompasses such benefits as increased health and safety throughout the working environment as well as optimization and reliability in manufacturing processes.

2.6. AUTONOMOUS ROBOTS FROM SUSTAINABILITY PERSPECTIVES

In today's manufacturing environment, pressures on ensuring competitive advantages over cost, increasing product variety, mass customization, and market volatility led to the adoption of innovative, flexible, and automated manufacturing approaches because even though the workforce is sufficient, there exist highly complex products requiring compatibility, precision, and reliability that are beyond the skills of human employees. Furthermore, such issues as enhanced human safety, production flexibility, process quality, and efficiency, and reductions in environmental impact stimulate the use of autonomous robots and systems in manufacturing environments (Esmaeilian et al., 2016).

The table below illustrates the relationship between autonomous robots and sustainability dimensions.

Table 6: An Overview of a Convergence of Autonomous Robots with Sustainability Dimensions

Authors	**Reviews**
(Pan et al., 2018; Bock and Linner, 2012; Hong et al., 2015).	Employment of automation and robotics is seen as a viable path to enhance sustainability performance including reductions in material consumption, energy consumption, air pollution, and greenhouse gas emissions in process refinement, construction waste reduction, natural resources preservation, workplace safety improvements, and high-quality living environment in an environmental pillar of sustainability, reductions in labor, resource, operation, maintenance, and waste management costs, and impacts on quality and competitiveness in the economic pillar of sustainability, reduction of injuries and fatalities, heavy works, working hours, improved job satisfaction, and impacts on job security and welfare in the social pillar of sustainability.
(Saidani et al., 2020).	Autonomous systems and solutions are anticipated to benefit the agricultural industry through the reduction of the ecological footprint of farming, production waste, and gardening tasks, cultivating and harvesting crops, monitoring favorable soil conditions, increase in profitable yieldings, thus contributing both on the economic and environmental sustainability.
(Bugmann et al., 2011).	According to research on the role of robotics in sustainable development, high precision autonomous systems can relatively drive down the labor costs and decrease the amount of waste of raw materials as well as increase the productivity of operators it works with, thus it can be deduced that improvements in the line of robotics and artificial intelligence could improve, accelerate, and support sustainable development.
(Çengelci and Çimen, 2005; Fitzgerald and Quasne, 2017).	The fundamental motives for using autonomous robots in industrial applications are as the followings: reducing labor costs, errors, reworks, and risk rates, substituting operators in hazardous, unpredictable, and risky working environments, thus improving safety and health, providing a more flexible production system and consistent quality control, increasing the amount of output and efficiency, meeting the shortage of skilled labor ability to work continuously even in the lights-out manufacturing environments, the ability to reach results faster than human beings, competence in tedious and repetitive jobs, hence humans could focus more on strategic efforts that cannot be controlled by automation, and enhancing revenue by improving order fulfillment rates, delivery speed, and ultimately, customer satisfaction. So, it is evident that these advantages are expected to contribute to social, environmental, and economic sustainability.

Furthermore, Kohl et al. (2020) investigated the social sustainability of service robots intertwined with environmental and economic aspects. The authors found out that the developments in autonomous systems and robots unveil further opportunities in the service sector having close interactions with humans in crowded urban environments, elder care, nursing, and surgeries using robotics. However, this has led to several changes in established social settings including workplaces, the public domain, and institutions. According to the study the authors conducted, it can be deduced that some occupations, particularly related to hazardous, monotonous, and repetitive tasks are assumed to be lost to automation and job loss as well as repositioning can be experienced however, new job descriptions are also expected to emerge. Moreover, autonomous robots and systems diminish physical barriers and accessibility problems in the working environment, thus equalizing opportunities (McKinsey and Company, 2017; Lowrey, 2018).

Technological developments and innovations have been shaping the working environment and even eradicating stereotypes and traditional approaches, as such human and robot operators effectively collaborate and learn from each other, resulting in efficient and value-added manufacturing processes, a vigorous working harmony, decreased waste and related costs, and thriving trusted autonomy. The collaborative robots, namely cobots, are designated as an apprentice, observing and digesting how an operator performs a task, then learning from its surroundings and embarking on the desired task. Moreover, as the cobots are aware of the collaborative working style and the presence of an operator, cobots handle safety and risk-related issues that might occur while laboring together (Nahavandi, 2019).

As a result, based on the studies analyzed even though autonomous robots and systems are regarded as the key to the social dimension of sustainability they also have potential effects on the environmental and economic dimensions of sustainability.

2.7. BIG DATA AND ANALYTICS FROM SUSTAINABILITY PERSPECTIVES

The massive amount of data availability has affected many fields and industries such as engineering, finance, marketing, production, management and has led to re-examining conventional use of data and techniques and propelled them to take the advantage of using big data analytics including gathering more precise and transparent, useful, and detailed information and, hence, creating sustainable opportunities with enhancing performance, improving decision-making, and optimizing processes (Qin, 2014: 2). In Table 7, an overview of convergence of big data and analytics with sustainability dimensions based on various studies is shown.

Table 7: An Overview of a Convergence of Big Data and Analytics with Sustainability Dimensions

Authors	Reviews
(Lv et al., 2018).	Big data analytics appears to be crucial in the employment of accurate predictions on weather and availability of such renewable energies as solar and wind, thus creating solutions for environmental sustainability issues and improving energy efficiency.
(Wang et al., 2018).	There exist operational and managerial benefits of big data analytics such as cost reduction, cycle time reduction, productivity and quality improvement, better resource management, improved decision making and planning, facilitating organizational learning and empowerment, and changing working patterns, hence providing economic sustainability.
(Marjani et al., 2017: 2).	Big data analytics can be applied to smart ecological environments, smart traffic, smart grids, and intelligent buildings, hence creating sustainable conditions both socially and environmentally.
(Belhadi et al., 2019).	Big data analytics can generate solutions for manufacturing process challenges including quality and process control, energy and environment efficiency, proactive diagnosis and maintenance, safety and risk analysis through enhanced transparency, improved performance, supported decision-making, and developed knowledge. In particular, with big data acquisition and mining, energy consumption patterns and smart grids, as well as energy and environment efficiency, could be provided.
(Zhang et al., 2019).	Authors attempted to apply big data analytics capabilities to air pollution management through the collection of real-time air quality data and take precautions to prevent pollution. Thereby, it can be deduced that big data analytics capabilities of reactive, preventive, and proactive can be applied in a sustainability context.
(Mani et al., 2017; Dubey et al., 2019).	According to the study, various issues including workforce safety and health, fuel consumptions monitoring, the physical condition of vehicles, unethical behavior, theft, speeding and traffic violations can be predicted, managed and controlled through big data analytics, hence providing social, environmental, and economic sustainability on supply chains.
(Raut et al., 2019).	Big data analytics positively affects sustainable business performance based on such factors as environment technology, air pollution control, carbon footprint, eco-packaging recycling efficiency, responsiveness, reduction in solid and water waste, improvement in organizational relevant knowledge.

Accordingly, big data analytics could be benefitted in diverse functional operations including inventory management, quality control management, revenue management and marketing, strategy and business development, supply chain and logistics management, risk and waste management, customer experience management, brand management. This is because big data analytics offers efficient data-driven decision-making processes, optimization of products and/or services in both delivery and after-sales operations, targeted marketing campaigns and promotions, understanding consumers' shopping habits and behaviors, developed customer experience, improved business processes, operations, and workforce allocation effectiveness along with optimization of resource allocation and auto-replenishment, and ideas for new products design (Choi et al., 2018; Watson, 2014: 5).

Furthermore, based on research conducted, adoption of big data analytics could emerge numerous potential benefits including customer-base segmentation, better-targeted marketing, recognition of sales and market potentials, accurate business insights, better planning and forecasting, identification of root causes of cost, the quantification of risks, and fraud detection with real-time monitoring (Russom, 2011: 11).

Thereby, discovering and disseminating patterns, trends, correlations, facts, insights, and knowledge over big data analytics could assist in making better, felicitous, and punctual decisions, detecting faults and deficiencies within the organization, and creating opportunities for operational quality improvements, cost efficiency, and lead time reductions, hence providing potentials for revenue growth, effectiveness, and competitive differentiation through innovation in the marketplace.

2.8. CLOUD SYSTEMS FROM SUSTAINABILITY PERSPECTIVES

Cloud computing tenders several advantages including reduced IT investments and such fixed costs as labor-power, maintenance, and infrastructure, hence reducing the total cost of ownership. Especially, for small-medium enterprises having cost-related difficulties, cloud computing drives down the costs radically and offers an opportunity to effective use of compute-intensive business analytics like understanding operational and functional processes within the enterprise, consumer purchase patterns and habits, as well as the supply chain tasks (Chou, 2015).

In Table 8 below a convergence of cloud computing with sustainability, dimensions are represented with various authors` views.

Table 8: An Overview of a Convergence of Cloud Computing with Sustainability Dimensions

Authors	Reviews
(Chang et al., 2010).	Cloud computing systems attempting on operational savings and green technology could improve organizational sustainability with the appropriate business models.
(Chang et al., 2011).	Based on a study, it is evident that cloud computing systems have the potential to offer not only economical and financial solutions but also environmental and social solutions such as reducing the organization's carbon footprint and the accumulation of greenhouse gases by alleviating the CO2 emissions, thus provide reductions in environmental destruction.
(Kumar and Vidhyalakshmi, 2012).	Using cloud computing reduces the cost of operations, additional staff, extra equipment and redundant data processes, thus decreasing capital spending on IT resources. Furthermore, according to Carbon Disclosure Project, organizations implementing cloud computing could drive down their energy consumptions, lower the level of carbon emissions and yield energy efficiency, environmental protection and sustainable development via the effective and efficient utilization of resources.
(Garg and Buyya, 2012).	Cloud computing is expected to turn traditional data centres into more energy-efficient centres via resource virtualization and workload consolidation. Furthermore, lower carbon emission is anticipated owing to energy-efficient infrastructure with cloud computing, particularly fewer carbon emissions in SMEs (Small-Medium Enterprises) compared to larger enterprises.
(Isaias et al., 2015).	According to the findings, cloud computing is a promising technology for organizations to become greener, reduce carbon footprint, and contribute to environmental sustainability.
(Balasooriya et al., 2016).	Green cloud computing is anticipated to ensure the efficient processing, utilization of resources, and reduction of energy consumptions, thus proving energy-efficient sustainable operations.

Overall, cloud computing systems provide various economical and financial opportunities in order to sustain the economical sustainability of the enterprises, in addition to these aspects cloud computing offers several benefits for ensuring environmentally sustainable working environments, thus achieving organizational sustainable growth.

2.9. CYBER-PHYSICAL SYSTEMS FROM SUSTAINABILITY PERSPECTIVES

Cyber-physical systems represent an environment that makes existing systems, processes, machines, and equipment smart and physically aware through generating real-time, digital information that ensures communication among each other along with the environment (Liu et. al, 2017). Table 9 gives information regarding the convergence of cyber-physical systems with sustainability dimensions.

Table 9: An Overview of a Convergence of Cyber-Physical Systems with Sustainability Dimensions

Authors	Reviews
(Pinzone et al., 2020).	Cyber-physical systems are anticipated to enhance both social and economic sustainability performances through ergonomics, knowledge and innovation, management, work-life balance, health and safety risks reduction, employee satisfaction, resource efficiency, less human-prone faults, cost reductions, labor/product/process/production efficiency, the resilience of production system, traceability, increasing internal and external quality, time efficiency, and scheduling robustness.
(Horcas et al., 2019).	According to the authors, the implementation of cyber-physical systems generates energy-aware systems and applications along with management and reducing energy consumption, thus creating environmental sustainability.
(Wang et al., 2015).	With the help of real-time integrity of cyber and physical environments and sensing technology, wireless communications and networking, effective solutions to water sustainability are to be provided via improved wastewater management and protection of water quality; and reductions in the risks of natural and human-induced water-related disasters, hence achieving environmental sustainability.
(Banerjee et al., 2011).	Cyber-physical systems bear the potential to enhance environmental sustainability via environmentally aware and energy-efficient computing units.
(Gupta et al., 2011)	Through the managerial and technical decision-making processes on workload, and power, resource energy-sustainable environments could be created and energy requirements could be managed and diminished, thereby environmental sustainability could be achieved.

Cyber-physical systems target synchronizing human interaction and learning theory with knowledge from electrical, mechanical, civil, chemical, biomedical, aeronautical, industrial, and other engineering disciplines (Baheti and Gill, 2011: 1). Therefore, cyber-physical systems could be applied to automotive systems, production management and manufacturing, health care, robotics, military and defence systems, agriculture, traffic control and safety, industrial process control, power generation and distribution, energy conservation, air and water management systems (Lee, 2015: 4838). Both at the plant and individual level, energy requirements including electricity, air, water, ventilation are determined, adjusted, and delivered, so a substantial amount of energy savings are guaranteed and outages could be avoided through detection and prevention systems enabled via cyber-physical systems. Moreover, cyber-physical systems entail the development of smart products and/or services, operations and processes that are manageable, adaptable, and reconfigurable. Thus, such smart applications as smart traffic management, smart agriculture, smart factory, smart cities, and other smart practices are remotely managed, optimized, and create such opportunities as reduced human-prone faults and accidents, optimized routing and scheduling, yield performance accelerations, downtime minimization, enhanced efficiency and effectiveness of processes, resources, and systems, and improved quality of products and/or services (Serpanos, 2018: 2). Thus, cyber-physical systems furnishing robustness, self-organization, self-maintenance, real-time control, transparency, and efficiency could be among the key enabling technologies for the proper implementation of Industry 4.0 within the production ecosystems (Monostori et al., 2016: 623).

Overall, cyber-physical systems are expected to ameliorate social, environmental, and economic factors, thus an effective adoption of such systems is required in order to fully execute Industry 4.0 and create competitive advantages. Moreover, through the interoperability aspect of cyber-physical systems sustainability metrics including social: workloads, working hours, safety, health, working conditions, economic: costs of material, energy, production, acquisition, and maintenance as well as wages, environmental: energy consumption, greenhouse gas emissions, recyclable materials, material extraction, the material choice could be evaluated, controlled, and required actions could be taken to provide sustainability proactively (Gürdür and Gradin, 2017).

2.10. INTERNET OF THINGS FROM SUSTAINABILITY PERSPECTIVES

An introduction of the IoT based products and services tender substantial economic and social benefits including enhanced business process management, cost reductions particularly in logistics and service industries, increased efficiency in automation and industrial manufacturing, improved customer relations, increased targeted sales, emerging business models involving smart production, smart products, smart home, smart security and transportation solutions, smart energy applications focusing on smart electricity, gas and water meters, thus improved quality of life owing to these smart assistance systems and associated smart services (Mattern and Floerkemeier, 2010). Owing to the bottlenecks in the energy, transportation, logistics sectors along with the increasing demands of individuals, the application and use of the IoT and information technologies are expanding to handle such issues encountered in social and economic frameworks (Xiaojiang et al., 2020). Next, in the table below a convergence of the Internet of Things with social, economic, and environmental sustainability dimensions are represented with various authors' views.

Table 10: An Overview of a Convergence of Internet of Things with Sustainability Dimensions

Authors	Reviews
(Bandyopadhyay and Sen, 2011).	According to the authors, IoT technologies have substantial impacts on green and environmental issues by monitoring the supply chain, revealing the emissions and redundant use of vehicles, supervising air quality, collecting recyclable materials, and reusing the packaging resources.
(Rose et al., 2015).	The implementation of IoT technologies offers solutions to environmental challenges, including resource management, water quality and use, climate change, and natural resource monitoring.
(Kopetz, 2011).	IoT technologies through embedded systems can play a prominent role in energy savings in various areas such as the enhanced fuel efficiency of automotive engines and the improved energy efficiency of household appliances. Furthermore, IoT has the potentials for the reduction of maintenance and diagnostic costs with the help of the computerized monitoring and visibility of industrial equipment, hence improved safety at the factory level.
(Nižetić et al., 2020).	An increased application of IoT technologies reveals a more intense utilization of energy resources via effective waste and power management as well as increased competition among firms with more efficient quality control and minimization in wastes.

Authors	Reviews
(Khatua et al., 2020).	Smart public services including emergency management, traffic management, e-public services, and street lighting management that controls the consumption of electricity; smart buildings and homes providing energy efficiency and effective energy management, water distribution management and leak detection are among the implementation of IoT that heralds such functions as traceability, visibility, and controllability.
(Bashar, 2020).	Through smart grids, smart control, real-time data tracking and control, effective management of water, waste, and energy can be ensured hence a more sustainable industrial environment.
(Maksimovic, 2018).	With the combination of green technology and IoT the term “Green IoT” emerges. Green IoT encapsulates smart city (traffic and parking management, waste management, smart lighting, and smart road) smart environment (quality of air, soil, and water), smart industry (smart factory, smart building, transportation management), and smart metering (water, power, gas, and radiation level measuring). So the utilization of these concepts leads to energy-efficient, lower carbon emissions and pollutions, and pose a great potential to strengthen both economic and environmental sustainability.

Based on the views above regarding IoT, it can be deduced that IoT technologies and applications serve widely for environmental sustainability Apart from its benefits to environmental sustainability, the deployment of the IoT can be also utilized in manufacturing processes. With the connection of physical items through embedded smart devices and/or unique identifiers and data carriers that can exchange information regarding themselves and their surroundings, manufacturing processes can be monitored, controlled and managed effectively from the design stage to the end stage, thus transparency and visibility of the production, inventory, and logistics functions can be enhanced and hassles encountered throughout these functions can be handled vigorously. Moreover, IoT can be applied to the aerospace and aviation industry in an attempt to increase the safety and operational reliability of the products. IoT applications can be also seen in the telecommunications and social media sectors with gathering information regarding individuals to promote social interaction and personal demands, medical and health care industry along with the pharmaceutical industry with the smart labels to drugs that track supply chain and provide a prompt medical intervention (Bandyopadhyay and Sen, 2011).

2.11. SYSTEM INTEGRATION FROM SUSTAINABILITY PERSPECTIVES

In today`s volatile market situations and a competitive working environment, a combination of vertical and horizontal integration, namely a holistic approach, based on the needs and scope of the organization is thought to be a more viable choice rather than just going for vertical integration or horizontal integration alone. With the vertical integration, control over the entire supply chain is possible while with the horizontal integration market share and market dominance of the firm is likely to enlarge so the combination of these integrations along with the end-to-end engineering integration might provide efficiency, flexibility and stability to business operations, customized production, new opportunities to increase market share and effective financial management (Naik et al., 2010: 6), thus achieving organizational sustainable growth. Table 11 below demonstrates an overview of the convergence of system integration and sustainability dimensions.

Table 11: An Overview of a Convergence of System Integration with Sustainability Dimensions

Authors	Reviews
(Zhou and Zhou, 2015: 2148).	A system integration could enable improved resource efficiency so this can balance and even reduce the impacts of resource use that cause environmental pollution and destruction. Furthermore, efficient and effective control over the entire value chain can affect the economic sustainability of the organizations that are entirely integrated. Ensuring a reliable and visible working environment can also increase working standards, safety and security, thus providing social sustainability.
(Rahman et al., 2020).	With the "horizontal interconnection across the supply chain, vertical interconnection across functional departments, and end-to-end engineering from product development to recycling" both economic and environmental sustainability could be provided. However, a requirement of a skilled workforce can affect the social sustainability dimension as the low-skilled workforce is thought to be redundant.
(Büyüközkan, and Göçer, 2018).	Apart from the traditional supply chains, integrated digital supply chains offer various opportunities on speed, flexibility, real-time inventory, cost-effectiveness, transparency, scalability, innovation, proactivity, and eco-friendly operation capabilities, thus leading to environmental and economic sustainability.

Overall, a system integration provides various economic and financial opportunities in order to maintain the economic sustainability of the enterprises, in addition to these aspects the system integration offers several benefits for environmentally and eco-friendly sustainable environments. However, there are some obstacles to creating an entirely integrated system such as the lack of technological and structural infrastructure, skilled workforce, therefore a proper investment in creating such an integrated system environment, and then management and control of these systems are crucial for ensuring economically and environmentally sustainable working conditions.

2.12. SIMULATION FROM SUSTAINABILITY PERSPECTIVES

Simulation provides various financial opportunities tendering economic sustainability, in addition to that simulation applications introduce many benefits for creating environmentally and eco-friendly sustainable environments. By balancing the workloads, optimizing the scheduling and increasing the safety of the working environments simulation also touches upon social sustainability. Table 12 demonstrates an overview of convergence of simulation with sustainability dimensions and gives potential views on the sustainability aspects of the simulation.

Table 12: An Overview of a Convergence of Simulation with Sustainability Dimensions

Authors	Reviews
(Widok and Wohlgemuth, 2011).	Simulation can affect social, environmental and economical sustainability through the utilization of resources, balancing the workloads, ensuring work safety, analyzing the bottlenecks, and increasing the efficiency and effectiveness of the systems.
(Moon, 2017).	The application of simulation in various fields including agriculture, construction, climate, energy, human health, information systems, manufacturing, supply chains, transportation, urban and community planning, waste, and recycling can lead to creating social, environmental and economical sustainability.
(Burinskiene et al., 2018).	Simulation is a beneficial tool for efficient resource utilization and contributes to the efficiency of processes, energy savings, waste reductions, and optimization of transportation time and related costs, thus creating environmental and economic sustainability.

Overall, it can be said that simulation affects all three pillars of sustainability. However, simulation software vendors are required to adapt into a manufacturing environment equipped with Industry 4.0 enablers like collaborative robots, autonomous machines, sensor technologies and advanced visualization and more importantly in order to create a digital twin, a simulation model of a machine, a process, or a whole factory, vendors are to make sure that their software can interact with the real systems (Gunal, 2019). These sorts of software and infrastructure issues along with the skilled workforce requirements should be sorted out to get the optimum benefit out of the simulation models and applications while offering social, environmental, and economical sustainability.

2.13. SMART FACTORIES FROM SUSTAINABILITY PERSPECTIVES

Smart factories that enable horizontal and vertical integration, self-optimizing, self-configuring, and interactive industrial robots, as well as real-time data flow, advanced automation and digitalization in the production, cyber-physical systems, and internet of things, constitute the key factors of the Industry 4.0 concept, further provide grounds for more productive, flexible, high quality, versatile, safer and collaborative ecosystems (Martín et al., 2017). According to Table 13 below, there are several views upon the triangle of smart factories, smart manufacturing systems, and sustainability dimensions.

Table 13: An Overview of a Convergence of Smart Factories with Sustainability Dimensions

Authors	Reviews
(Büchi et al., 2020).	The performance of the smart factory through the Industry 4.0 enabling technologies can be pointed out as production flexibility, higher output capacity, decreased set-up costs, fewer errors and machine downtimes, better product quality, and customers' improved feedbacks on products, hence providing economic sustainability.
(Radziwon et al., 2014).	A smart factory provides flexible manufacturing processes and optimization of manufacturing resulting in the reduction of unnecessary labor and waste of resources.
(Wang et al., 2016b).	It is suggested that with the emerging information technologies including IoT, big data, and cloud computing, and artificial intelligence, smart factory of Industry 4.0 leading to sustainable production ecosystems and novel business models could be adopted.

Authors	Reviews
(Chen et al., 2017).	The smart factory is a flexible and dynamic manufacturing solution through the analysis of production data for fulfilling industrial demands and production optimization, hence creating economically sustainable opportunities.
(Strozzi et al., 2017).	It is evident that today's factories are being converted into smarter, more efficient and sustainable, and safer facilities through the convergence of production technologies and devices together with emerging information and communication systems and infrastructures.
(Mabkhot et al., 2018).	With the integration of such technologies as cyber-physical systems, semantic web, and virtualization smart factories are anticipated to enhance performance, flexibility, quality, manageability, and traceability of manufacturing processes.
(Shi et al., 2020).	The smart factory does not necessarily mean lights-out manufacturing instead within the smart factory human-machine collaboration is emphasized, thus promoting more flexible and effective production and leading to both social and economic sustainable benefits.

According to Lucke et al. (2008), a smart factory is envisioned as a manufacturing environment through the collaboration of the human workforce with computer-based systems to ensure non-stop manufacturing, enhanced output quality as well as flexibility. Smart factories are designated to deal with dynamics in manufacturing environments and effective management of production processes through the use of real-time and relevant information. Furthermore, smart factories can increase visibility as the real-time information is available to inventory management, warehouse management, material requirements planning, production and operations, sales and order management, thus achieving on-time delivery, resource utilization, energy efficiency, reduction in costs, and customer satisfaction. Additionally, decision-making within all processes and operations at the factory level can become easier and more effective through real-time and complete data (Shi et al., 2020). The framework of a smart factory is shaped through the entire linked production systems that build, process, manage required data to carry out all scheduled tasks for producing various sorts and batches of products (Osterrieder et al., 2020). Based on several resources regarding smart manufacturing, a smart factory consists of eight main pillars including decision-making, CPSs, data handling, digital transformation, human-machine interaction, IoT, cloud manufacturing, and service (Wang et al., 2016a).

Moreover, within the smart factory environment, smart devices and tools in cooperation with human beings provide flexibility, quality, and efficiency in production, while providing a safe work environment by undertaking hazardous tasks, thus leading to social and economic sustainability opportunities (Wang et al., 2016b).

CHAPTER THREE

INDUSTRY 4.0 TECHNOLOGY ALTERNATIVES` SELECTION BASED ON SOCIAL, ENVIRONMENTAL, ECONOMIC SUSTAINABILITY CRITERIA: A CASE STUDY WITHIN VARIOUS INDUSTRIES

This chapter compasses the aim and objectives of the study, the conceptual background of the decision theory as well as the virtual representation of the convergence of sustainability dimension with Industry 4.0 technologies in a holistic way, questionnaire design, sample and data collection, data analysis and measurement as well as the empirical findings.

3.1. AIM AND OBJECTIVES OF THE RESEARCH

The main research question of this thesis is “Do Industry 4.0 applications and technologies play a role in creating a sustainable working environment?”. In order to find out an answer to this research question, hence actualize the aim of the study versatile objectives have been proposed. The first objective is to gain information on creating sustainable social, economic, and environmental value through the use of Industry 4.0 technologies and practice with presenting a systematic and comprehensive original framework that examines the role and effects of Industry 4.0 technologies and practices in creating a sustainable production ecosystem. Therefore, to achieve this firstly, a systematic literature review has done and then the main and sub-criteria of the sustainability framework with focus group study were determined and Industry 4.0 technology and applications that meet the social, economic and environmental sustainability sub-criteria were ranked. Lastly, Industry 4.0 technologies and applications that are most suitable for the sustainability sub-criteria were selected.

Another objective of this study is to reveal whether Industry 4.0 technologies and applications are differentiated on the basis of different sectors in terms of the mindset of social, economic, and environmentally sustainable value. Therefore, analysis has been conducted in various sectors including petrochemical, metal production, textile, automotive, and food and then the differences while weighting the sub-criteria of sustainability along with the ranking of Industry 4.0 technologies based on the sub-criteria and selection the most appropriate Industry 4.0 technologies under the umbrella of sustainability dimensions were revealed.

3.2. CONCEPTUAL BACKGROUND

To form a basis for the analysis of this study, various academic articles, books, and book chapters were gathered from the Scopus database with the keywords "Industry 4.0 and Sustainability". In total 720 academic resources have been found varying from the year 2021 to 2014. In this manner, the framework of Industry 4.0 technologies under environmental, economic, and social dimensions of sustainability have been evaluated with a holistic perspective. The academic resources have been used in the bibliometric analysis to add depth to the study and a word cloud was created by using the abstracts of the academic resources to provide visual insight into certain texts or concepts. The image of the word cloud that emerged as a result of this analysis is given in Figure 5, shown below.

Figure 5: A Visual Representation of the most used words

Source: Aria and Cuccurullo, 2017.

What stands out in this figure are the patterns of concepts such as Industry 4.0, sustainability, supply chain management, IoT, sustainable manufacturing, industrial development, artificial intelligence, competition, digital transformation, innovation, energy efficiency, decision making, manufacturing, embedded systems, industrial economic, environmental impact. It is an expected result that these concepts come to the fore in the visual analysis of the studies examined using certain keywords. In addition, words that contribute to environmental, economic, and social sustainability such as flexibility, optimization, autonomy, energy, performance, autonomy, efficiency, cooperation, efficiency, sensitivity, management, recycling, emissions, carbon emissions are also mentioned in the abstracts of the selected academic resources apart from this word cloud analysis. In other words, the findings obtained from the relevant literature review, which deals with the contribution and benefits of Industry 4.0 technologies to sustainability pillars support this visual tool.

Overall, it can be deduced from the analysis of the studies, which were examined through the keywords, mainly qualitative methods are preferred and there are deficiencies in the practical studies. The biggest reason for this deficiency can be shown as the fact that the enterprises could not fully incorporate Industry 4.0 technologies, due to problems such as insufficient technological infrastructure and high cash capital requirements. Moreover, enabling technologies of Industry 4.0 including cyber-physical systems, IoT, autonomous robots, augmented reality, big data and analytics, cloud computing, artificial intelligence technologies, and smart factories pave the way for creating a sustainable working environment. Internet of Things enables all objects to access the internet and interact and communicate with other devices. Autonomous robots in cooperation with human beings provide flexibility, quality and efficiency in production while providing a safe work environment by undertaking dangerous tasks. To promote the human-centred industrial environment, augmented reality coordinates real and virtual elements with each other, providing flexible and real-time information, while also filling the gap between users in physical and digital environments. Big data and analytics enable storing, analyzing, interpreting the exponentially increasing data rate, and understanding customer profiles and consumption habits in this way create an opportunity to highlight the companies that are in constant competition with each other in today’s global world. Lastly, cloud computing provides faster innovation, flexible resources and economical scaling by providing information technology services over the internet. Aforementioned Industry 4.0 technologies and extensions are anticipated to generate a horizontal, vertical, and end-to-end digital integration of such backbone functions of a factory as engineering, production and management, thus converting traditional factory systems into smart factory systems that are highly flexible, manageable and more importantly sustainable (Mattern and Floerkemeier, 2010; Esmaeilian et al., 2016; Qin, 2014; Grieves, 2014; Chou, 2015).

After gathering the terms Industry 4.0 and sustainability together and demonstrating their relationships in a broad framework, the research question of this study, that is to say, revealing the role of Industry 4.0 technology alternatives in creating a sustainable working environment and decision making the best Industry 4.0 technology alternatives providing the sustainability criteria can be answered. As the research question suggests, this is a decision question. Therefore, this study is constructed based on a decision theory. According to Rapoport (1998: 3),

> *Decision theory deals with situations in which one or more actors must make choices among given alternatives. Decision theory is based on an assumption that each choice (decision) entails consequences called outcomes and that each of the actors making the decisions has preferences for the different outcomes. It is not assumed that an actor necessarily has full knowledge of just what those consequences will be, but it is assumed that an actor envisages at least some of them, and it is these envisaged consequences that he prefers in varying degrees.*

Accordingly, North (1968) suggested that decision theory is a technique of putting common sense into words. The decision-maker considers the potential consequences of his/her available options in two dimensions: value (as determined by utility theory) and the likelihood of occurrence. The decision-maker then selects the one he/she believes to be the most valuable. It is not guaranteed that the result will be as excellent as the decision-maker hopes, but he/she has made the best decision based on his/her preferences and available information. Decision-making can be regarded as an indispensable part of life that changes from a simple decision to a complex one. In our daily lives, we deal with such basic decision problems as purchasing decisions, dinner plans, and traveling options whereas in a business environment there are critical decisions to make within the levels of strategic, managerial, and operational including new product launch, facility location selection, scheduling and so on. No matter the size of the decision it consists of a process. This process in decision making has some basic steps including:

1. setting goals or defining problems
2. examining goals and problems, determining priorities
3. identifying alternatives
4. examining and valuing alternatives
5. determining and choosing selection criteria (Can, 2015).

In this decision-making process the nature of the decision-making problem, decision-maker, time, decision-making environment, physiological factors, risks, criteria, goals, and alternatives play a role while choosing the decision analysis methods (Özbek, 2017). Therefore, within the scope of this study, based on the nature of the decision-making problem, Multi-Criteria Decision Making Methods (MCDM) have been chosen to answer the research question. Next, the methodology part will be given.

3.3. METHODOLOGY

In the methodology part, information regarding questionnaire design, sample and data collection as well as the data analysis and measurement will be explained in a detailed manner.

2.3.1. Questionnaire Design

The questionnaire form was designated with several steps. Firstly, a purposely selected group of nine representatives from various sectors including the petrochemical, metal production, and textile industry gathered together to conduct a focus group study, which is a form of qualitative research gathering various views, ideas, and perceptions together to gain an in-depth understanding on the matter (Nyumba et al. 2018). Within this focus group study, brainstorming and mind mapping techniques were utilized by using the Xmind tool and sub-criteria of the sustainability dimensions that were considered to be related to the Industry 4.0 framework along with the Industry 4.0 technology alternatives were determined. After that, for a preliminary test of the questionnaire form, a pilot study is done by three experts working within the metal production industry. Furthermore, in order to provide consistency, five academics from various backgrounds were gathered together and asked for a close examination of the questionnaire. Based on the outputs of the pilot study and feedbacks from the academics, some redundant and overlapping expressions were eliminated from the questionnaire form to provide clarity and enhance understandability. The table below shows the final version of the criteria, sub-criteria, and Industry 4.0 technology alternatives that are determined in the wake of focus group and pilot studies.

Table 14: Hierarchy of the proposed model

Main Goal	**Main Criteria**	**Sub-Criteria**	**Alternatives**
To find out the best Industry 4.0 alternative.	Social Sustainability	Workplace Safety Improvement in working standards and conditions The emergence of new job definitions Demand for a qualified workforce Increase in social welfare	Additive Manufacturing Augmented Reality Autonomous Robots Big Data Analytics Cloud Computing Cyber-Physical Systems Internet of Things System Integration Simulation Smart Factories
	Economic Sustainability	Increase in profitability Cost Reductions Productivity in production Flexibility in production Quality Control and Assurance Delivery and lead time reductions Transparency and monitoring in production Process Optimization Standardization in Production	
	Environmental Sustainability	Increasing the use of renewable energy resources Environmental pollution prevention, management and control Increasing recovery, recycling and reusing rates Reducing Greenhouse Gas Emissions Ensuring efficiency in resource and energy use Developing green innovative strategies	

Source: Created by the author.

The main criteria and alternatives have been explained in a detailed manner throughout the previous chapters. As for the sub-criteria, they were developed by taking the GRI`s economic, environmental and social standards as well as the decision-makers focus group study results into account. During the sub-criteria development process, Industry 4.0 technology alternatives and their potential relationships with these sub-criteria were considered. As a result of the focus group study, workplace safety, improvement in working standards and conditions, the emergence of new job definitions, demand for a qualified workforce, and an increase in social welfare have been evaluated under the social sustainability criteria. Ensuring workplace safety encompasses such factors as elimination of unsafe working conditions provoked by hazardous equipment, machinery, processes, and practices along with the enhanced occupational health and well-being of the employees. Improvement in working standards and conditions refers to the fair and equal compensation policies, work schedules, and other perks of jobs. The emergence of new job definitions and demand for a qualified workforce can be treated under the job creation and/or employment approaches of the organizations. These variables are expected to be a reflection of Industry 4.0 adoption as in shifting from labor-intensive to mind-intensive works and be ameliorated with the hiring, recruitment and human resource departments' initiatives. An increase in social welfare for both employees and employers refers to the enrichment in both work and social life standards. Such factors as an increase in profitability, reductions in cost such as operational, maintenance, and labor, enhancing productivity, flexibility, standardization in production, quality control and assurance as in reductions in the margin of error by eliminating the waste, delivery and lead time reductions, hence ensuring customer satisfaction, transparency and monitoring in production, thereby prevention any errors across the manufacturing processes, process optimization with continuous improvement, and increase in competitiveness are related to economic performance and economic impacts, hence economic sustainability. As for the environmental sustainability sub-criteria, increasing the use of renewable energy resources, prevention, management and control of environmental pollution such as air, water, soil, and noise, increasing recovery, reusing and recycling rates as in the strategies of waste management, reducing greenhouse gas emissions, ensuring efficiency in resource and energy use, and developing green innovative strategies were generated. The use of renewable energy is of great importance in an attempt to combat climate change and reduce an organization's overall environmental footprint. Effective management, control, and prevention of environmental pollution are critical to reducing an organization's environmental impact. The type and amount of materials that are used in recovery, reusing and recycling indicate organizational approaches to waste management. As greenhouse gas emissions are a primary enabler to climate change, reducing the emissions volume can have benevolent and decent impacts on ecosystems, air quality, agriculture, human, and animal health. Moreover, the efficient use of energy and resources along with the development of green strategies approaches can help evade the deterioration of ecosystems, thereby ensuring environmental sustainability (GRI, 2016). These aforementioned sub-criteria are thought to be actualized with the implementation of Industry 4.0 technologies.

Based on the hierarchy proposed model above, the questionnaire form contains three sections including matrices for evaluation of criteria and sub-criteria relationships, matrices for determining relations between alternatives and sub-criteria along with the open-ended questions regarding the business size, personal information such as respondents' roles and working durations in their working environment, technical information within the scope of sustainability and Industry 4.0 as well as the general views on the predictions about these terms.

2.3.2. Sample and Data Collection

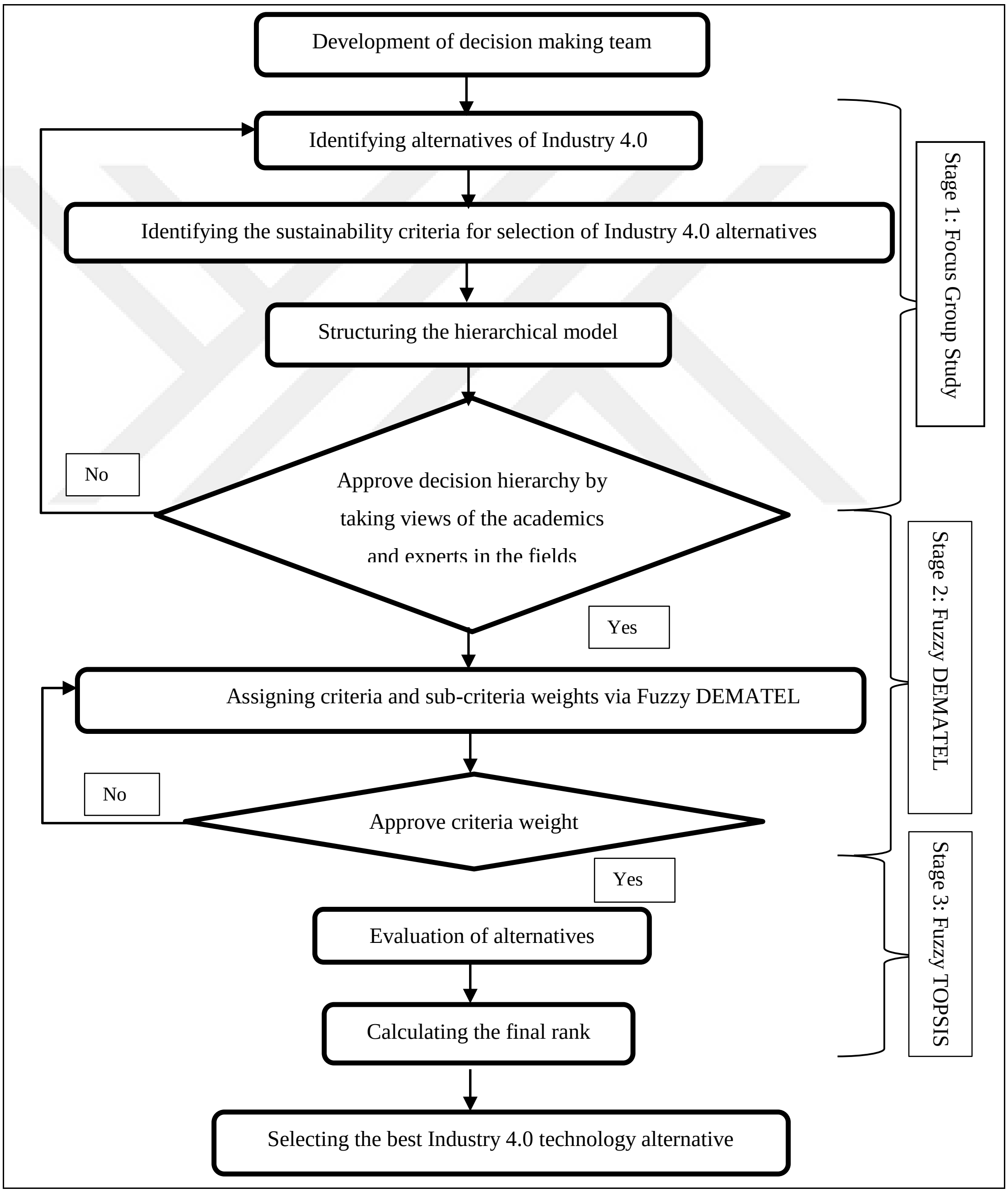
The sample of the implementation constitutes respondents from a blend of various departments spanning from R&D, production, marketing, occupational safety and health, supply chain management, human resource departments to top management among five sectors functioning in petrochemical, metal production, automotive, textile and food industries. The issue of determining the sample size in an effort to obtain high accuracy rates by providing error minimization and viable comparison matrices in multi-criteria decision-making-based methods were debated. Although there is no certain rule for determining the number of decision-makers whom data is collected, it is suggested that it should be between 5-10 respondents. (Chang et al., 2019; Özbekler and Akgül, 2020). Therefore, for this study, three decision-makers from each sector and in total 15 respondents were selected. That is to say, multi-industry sample was employed in an attempt to increase observed variance and to enhance the generalization of the findings (Morgan et al., 2004: 94). Furthermore, for this analysis, a convenience and purposive sampling approach was preferred. The convenience sampling is a type of nonprobability or nonrandom sampling in which individuals of the target population fulfill particular practical criteria, such as ease of access, closeness, availability at a certain time, or desire to participate (Dornyei, 2007). Furthermore, the purposive sampling is commonly employed in implementation research in an effort to determine and opt for information-rich examples linked to the topic of interest (Patton, 2014). Additionally, the respondents in the sample are deliberately chosen on account of the qualities the respondents have. Hence, being among the types of the purposive sampling method, expert sampling was utilized. As the name implies, the expert sampling method advocates for purposive sampling to be conducted on experts in a certain field. When looking into new topics of research, expert sampling is considered to be a useful technique to provide solid results or when there is currently a lack of observational evidence (Etikan et al., 2016). Apart from the knowledge and experience, Bernard (2017) emphasized the significance of volunteerism to participate and convenience in this sampling approach. Thereafer, the reasons for choosing these sectors along with the general information regarding the selected firms are as follows:

The petrochemical industry is one of the most polluting industries with its carbon footprint ratios and the selected firm gives specific importance to sustainability issues and waste management as well as holds the certifications including “ISO 9001 Quality Management System, OHSAS 18001 Occupational Health and Safety Management System and ISO 14001 Environmental Management System”. The selected petrochemical firm is regarded as a large enterprise, located in Aliağa, İzmir and the leading petrochemical company of Turkey. The outputs of the fırm are used in many sectors such as plastics, chemicals, packaging, construction, agriculture, automotive, textiles, and pharmaceuticals. The firm operating in the metal production industry is managed as a group of companies combining valve, cable, metal factories, and ship recycling facilities in itself. The metal production facility of the firm is located in Kemalpaşa Organized Industrial Zone, İzmir and produces brass and bronze. The firm launched a department concerning the adoption of the Industry 4.0 technologies and pays attention to issues including creating employment, employee training and development, product and service responsibility, business ethics, social policies, environmental awareness, energy efficiency, waste management, and reducing water use within its operations. The firm in the textile industry with its eight production facilities is among the largest garment manufacturers in Turkey. One of the headquarters of the company, which is a large enterprise, is located in Işıkkent Organized Industrial Zone, İzmir. This firm implements waste management policies and aims to minimize environmental impact. Moreover, the firm focuses on diversity in the workplace, supports supporting women's empowerment and education, thus having a strong corporate social responsibility. The firm in the food industry is located in Sarıçam Organized Industrial Zone, Adana and produces traditional soft drinks like turnip and lemonade as well as sauces segments. This firm has green deal strategies and gives importance to sustainability issues. Moreover, the firm aims to minimize its negative impacts on nature in all its production processes along with the firm holds "ISO 22000 Food Safety Management System, ISO 9001 Quality Management System, HACCP (Hazard Analysis Critical Control Point), and Turkish Standards Institution certifications". As for the firm in the automotive industry it is located in Tarsus, Mersin and manufactures semi-trailers for the transportation and logistics sector as well as tactical wheeled vehicles for use in the defence industry. The firm also offers sales and after-sales services and does vehicle superstructure and assembly works of one of the most leading automotive brands worldwide. The firm applies lean manufacturing strategies and attempts to adopt Industry 4.0 technologies and has the mindset of zero environmental accidents by complying with the legal and other requirements to protect the environment, ensuring the disposal of non-recoverable wastes, and taking measures to reduce the pollution load of air emissions and wastewater. As a result, determined firms are selected owing to their interests in sustainability and Industry 4.0 technologies. Moreover, only volunteer respondents were selected because of difficulties in availability, time, and budget constraints. The prepared questionnaire forms were sent to respondents via e-mail and the survey collection period was between August to December 2021.

2.3.3. Data Analysis and Measurement

Within the data analysis and measurement, the methods used are called MCDM, also known as Multiple-Criteria Decision Analysis (MCDA) or Multi-Attribute Decision-Making (MADM). The main idea lying behind the MCDM is that multiple objectives and multiple criteria conflict with each other (Nădăban et al., 2016). MCDMs are applied in decision-making processes within various areas including engineering, construction, tourism, management, and finance to choose and/or rank alternatives based on the determined criteria. The structure that constitutes the background of the multi-criteria decision-making methods has been developed based on the decision makers' alternative preferences along with the criteria requirements (Yang and Tzeng, 2011). Although there exist different sorts of MCDM methods in the literature, there is no consensus on which method is the most appropriate for a certain decision-making process. Therefore, technical and practical limitations, the dataset type whether it has qualitative or quantitative attributes as well as the aim of the decision-making problem itself lead the way while choosing the MCDM methods (Mulliner et al., 2013). In this study, a multicriteria decision-making approach for the evaluation and selection of Industry 4.0 technology alternatives under a fuzzy environment has been performed. Based on the nature of the problem, the criteria can be subjective with linguistic/qualitative definition and/or objective with monetary/quantitative terms. So, to eliminate the ambiguity and vagueness stemming from the qualitative expressions a fuzzy set theory was put forward by Zadeh (1965) and applied in MCDM methods. Another reason why fuzzy methods have been used in MCDM methods is describing the subjective judgment of a decision-maker quantitatively gives much more meaningful and efficient results (Nădăban et al., 2016). Overall, the followings explain some of the benefits of fuzzy logic are: it is extremely near to the human thinking style, in the application, there is no need for too many mathematical models and expensive software, thereby both time and cost-effectiveness, it is more versatile than other control systems due to the usage of membership values, and modelling or a system based on fuzzy logic may be simply created using only the expertise of decision-makers. However, fuzzy logic also has some drawbacks. As a method, the fuzzy logic is suitable for trial and error and there is no certain method that gives definite results in the determination of membership functions (Albertos and Sala, 1998). Due to its benefit outweighs the drawbacks along with the structure of our research problem and criteria gathered, the fuzzy logic was applied. Table 15 below shows the steps taken throughout the application stage.

Table 15: Proposed Model for Industry 4.0 Technology Selection Problem



Source: Created by the author.

Hence, in this study Fuzzy-DEMATEL for criteria weighting and fuzzy-TOPSIS for selecting out of the alternatives, that are among the MCDM methods, have been used owing to the structure of the criteria gathered. The first method used in the analysis is Decision Making Trial and Evaluation Laboratory (DEMATEL) method and was proposed between 1972 and 1976 by American scientists in the Science and Human Affairs Program to tackle the complex and interconnected problem group. DEMATEL is based on a graph theory and allows users to evaluate and solve problems using a visualization method. To depict the interdependent relationships and the values of effects between criteria, this structural modeling approach uses a cause-effect relationship diagram. DEMATEL deploys mathematical techniques to acquire analysis of logical and direct impact relations among systematic criteria. Furthermore, this method can improve understanding of respondents' perspectives on intertwined factors, criteria, as well as propose a viable solution with the help of a visualization structure model (Gabus and Fontela, 1972, 1973). So, with the help of this method, it can be found out which aspects are more fundamentally important for the whole system and which are not by evaluating and discussing the structural model. For understanding the criteria relationships and weighting them other MCDM methods exist like "Analytic Hierarchy Process (AHP), Analytic Network Process (ANP)", "Step-Wise Assessment Ratio Analysis", and "Entropy". The AHP method relies on the pairwise comparisons, however, in our model due to the large number of sub-criteria the analysis using the AHP method would transform the model into a rather complex task. Moreover, in our research problem determined sub-criteria might have potential relationships among them so it is not possible to denote the causality and dependency with the AHP method. As for the use of the ANP method in such circumstances, it is also not recommended because of the fact that there are more than seven sub-criteria and alternatives and that their heterogeneity creates a problem (Özbek, 2017). Moreover, in decision-making problems rather than the superiority of methods to each other, what is necessary is that to determine the most suitable method according to the structure and nature of the problem. Therefore, in this study DEMATEL method was preferred. However, due to the environments that are unclear and hard to estimate by exact numerical values caused by human judgment in decision-making, fuzzy logic is required. Thus, the DEMATEL method is extended to fuzzy DEMATEL to make better decisions in hesitant environments (Wu and Lee, 2007).

Fuzzy DEMATEL has been extensively used in various fields as an effective decision-making method. Table 16 below gives a demonstration of the several studies conducted with the use of fuzzy DEMATEL.

Table 16: Fields of Research Using Fuzzy DEMATEL Method

Related Authors	Fields of Research using Fuzzy DEMATEL
(Lin, 2013;	Green supply chain management
Lin et al., 2018;	Sustainable Supply Chain Management
Govindan et al., 2015).	Eco-efficiency based Green Supply Chain Management
(Chang et al., 2011).	Supplier Selection
(Zhou et al., 2011).	Identification of Critical Success Factors in Emergency Management
(Özdağoğlu et al., 2021).	Sorting of Airports
(Organ, 2013).	Machine Selection for a Textile Company
(Chen Yi et al., 2007).	Determining the Factors Affecting Customers' Purchasing Decisions

As for the functioning of the fuzzy DEMATEL, it contains seven stages. In the first stage, the interactions between the criteria are evaluated by experts (Altan and Aydın, 2015, 103-105). The linguistic expressions and triangular fuzzy number equivalents used for this process are given in Table 17.

Table 17: Fuzzy DEMATEL Scale

Linguistic Variable	Corresponding Triangle Fuzzy Numbers
No interaction between the two criteria	0,00; 0,00; 0,00
There is very little interaction between the two criteria	0,00; 0,00; 0,25
There is little interaction between the two criteria	0,00; 0,25; 0,50
There is normal interaction between the two criteria	0,25; 0,50; 0,75
There is much interaction between the two criteria	0,50; 0,75; 1,00
There is too much interaction between the two criteria	0,75; 1,00; 1,00

Source: Wu and Lee, 2007.

Based on the abbreviations and explanations denoted below, the analysis was designated and carried out.

$$i, j: criterion; i = 1,2,3, \dots, n; j = 1,2,3, \dots, n$$

$$K: decision\ maker; K = 1,2,3, \dots, k$$

$$l_{ijK}: The\ lower\ limit\ value\ of\ K. decision\ maker's\ opinion\ on\ the\ effect\ of$$
$$i. criterion\ on\ j. criterion$$

$$m_{ijK}: The\ point\ at\ which\ the\ membership\ degree\ is\ 1$$
$$in\ the\ decision\ maker's\ view\ of\ the\ effect\ of\ criterion\ i\ on\ criterion\ j.$$

$$u_{ijK}: The\ upper\ limit\ value\ of\ K. decision\ maker's\ opinion\ on\ the\ effect\ of$$
$$i. criterion\ on\ j. criterion$$

$$\tilde{d}_{ijK}: Triangular\ fuzzy\ number\ consisting\ of\ K. decision\ maker's\ view$$
$$on\ the\ effect\ of\ i. criterion\ on\ j. criterion$$

The triangular fuzzy number showing the effect of the criterion in the row on the criterion in the column can be shown by the expert as in equation 1.

$$d_{ijK} = l_{ijK};\ m_{ijK};\ u_{ijK} \tag{1}$$

In the second stage, an initial direct-relation matrix is generated. The expert opinions form the fuzzy initial direct relationship matrix for that expert. The structure of the fuzzy initial direct relationship matrix is shown in equation 2.

$$\widetilde{D_K}: K. fuzzy\ initial\ direct\ relationship\ matrix\ of\ the\ decision\ maker$$

$$\widetilde{D}_K = \begin{bmatrix} \tilde{d}_{11K} & \tilde{d}_{12K} & \dots & \tilde{d}_{1nK} \\ \tilde{d}_{21K} & \tilde{d}_{22K} & \dots & \tilde{d}_{2nK} \\ \dots & \dots & \dots & \dots \\ \tilde{d}_{n1K} & \tilde{d}_{n2K} & \dots & \tilde{d}_{nnK} \end{bmatrix} \tag{2}$$

In the next step, expert opinions are blended in to form a single fuzzy initial direct relationship matrix.

$$l_{ij}: Combined\ lower\ limit\ value\ for\ the\ effect\ of\ criterion\ i\ on\ criterion\ j$$

$$m_{ij}: The\ point\ at\ which\ the\ combined\ degree\ of\ membership\ for\ the\ effect\ of$$
$$criterion\ i\ on\ criterion\ j\ is\ 1$$

$$u_{ij}: Combined\ upper\ limit\ value\ for\ the\ effect\ of\ criterion\ i\ on\ criterion\ j$$

$$\tilde{d}_{ij}: Combined\ triangular\ fuzzy\ number\ regarding\ the\ effect\ of$$
$$criterion\ i\ on\ criterion\ j$$

The joining operations are shown in equations 3, 4, and 5.

$$l_{ij} = \frac{\sum_{K=1}^{k} l_{ijK}}{k} \tag{3}$$

$$m_{ij} = \frac{\sum_{K=1}^{k} m_{ijK}}{k} \tag{4}$$

$$u_{ij} = \frac{\sum_{K=1}^{k} u_{ijK}}{k} \tag{5}$$

The resulting fuzzy initial direct relationship matrix is formed as in equation 6.

$$\tilde{D}_K = \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \dots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \dots & \tilde{d}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{d}_{n1} & \tilde{d}_{n2} & \dots & \tilde{d}_{nn} \end{bmatrix} \tag{6}$$

In the third stage, the normalized fuzzy direct relationship matrix is prepared. The steps to be applied for the normalization process are given in equations 7, 8, and 9.

$\tilde{x}_{ij}$: *Normalized triangular fuzzy number regarding the effect of criterion i on criterion j.*

$\sum_{j=1}^{n} u_{ij}$, $\forall$ *for i*

$\sum_{i=1}^{n} u_{ij}$, $\forall$ *for j*

$$\tilde{x}_{ij} = \frac{l_{ij}}{max\left\{\sum_{j=1}^{n} u_{ij}, \forall\ for\ i\ ;\ \sum_{i=1}^{n} u_{ij}, \forall\ for\ j\right\}}; \tag{7}$$

$$\frac{m_{ij}}{max\left\{\sum_{j=1}^{n} u_{ij}, \forall\ for\ i\ ;\ \sum_{i=1}^{n} u_{ij}, \forall\ for\ j\right\}}; \tag{8}$$

$$\left.\frac{u_{ij}}{max\left\{\sum_{j=1}^{n} u_{ij}, \forall\ for\ i\ ;\ \sum_{i=1}^{n} u_{ij}, \forall\ for\ j\right\}}\right\} \tag{9}$$

The normalized fuzzy direct relationship matrix obtained as a result of these operations is demonstrated in equation 10.

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \dots & \tilde{x}_{nn} \end{bmatrix} \tag{10}$$

In the fourth stage, the total relationship matrix and/or the fuzzy sum relationship matrix is calculated with the help of equation 11.

$\tilde{T}$: *fuzzy sum relationship matrix*

I: *unit matrix*

$$\tilde{T} = \frac{\tilde{X}}{I - \tilde{X}} \tag{11}$$

Accordingly, the fuzzy sum relationship matrix is formed as in equation 12.

$\tilde{t}_{ij}$: *The fuzzy sum correlation matrix value regarding the effect of i. criterion on j. criterion*

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \dots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{22} & \dots & \tilde{t}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \dots & \tilde{t}_{nn} \end{bmatrix} \tag{12}$$

In the fifth stage, the row and column totals in the fuzzy sum relationship matrix are obtained. Row totals are calculated using equation 13, column totals are calculated using equation 14.

$$\tilde{R}_i\text{: row total for criterion } i$$

$$\tilde{C}_i\text{: column sum for criterion } i$$

$$\tilde{R}_i = \sum_{j=1}^{n} \tilde{t}_{ij}, \forall \text{ for } i \quad (13)$$

$$\tilde{C}_i = \sum_{i=1}^{n} \tilde{t}_{ji}, \forall \text{ for } i \quad (14)$$

$$a_i\text{: } \tilde{R}_i \text{ fuzzy number lower limit value for } i.\text{criterion}$$

$$b_i\text{: } \tilde{R}_i \text{ fuzzy number mean value for } i.\text{criterion}$$

$$c_i\text{: } \tilde{R}_i \text{ fuzzy number upper limit value for } i.\text{criterion}$$

$$d_i\text{: } \tilde{C}_i \text{ fuzzy number lower limit value for } i.\text{criterion}$$

$$e_i\text{: } \tilde{C}_i \text{ fuzzy number mean value for } i.\text{criterion}$$

$$f_i\text{: } \tilde{C}_i \text{ fuzzy number upper limit value for } i.\text{criterion}$$

By taking the sums and differences of the values in equations 15 and 16, the degree of influence and influence for each criterion is determined.

$$\tilde{R}_i + \tilde{C}_i = \{a_i + d_i;\ b_i + e_i;\ c_i + f_i\} \quad (15)$$

$$\tilde{R}_i - \tilde{C}_i = \{a_i - f_i;\ b_i - e_i;\ c_i - d_i\} \quad (16)$$

In the sixth stage, the defuzzification process is performed by taking the average of the values that make up the triangular fuzzy number. The clarification processes are shown in equations 17 and 18.

$$R_i + C_i = \frac{a_i + d_i + b_i + e_i + c_i + f_i}{3} \quad (17)$$

$$R_i - C_i = \frac{(a_i - f_i) + (b_i - e_i) + (c_i - d_i)}{3} \quad (18)$$

Unnormalized criterion weights are found with the help of these defuzzified values. Finding unnormalized criterion weights is shown in equation 19.

$$nw_i\text{: Unnormalized weight value of criterion i}$$

$$nw_i = \sqrt{(R_i + C_i)^2 + (R_i - C_i)^2} \quad (19)$$

Finally, the weight values are normalized with the help of equation 20. After the normalization process, the sum of the weight values of the criteria is equal to 1.

$$w_i\text{: Normalized weight value of criterion i}$$

$$w_i = \frac{nw_i}{\sum_{i=1}^{n} nw_i};\ \forall \text{ for i} \quad (20)$$

The largest value among these values represents the most important criterion to be considered in the decision-making problem.

As for the TOPSIS, the method was first proposed by Hwang and Yoon (1981) and has been used in various fields for tackling ranking and selecting problems. The main purpose of this method is to determine the alternative that is closest to the positive ideal solution minimizing the cost criteria and maximizing the benefit criteria and the farthest from the negative ideal solution. The advantages of this method include its ease of use, having the ability to rank the best alternatives quickly, handling conflicting situations, and requiring low mathematical complexity (Rajak and Shaw, 2019). However, in order to eliminate vagueness and ambiguity arising from experts' judgments, opinions, and views fuzzy logic is applied. Moreover, the use of TOPSIS with fuzzy logic covering linguistic evaluations leads to feasible solutions as the number of alternatives increases the complexity of the decision making processes gets complicated (Özdağoğlu and Güler, 2016).

Table 18 gives a demonstration of the several studies conducted with the use of the fuzzy TOPSIS method.

Table 18: Fields of Research Using Fuzzy TOPSIS Method

Related Authors	**Fields of Research using Fuzzy TOPSIS**
(Chen et al., 2006).	Supplier Selection
(Özdağolu and Güler, 2016).	Evaluation of E-Service Quality of Internet-Based Banking Alternatives
(Kaya and Kahraman, 2011).	Selection of the Best Energy Technology Alternative
(Awasthi et al., 2011).	Evaluating Sustainable Transportation Systems
(Maldonado-Macías et al., 2014).	Ergonomic Compatibility Evaluation of Advanced Manufacturing Technology
(Kabir and Hasin, 2012).	Evaluation of Travel Website Service Quality
(Chu and Lin, 2003).	Robot Selection
(Chu, 2002).	Plant Location Selection

Apart from these studies, fuzzy TOPSIS methods are also used in areas related to energy sources, business, environment, and supply chain as the method offers simplicity, computational efficiency, and simultaneous consideration of the ideal and the anti-ideal solutions (Palczewski and Sałabun, 2019).

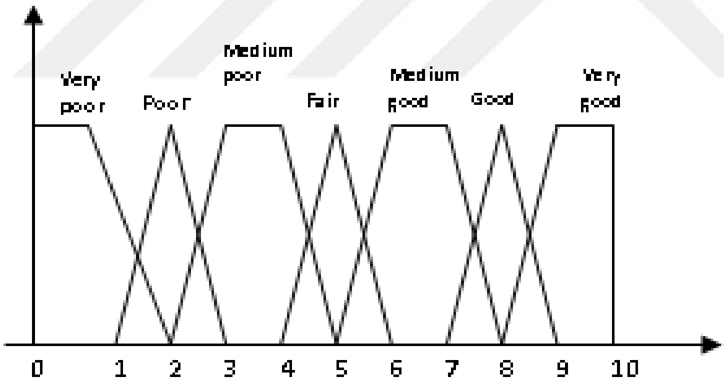
After demonstrating the usage area of the fuzzy TOPSIS method, the steps of the method will be given. The fuzzy TOPSIS model fundamentally is implemented according to the following steps:

1. Evaluate the relationship between sub-criteria and alternatives.
2. Transform the evaluation results into trapezoidal fuzzy numbers.

Fuzzy triangular and trapezoidal numbers are employed to assess each technology alternative. The linguistic variable for assessment lies between "very poor" and "very good", the membership function set is shown in Figure 6, and as an example, the linguistic variable ''Very Good (VG)'' can be demonstrated as (8,9,9,10), the membership function of which is given in Equation 21:

$$\mu_{Very\,Good}(x) = \begin{cases} 0, & x < 8 \\ \dfrac{x-8}{9-8}, & 8 \le x \le 9 \\ 1, & 9 \le x \le 10 \end{cases} \tag{21}$$

Figure 6: Linguistic variables for ratings



Source: Chen et al., 2006.

An evaluation of Industry 4.0 technology alternative can be regarded as a multi-criteria decision-making problem and this problem can be described by means of the following sets (Chen et al., 2006):

- a set of K users called E = {D_1; D_2; . . .; DK}
- a set of m possible Industry 4.0 technology alternatives called A = {A_1; A_2; . . .; A_m}

- a set of n criteria, $C = \{C_1; C_2; \ldots; C_n\}$ with which Industry 4.0 technology alternatives` performances are measured;
- a set of performance ratings of A_i ($i = 1; 2; \ldots; m$) with respect to criteria C_j ($j=1; 2; \ldots; n$), called $X = \{x_{ij}; i = 1; 2; \ldots; m; j = 1; 2; \ldots; n\}$

Suppose that a decision group has K decision-makers, and the fuzzy rating of each decision-maker D_k ($k= 1; 2; \ldots; K$) can be represented as a positive trapezoidal fuzzy number $\tilde{R}_k$ ($k= 1; 2; \ldots; K$) with membership function $\mu_{\tilde{R}_k}(x)$.

3. Construct the aggregated fuzzy rating matrix.

A good aggregation method should be considered the range of fuzzy ratings of each decision-maker. That is to say, the range of aggregated fuzzy ratings must consist of the ranges of all decision-makers' fuzzy ratings. Let the fuzzy ratings of all decision-makers be trapezoidal fuzzy numbers $\tilde{R}_k = (a_k; b_k; c_k; d_k,)$, $k = 1; 2; \ldots; K$. Thereafter, the aggregated fuzzy rating can be defined as $\tilde{R} = (a; b; c; d)$, $k = 1; 2; \ldots; K$. Equation 22 to 25 shows the detailed computations:

where,

$$a = \min_k \{a_k\} \tag{22}$$

$$b = \frac{1}{K}\sum_{k=1}^{K} b_k \tag{23}$$

$$c = \frac{1}{K}\sum_{k=1}^{K} c_k \tag{24}$$

$$d = \max_k \{d_k\} \tag{25}$$

4. Normalize the aggregated fuzzy rating matrix.

After the ratings are aggregated into one matrix the normalized weighted matrix is calculated by Equation 26:

$$V_{ij}=w_{ij} \text{ x } r_{ij}. \tag{26}$$

X_{ij} is the aggregated fuzzy rating matrix R of alternative i under the evaluation criterion j. After normalization, the elements of matrix R are converted into r_{ij}. Normalization is carried out by one of the methods which transform them into the numerical value, i.e. between 0-1, according to the structure of the problem (Chen et al., 2006).

5. Construct the weighted normalization matrix according to the values determined for each criterion.

Weights (w_{ij}) can be gathered by any method such as eigenvector, fuzzy numbers, linear programming models, etc., then the weight vector is multiplied by normalized matrix R to obtain the weighted normalized matrix v_{ij}. In this analysis, as mentioned before, the weight of each criterion is calculated using the Fuzzy-DEMATEL method which produces crisp weights through fuzzy numbers. Hence, in order to aggregate weights with ratings, weights are supposed trapezoidal fuzzy numbers which have equal values (a=b=c=d). Then rating matrix is multiplied by the weight matrix and finally weighted normalized matrix is procured.

6. Determine the negative and positive ideal solutions.

According to the weighted normalized fuzzy-decision matrix, normalized positive trapezoidal fuzzy numbers can also approximate the elements $\tilde{v}_{ij}, \quad \forall i, j$. Then, the fuzzy positive-ideal solution (FPIS, A^*) and fuzzy negative-ideal solution (FNIS, A^-) can be demonstrated as:

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, ..., \tilde{v}_n^*), \qquad A^- = (\tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_n^-),$$

where the values can be constructed by Equations 27 and 28:

$$\tilde{v}_j^* = \max_i \{v_{ij4}\} \tag{27}$$

$$\tilde{v}_j^- = \min_i \{v_{ij1}\}\ \mathrm{i} = 1; 2; \ldots; \mathrm{m},\ \mathrm{j} = 1; 2; \ldots; \mathrm{n}. \tag{28}$$

7. Calculate the distance measure.

The distance measure can be chosen from among the measurements to calculate distances such as the Euclidean distance or vertex distance (Chen and Tzeng, 2004; Chen et al., 2006). The distance of each alternative from A^* and A^- can be calculated with Equation 29 and 30:

$$d_i^* = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^*), \quad i = 1,2,....., m \tag{29}$$

$$d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1,2,....., m \tag{30}$$

where d_v (.,.) is the vertex distance measurement between two trapezoidal fuzzy numbers that are calculated by Equation 31:

$$d_v(\tilde{m},\tilde{n}) = \sqrt{\frac{\left[(m_1-n_1)^2+(m_2-n_2)^2+(m_3-n_3)^2+(m_4-n_4)^2\right]}{4}} \quad (31)$$

8. Calculate the negative closeness to the ideal solution.

The relative closeness of the i^th alternative concerning the ideal solution is calculated by negative distance over total distance. A closeness coefficient is described to establish the ranking order of all possible d_i^* and d_i^- of each Industry 4.0 technologies A_i (i=1; 2; . . . ;m) has been calculated. The closeness coefficient demonstrates the distances to the fuzzy positive-ideal solution (A^*) and the fuzzy negative-ideal solution (A^-) simultaneously by taking the relative closeness to the fuzzy positive-ideal solution. The closeness coefficient (CC_i) of each alternative is calculated in Equation 32:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad (24), \quad i = 1,2,..., m. \quad (32)$$

9. Rank the priority: a set of alternatives are sorted according to descending order of relative closeness.

It is clear that $CC_i = 1$ if $A_i = A^*$ and $CC_i = 0$ if $A_i = A^-$. That is to say, alternative A_i is closer to the FPIS (A^*) and farther from FNIS (A^-) as CC_i approaches 1. According to the descending order of CC_i, the ranking order of all technology alternatives can be determined and the best one among a set of feasible Industry 4.0 technology alternatives can be selected.

For the evaluation process, the approval status for each alternative is defined in Table 19 which can also be used for further evaluation when a decision is required for any technology alternatives.

Table 19: Approval status

Closeness coefficient (CCi)	**Evaluation status**
$CC_i \in [0;0,2)$	Do not recommend
$CC_i \in [0,2;0,4)$	Recommend with high risk
$CC_i \in [0,4;0,6)$	Recommend with low risk
$CC_i \in [0,6;0,8)$	Approved
$CC_i \in [0,8;1,0)$	Approved and preferred

Source: Chen et al., 2006:8.

The formulations, steps and usage areas of fuzzy DEMATEL and fuzzy TOPSIS are mentioned separately however these two methods also have been used together to find out solutions for various business applications including logistics, transportation, supply chain, manufacturing, project selection, purchasing, and technology selection decisions.

Table 20 below depicts the studies that benefit these two methods collaboratively.

Table 20: Fields of Research Using both Fuzzy DEMATEL and Fuzzy TOPSIS Methods

Related Authors	Fields of Research using Fuzzy DEMATEL and Fuzzy TOPSIS together
(Zhang and Su, 2019).	Estimation of participants in knowledge-intensive crowdsourcing
(Sangaiah et al., 2017).	The offshore/onsite teams' knowledge transfer effectiveness is based on knowledge, team, technology, and organizational factors
(Ocampo et al., 2020).	Determination of a Mapping Strategy for Sustainable Food Manufacturing
(Petrovic and Kankaras, 2020).	Selection and Evaluation of Criteria for Determination of Air Traffic Control Radar Position
(Vinodh et al., 2016).	Agile Manufacturing Selection
(Vinodh and Swarnakar, 2015).	Lean Six Sigma Project Selection
(Büyüközkan and Çifçi, 2012).	Evaluation of Green Suppliers

As it can be seen from the table above, a combination of fuzzy DEMATEL and fuzzy TOPSIS has been applied in various areas, especially in manufacturing problems. By virtue of ease of use and effective interpretation of the results of these methods as well as the nature of the research problem and properties of the determined sub-criteria these two methods are planned to be combined within the scope of this study.

Next, the empirical findings obtained through the responses of the selected firms will be mentioned based on these formulations and steps given in this section.

3.4. EMPIRICAL FINDINGS

In this study, an Excel sheet on the basis of equations and formulations given in the previous section was prepared with 3 main criteria, 21 sub-criteria, and 10 alternatives. The questionnaire form is then conducted with the participation of 15 experts from various sectors. Participants expressed their own opinions and knowledge on a questionnaire form and later the scoring and evaluations of participants were entered into a prepared Excel in order to solve the equations of fuzzy DEMATEL and fuzzy TOPSIS methods.

Due to the length of the definitions of the criteria and alternatives, coding was made before the analysis for ease of handling and is shown in the table below.

Table 21: Coding the Criteria and Alternatives

Coding	**Main Criteria**
A	Social Sustainability
B	Economic Sustainability
C	Environmental Sustainability
Coding	**Sub- Criteria**
A1	Workplace Safety
A2	Improvement in working standards and conditions
A3	The emergence of new job definitions
A4	Demand for a qualified workforce
A5	Increase in social welfare
B1	Increase in profitability
B2	Cost Reductions
B3	Productivity in production
B4	Flexibility in production
B5	Quality Control and Assurance
B6	Delivery and lead time reductions
B7	Increasing competitiveness
B8	Transparency and monitoring in production
B9	Process Optimization
B10	Standardization in Production
C1	Increasing the Use of Renewable Energy Resources
C2	Environmental Pollution Prevention, Management and Control
C3	Increasing Recovery, Recycling and Reusing Rates
C4	Reducing Greenhouse Gas Emissions
C5	Ensuring Efficiency in Resource and Energy Use
C6	Developing Green Innovative Strategies
Coding	**Alternatives**
A1	Additive Manufacturing
A2	Augmented Reality
A3	Autonomous Robots
A4	Big Data Analytics
A5	Cloud Computing
A6	Cyber-Physical Systems
A7	Internet of Things
A8	System Integration
A9	Simulation
A10	Smart Factories

Source: Created by the author.

Thereafter coding the main and sub-criteria as well as the alternatives, the required steps given in the data analysis and measurement section will be employed for both determining the main and sub-criteria relationships and weights along with the evaluation of the alternatives.

2.3.4. Determining the Main and Sub-Criteria: Relationships and Weights

At this stage, firstly 15 decision-makers have evaluated the main criteria, the relationships between the main criteria as well as the weights of the main criteria and the analysis of these evaluations are handled with the fuzzy DEMATEL method. As the analysis includes 15 respondents from five different sectors and only one sector results, that is textile, will be given step by step to set an example and later all results of the main criteria will be indicated according to sectors.

Step 1. Expert's main criteria evaluation results and their conversion to fuzzy numbers. The evaluation results of the first expert are given numerically in Table 22, and their converted versions into triangular fuzzy number equivalents that are explained in the fuzzy DEMATEL scale in Table 16 and with equation 1 are given in Table 23 as an example.

Table 22: Evaluation of the Main Criteria

Expert 1	**A**	**B**	**C**
A	0	3	2
B	4	0	4
C	4	3	0

Source: Created by the author.

Table 23: Converting the Main Criteria to Fuzzy Numbers

Expert 1	**A**			**B**			**C**		
	l	m	u	l	m	u	l	m	u
A	0.00	0.00	0.00	0.25	0.50	0.75	0.00	0.25	0.50
B	0.50	0.75	1.00	0.00	0.00	0.00	0.50	0.75	1.00
C	0.50	0.75	1.00	0.25	0.50	0.75	0.00	0.00	0.00

* The same calculations are also done with the expert 2 and expert 3.

Source: Created by the author.

Step 2. Preparation of a single fuzzy initial direct relationship matrix of the experts. The single fuzzy initial direct relationship matrix is formed as in the table below by taking the average of each cell of the matrices created in Table 23, which was prepared based on the data received from three expert decision-makers.

Table 24: The Single Fuzzy Initial Direct Relationship Matrix

Expert 1, 2, 3	A			B			C		
	l	m	u	l	m	u	l	m	u
A	0.00	0.00	0.00	0.25	0.50	0.75	0.08	0.33	0.58
B	0.50	0.75	0.91	0.00	0.00	0.00	0.41	0.66	0.91
C	0.41	0.66	0.91	0.25	0.50	0.75	0.00	0.00	0.00

Source: Created by the author.

Step 3. Forming the normalized fuzzy direct relationship matrix.

The normalized fuzzy direct relationship matrix is prepared by dividing the total u value which is 1.83 for this example into the fuzzy initial direct relationship matrix. The calculations are also given in equations 7,8,9 and 10. The table below shows the normalized fuzzy direct relationship matrix.

Table 25: The Normalized Fuzzy Direct Relationship Matrix

Expert 1, 2, 3	A			B			C		
	l	m	u	l	m	u	l	m	u
A	0.00	0.00	0.00	0.13	0.27	0.40	0.04	0.18	0.31
B	0.27	0.40	0.50	0.00	0.00	0.00	0.22	0.36	0.50
C	0.22	0.36	0.50	0.13	0.27	0.40	0.00	0.00	0.00

Source: Created by the author.

Step 4. Forming the fuzzy sum relationship matrix

The total relationship matrix and/or the fuzzy sum relationship matrix is calculated with the help of equation 11. First of all, l, m, u matrices are formed then by extracting the unit matrix and taking the reverse l (l-X)^(-1), m (I-X)^(-1), u (I-X)^(-1) matrices are obtained to further use in the fuzzy sum relationship matrix. The table below gives the fuzzy sum relationship matrix.

Table 26: The Fuzzy Sum Relationship Matrix

	A			**B**			**C**		
	l	m	u	l	m	u	l	m	u
A	0.06	0.35	2.00	0.15	0.48	2.03	0.08	0.42	1.97
B	0.35	0.81	2.83	0.08	0.40	2.17	0.26	0.65	2.49
C	0.28	0.71	2.66	0.18	0.55	2.32	0.05	0.33	2.00

Source: Created by the author.

Step 5. The row and column totals in the fuzzy sum relationship matrix are calculated to obtain $\tilde{R}_i$ and $\tilde{C}_i$ values as well as the $\tilde{R}_i + \tilde{C}_i$ and $\tilde{R}_i - \tilde{C}_i$ values and given in the table below.

Table 27: Row and Column Values

$\tilde{\boldsymbol{R}}_{\boldsymbol{i}}$			$\tilde{\boldsymbol{C}}_{\boldsymbol{i}}$			$\tilde{\boldsymbol{R}}_{\boldsymbol{i}} + \tilde{\boldsymbol{C}}_{\boldsymbol{i}}$			$\tilde{\boldsymbol{R}}_{\boldsymbol{i}} - \tilde{\boldsymbol{C}}_{\boldsymbol{i}}$		
l	M	u	l	m	u	l	m	u	l	m	u
0.30	1.25	6.02	0.70	1.87	7.50	1.00	3.13	13.53	-7.20	-0.61	5.31
0.70	1.86	7.50	0.42	1.44	6.53	1.12	3.31	14.04	-5.83	0.42	7.08
0.52	1.60	6.99	0.40	1.41	6.47	0.92	3.01	13.46	-5.94	0.19	6.59

Source: Created by the author.

Step 6. In this step, the defuzzification process is performed by taking the average of the values that make up the triangular fuzzy number. Unnormalized criterion weights are found with the help of these defuzzified values. The table below shows the values of defuzzified and unnormalized weights.

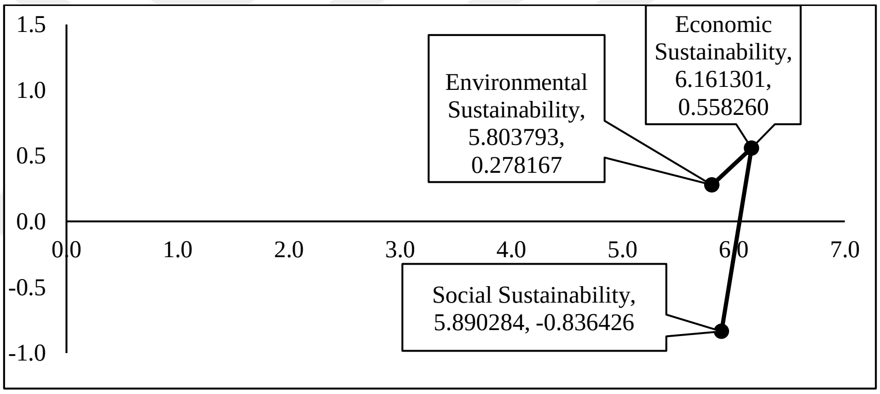
Table 28: Defuzzied Values and Unnormalized Weights

Defuzzied Values		Unnormalized Weights
5.89	-0.83	5.94
6.16	0.55	6.18
5.803	0.278	5.81

Source: Created by the author.

With the defuzzied values, a causal diagram for the textile sector is created and given in the figure below.

Figure 7: The Casual Diagram for Textile Sector



Source: Created by the author.

Based on this casual diagram, it can be said that social sustainability criterion is affected whereas environmental and economic sustainability criteria are affecting and the most affecting criteria is economic sustainability according to the data gathered from the textile sector.

Next, the weight values are normalized and after the normalization process, the sum of the weight values of the criteria is equal to 1. The normalized weights of the main criteria gathered through the responses of the decision-makers working in the textile sector are 0.33, 0.34, and 0.33 for social, economic, and environmental sustainability, respectively. This method suggests that the largest value among the weight values represents the most important criterion to be considered in the decision-making problem (Wu and Lee, 2007). Accordingly, although the values are quite close to each other, it is possible to say by seizing upon the results the most important criterion for the textile industry is economic sustainability, followed by social and finally, environmental sustainability and this result is also similar to the causal diagram.

The same logic, as well as the formulations of fuzzy DEMATEL, are applied and the same steps are taken for determining the weights and relationships of sub-criteria and other sectors' main and sub-criteria. The weights of the main and sub-criteria for each sector are given in the table below in which local weights refer to the weights of each criterion separately and global weights clarify the weights of each criterion when considering their interrelationships among each other.

Based on the table below, for the metal production sector, the most important main criterion is environmental sustainability followed by social and finally economic sustainability. As for the automotive sector, social and environmental sustainability are equally important and the least important criterion seems to be economic sustainability. The petrochemical industry focuses predominantly on social sustainability and economic as well as environmental sustainability have the same importance level. Lastly, for the food sector, social sustainability is the most essential criterion followed by economic and environmental sustainability, respectively.

Table 29: The Weights of the Main and Sub-Criteria for Each Sector

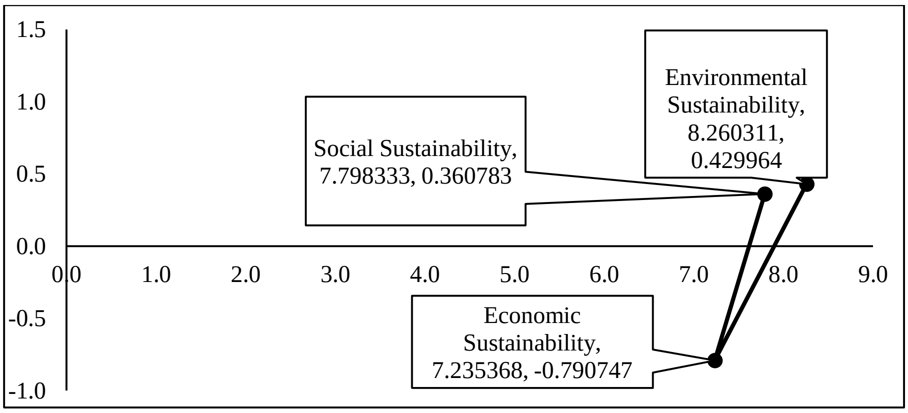
Main and Sub-Criteria	**Metal Production Sector**		**Automotive Sector**		**Petrochemical Industry**		**Textile Sector**		**Food Sector**	
	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global
A	0.33		0.34		0.34		0.33		0.35	
B	0.31		0.33		0.33		0.34		0.33	
C	0.35		0.34		0.33		0.32		0.32	
A1	0.24	0.08	0.21	0.07	0.18	0.06	0.19	0.06	0.19	0.07
A2	0.24	0.08	0.21	0.07	0.22	0.08	0.23	0.07	0.21	0.07
A3	0.12	0.04	0.19	0.06	0.18	0.06	0.17	0.06	0.20	0.07
A4	0.20	0.07	0.18	0.06	0.21	0.07	0.20	0.07	0.21	0.07
A5	0.20	0.07	0.20	0.07	0.21	0.07	0.22	0.07	0.20	0.07
B1	0.10	0.03	0.10	0.03	0.11	0.03	0.11	0.04	0.10	0.03
B2	0.09	0.03	0.10	0.03	0.10	0.03	0.10	0.04	0.11	0.04

Main and Sub-Criteria	Metal Production Sector		Automotive Sector		Petrochemical Industry		Textile Sector		Food Sector	
	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global
B3	0.13	0.04	0.10	0.03	0.10	0.03	0.10	0.04	0.11	0.04
B4	0.09	0.03	0.09	0.03	0.10	0.03	0.10	0.03	0.09	0.03
B5	0.10	0.03	0.11	0.03	0.10	0.03	0.09	0.03	0.10	0.03
B6	0.09	0.03	0.11	0.04	0.10	0.03	0.10	0.03	0.09	0.03
B7	0.11	0.03	0.10	0.03	0.11	0.04	0.10	0.04	0.10	0.03
B8	0.09	0.03	0.09	0.03	0.09	0.03	0.09	0.03	0.10	0.03
B9	0.11	0.04	0.09	0.03	0.10	0.03	0.10	0.03	0.10	0.03
B10	0.10	0.03	0.10	0.03	0.10	0.03	0.10	0.03	0.10	0.03
C1	0.16	0.06	0.16	0.05	0.16	0.05	0.17	0.05	0.17	0.05
C2	0.17	0.06	0.16	0.05	0.17	0.06	0.17	0.05	0.17	0.05
C3	0.14	0.05	0.16	0.05	0.16	0.05	0.17	0.05	0.17	0.05
C4	0.17	0.06	0.18	0.06	0.17	0.05	0.17	0.05	0.16	0.05
C5	0.18	0.06	0.18	0.06	0.17	0.06	0.17	0.05	0.17	0.05
C6	0.18	0.06	0.16	0.05	0.17	0.06	0.16	0.05	0.16	0.05

Source: Created by the author.

In order to support the findings and enhance the validity of the results casual diagrams for the main criteria were built relying on the defuzzied values and denoted in the figures below.

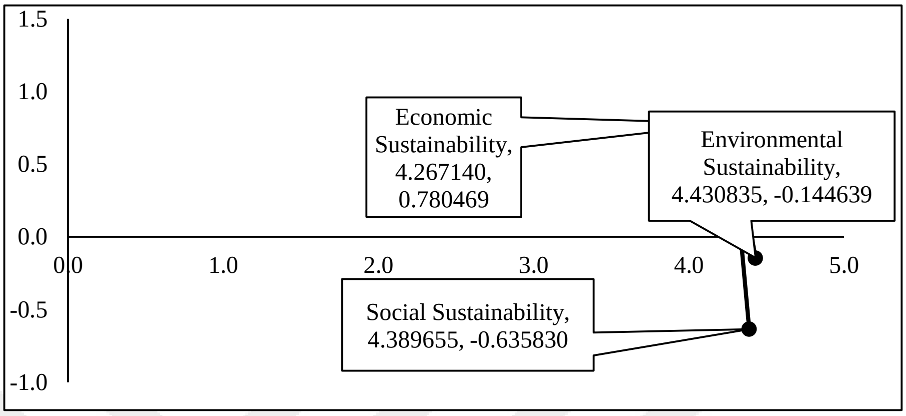
Figure 8: The Casual Diagram for Metal Production Sector



Source: Created by the author.

Based on this casual diagram, it can be said that the economic sustainability criterion is affected (an effect group) whereas environmental and social sustainability criteria are affecting (a cause group) and the most influencing criterion is environmental sustainability according to the data gathered from the metal production sector.

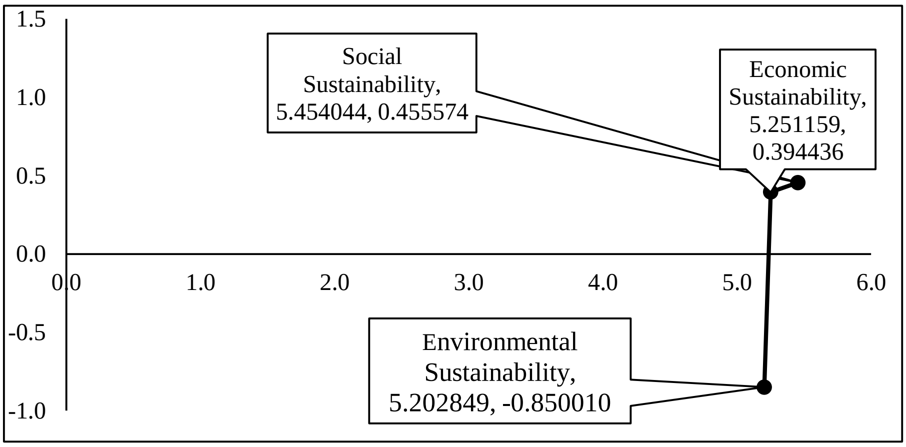
Figure 9: The Casual Diagram for Automotive Sector



Source: Created by the author.

Although the weights of the environmental and social sustainability criteria are the same, when looking at the casual diagram it is evident that environmental sustainability is slightly more important than the other sustainability pillars and both environmental and social sustainability are in the position of affected criteria whereas economic sustainability is an affecting criterion.

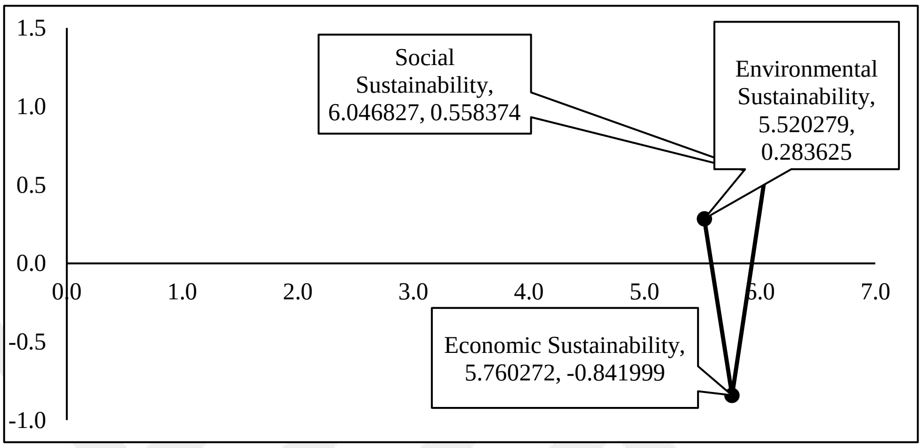
Figure 10: The Casual Diagram for Petrochemical Industry



Source: Created by the author.

According to the petrochemical industry, parallel with the results of the weight of the criteria, social sustainability is the most affecting criterion followed by the economic sustainability criterion though environmental sustainability is an affected criterion.

Figure 11: The Casual Diagram for Food Sector



Source: Created by the author.

In the food sector, environmental and social sustainability are considered to be the affecting criteria while economic sustainability is regarded as an affected criterion for the food sector, social sustainability is attributed to the most important criterion within the sustainability perspective and the deductions coincide with the results of the weight.

As for the evaluation of sub-criteria according to Table 30 above, A1 (workplace safety), B3 (productivity in production), and C6 (developing green innovative strategies) are the most significant criteria whereas A3 (the emergence of new job definitions), B6 (delivery and lead time reductions), and C3 (increasing recovery, recycling, and reusing rates) are the least significant criteria for the metal production sector when taking into social, economic, and environmental sustainability perspectives account. Thereafter calculating the effects of each criterion with one another it is found out that the most critical criterion for the metal production sector is A1 (workplace safety) while the least critical one is B2 (cost reductions).

For the automotive sector, A1 (workplace safety), B6 (delivery and lead time reductions), and C4 (reducing greenhouse gas emissions) are the most prominent criteria while A4 (demand for a qualified workforce), B9 (process optimization), and

C1 (increasing the use of renewable energy) are the least important among the social, economic, and environmental sustainability, respectively. Overall, the least important criterion is process optimization and the most important one is workplace safety for the automotive sector.

The data gathered from the experts working in the petrochemical industry implies that A2 (improvement in the working standards and conditions), B7 (increasing competitiveness), and C6 (developing green innovative strategies) precede the other criteria and A1 (workplace safety), B8 (transparency and monitoring in production), and C1(increasing the use of renewable energy) fall behind the remaining criteria. Furthermore, A2 (improvement in the working standards and conditions) and A5 (increase in social welfare) are the most important criteria whereas the B8 (transparency and monitoring in production) B4 (flexibility in production) and B6 (delivery and lead time reductions) are the least important ones.

Textile sector's data indicates that A2 (improvement in the working standards and conditions), B1 (increase in profitability), and C3 (increasing recovery, recycling, and reusing rates) are among the most remarkable criteria. On the other hand, A3 (the emergence of new job definitions), B5 (quality control and assurance), C6 (developing green innovative strategies) are insignificant when compared to other criteria. Overall, for the textile sector A2 (improvement in the working standards and conditions) is the most significant and B5 (quality control and assurance) is the least significant criteria.

Lastly, for the food sector A4 (demand for a qualified workforce), B2 (cost reductions), and C3 (increasing recovery, recycling, and reusing rates) have the highest weights while A1 (workplace safety), and B6 (delivery and lead time reductions), and C6 (developing green innovative strategies) have the lowest weights out of the remaining criteria. Moreover, A4 (demand for a qualified workforce) is the leading criterion whereas B6 (delivery and lead time reductions) is the least important criterion.

2.3.5. Determining the Alternatives: Selection Process of the Best Alternative

At this stage, 15 decision-makers evaluate the relations between the sub-criteria and the alternatives, and the alternative rankings are derived from these relations with the fuzzy TOPSIS method. First of all, it has been determined that there are 10 different solution alternatives after the evaluation of the decision-maker group, who has the authority to decide on the solution of the problem and determine the main and sub-criteria weights.

Step 1. Evaluation of the relationship between sub-criteria and alternatives. Based on the table below, 15 decision-makers evaluated the alternatives according to sub-criteria.

Table 30: Linguistic Variables and Corresponding Values

Linguistic Expression	**Value**
Very poor level by alternative criteria	1
Poor by alternative criteria	2
Bad to moderate according to alternative criteria	3
Intermediate by alternative criterion	4
Good to moderate according to alternative criteria	5
Good by alternative criteria	6
Very good by alternative criteria	7

Source: Converted from Chen et al., 2006.

As the analysis includes 15 decision-makers from five different sectors with 10 alternatives and 21 sub-criteria, only one sector's partial results will be given step by step to set an example, and later all results of alternatives will be given according to sectors. Table 32 depicts the first decision-maker reviews of alternatives based on the sub-criteria A1 and A2, other tables shown in the rest of this analysis also belong to the reviews of the same decision-maker working in the textile sector.

Table 31: An Evaluation of the Social Sustainability Sub-criteria and Alternatives

Sub-Criteria	A1	A2
Alternative 1	1	2
Alternative 2	1	2
Alternative 3	3	4
Alternative 4	2	3
Alternative 5	1	2
Alternative 6	2	2
Alternative 7	1	2
Alternative 8	1	2
Alternative 9	1	2
Alternative 10	2	2

Source: Created by the author.

Step 2. Transforming the evaluation results into trapezoidal fuzzy numbers. Evaluations made in the first step are converted into trapezoidal fuzzy numbers according to the membership function set given in Figure 6 and the table below shows these transformations of the evaluations of the expert 1 into the trapezoidal fuzzy numbers.

Table 32: The Trapezoidal Fuzzy Numbers

Trapezoidal Fuzzy Numbers	a	b	c	d	a	b	c	d
Sub-Criteria	A1	A1	A1	A1	A2	A2	A2	A2
Alternative 1	0	0	1	2	1	2	2	3
Alternative 2	0	0	1	2	1	2	2	3
Alternative 3	2	3	4	5	4	5	5	6
Alternative 4	1	2	2	3	2	3	4	5
Alternative 5	0	0	1	2	1	2	2	3
Alternative 6	1	2	2	3	1	2	2	3
Alternative 7	0	0	1	2	1	2	2	3
Alternative 8	0	0	1	2	1	2	2	3
Alternative 9	0	0	1	2	1	2	2	3
Alternative 10	1	2	2	3	1	2	2	3

Source: Created by the author.

Step 3. Forming the aggregated fuzzy rating matrix. Based on the Equations given from 22 to 25 aggregated fuzzy ratings are prepared as a matrix and given in the table below.

Table 33: The Aggregated Fuzzy Rating Matrix

Trapezoidal Fuzzy Numbers	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Sub-Criteria	A1	A1	A1	A1	A2	A2	A2	A2
Alternative 1	0.00	2.66	3.33	9.00	0.00	2.66	3.33	8.00
Alternative 2	0.00	2.00	3.00	8.00	0.00	2.66	3.33	8.00
Alternative 3	2.00	4.66	5.33	8.00	4.00	5.33	5.66	8.00
Alternative 4	0.00	2.33	2.66	6.00	1.00	3.33	3.66	6.00
Alternative 5	0.00	1.66	2.33	6.00	1.00	3.00	3.00	6.00
Alternative 6	1.00	4.00	4.00	9.00	1.00	3.00	3.00	6.00
Alternative 7	0.00	2.33	2.66	6.00	1.00	3.00	3.00	6.00
Alternative 8	0.00	2.33	2.66	6.00	1.00	3.00	3.00	6.00
Alternative 9	0.00	3.66	4.33	9.00	1.00	5.00	5.00	9.00
Alternative 10	1.00	6.00	6.00	9.00	1.00	6.00	6.00	9.00

Source: Created by the author.

Step 4. Constructing the normalized aggregated fuzzy rating matrix**.**
The aggregated matrix above is normalized by dividing each column by 10 and the normalized version is given in the table below.

Table 34: The Normalized Aggregated Fuzzy Rating Matrix

Trapezoidal Fuzzy Numbers	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Sub-Criteria	A1	A1	A1	A1	A2	A2	A2	A2
Alternative 1	0.00	0.26	0.33	0.90	0.00	0.26	0.33	0.80
Alternative 2	0.00	0.20	0.30	0.80	0.00	0.26	0.33	0.80
Alternative 3	0.20	0.46	0.53	0.80	0.40	0.53	0.56	0.80
Alternative 4	0.00	0.23	0.26	0.60	0.10	0.33	0.36	0.60

Trapezoidal Fuzzy Numbers	a	b	c	d	a	b	c	d
Alternative 5	0.00	0.16	0.23	0.60	0.10	0.30	0.30	0.60
Alternative 6	0.10	0.40	0.40	0.90	0.10	0.30	0.30	0.60
Alternative 7	0.00	0.23	0.26	0.60	0.10	0.30	0.30	0.60
Alternative 8	0.00	0.23	0.26	0.60	0.10	0.30	0.30	0.60
Alternative 9	0.00	0.36	0.43	0.90	0.10	0.50	0.50	0.90
Alternative 10	0.10	0.60	0.60	0.90	0.10	0.60	0.60	0.90

Source: Created by the author.

Step 5. Constructing weighted normalization matrix. The weighted normalization matrix is formed according to the values determined for each criterion. These weights (w_{ij}) are obtained by multiplying the normalized aggregated matrix to the weights found by the fuzzy DEMATEL. The table below shows the weights of the sub-criteria obtained from the fuzzy DEMATEL and weighted normalization matrix.

Table 35: Weighted Normalization Matrix with Fuzzy DEMATEL Weights

Fuzzy DEMATEL Weights	A1	A1	A1	A1	A2	A2	A2	A2
W	**0.062**	**0.062**	**0.062**	**0.062**	**0.074**	**0.074**	**0.074**	**0.074**
Trapezoidal Fuzzy Numbers	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Sub-Criteria	**A1**	**A1**	**A1**	**A1**	**A2**	**A2**	**A2**	**A2**
Alternative 1	0.0000	0.0167	0.0209	0.0564	0.0000	0.0199	0.0249	0.0597
Alternative 2	0.0000	0.0125	0.0188	0.0501	0.0000	0.0199	0.0249	0.0597
Alternative 3	0.0125	0.0292	0.0334	0.0501	0.0298	0.0398	0.0423	0.0597
Alternative 4	0.0000	0.0146	0.0167	0.0376	0.0075	0.0249	0.0274	0.0448
Alternative 5	0.0000	0.0104	0.0146	0.0376	0.0075	0.0224	0.0224	0.0448
Alternative 6	0.0063	0.0251	0.0251	0.0564	0.0075	0.0224	0.0224	0.0448
Alternative 7	0.0000	0.0146	0.0167	0.0376	0.0075	0.0224	0.0224	0.0448
Alternative 8	0.0000	0.0146	0.0167	0.0376	0.0075	0.0224	0.0224	0.0448
Alternative 9	0.0000	0.0230	0.0271	0.0564	0.0075	0.0373	0.0373	0.0671
Alternative 10	0.0063	0.0376	0.0376	0.0564	0.0075	0.0448	0.0448	0.0671

Source: Created by the author.

Step 6. Determination of fuzzy negative and fuzzy positive ideal solutions. The fuzzy positive-ideal solution is represented by FPIS, A^* and fuzzy negative-ideal solution is represented by FNIS, A^-. With the help of equations 27 and 28, these values of A* and A^-. are found and shown in the table below.

Table 36: Fuzzy Positive and Fuzzy Negative Ideal Solutions

Trapezoidal Fuzzy Numbers	**a**	**b**	**c**	**d**	**a**	**b**	**c**	**d**
Sub-Criteria	A1	A1	A1	A1	A2	A2	A2	A2
A*	0.056	0.056	0.056	0.056	0.067	0.067	0.067	0.067
A-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Created by the author.

Step 7. Calculation of the distance of each alternative from A^* and A^-. Based on equations 29 and 30 as well as the vertex distance method shown in equation 31, the distance of each alternative from positive and negative ideal solutions are calculated and represented in the table below.

Table 37: Distances of Each Alternative from A^* and A^-

d*	**Sub-Criteria**	**A1**	**A2**	**d-**	**Sub-Criteria**	**A1**	**A2**
	Alternative 1	0.0388	0.0463		**Alternative 1**	0.0312	0.0338
	Alternative 2	0.0405	0.0463		**Alternative 2**	0.0275	0.0338
	Alternative 3	0.0284	0.0265		**Alternative 3**	0.0341	0.0442
	Alternative 4	0.0414	0.0431		**Alternative 4**	0.0218	0.0293
	Alternative 5	0.0430	0.0449		**Alternative 5**	0.0208	0.0277
	Alternative 6	0.0334	0.0449		**Alternative 6**	0.0334	0.0277
	Alternative 7	0.0414	0.0449		**Alternative 7**	0.0218	0.0277
	Alternative 8	0.0414	0.0449		**Alternative 8**	0.0218	0.0277
	Alternative 9	0.0359	0.0365		**Alternative 9**	0.0333	0.0429
	Alternative 10	0.0284	0.0338		**Alternative 10**	0.0389	0.0463

Source: Created by the author.

Step 8. Calculation of closeness coefficient for each alternative. A closeness coefficient is defined to determine the ranking order of all possible d_i^* and d_i^- of each

Industry 4.0 technology. The closeness coefficient demonstrates the distances to the fuzzy positive-ideal solution (A^*) and the fuzzy negative-ideal solution (A^-) simultaneously by taking the relative closeness to the fuzzy positive-ideal solution. The closeness coefficient (CC_i) of each alternative is calculated with Equation 32 and shown in the table below.

Table 38: The Closeness Coefficient (CCi) of Each Alternative

	Sum d*	**Sum d-**	**CC_i**
Alternative 1	0.5670	0.4295	0.4295
Alternative 2	0.6130	0.3846	0.3846
Alternative 3	0.4361	0.5568	0.5568
Alternative 4	0.5016	0.4752	0.4752
Alternative 5	0.5524	0.4425	0.4425
Alternative 6	0.5753	0.4290	0.4290
Alternative 7	0.4779	0.5145	0.5145
Alternative 8	0.4125	0.5704	0.5704
Alternative 9	0.4580	0.5443	0.5443
Alternative 10	0.3595	0.6385	0.6385

Source: Created by the author.

Step 9. Ranking the alternatives. Here, it can be said that if an alternative A_i is closer to the FPIS (A^*) and farther from FNIS (A^-) CC_i approaches to 1. According to the descending order of CC_i, the ranking order of all technology alternatives is determined. The same logic, as well as the formulations of fuzzy TOPSIS, are applied and the same steps are taken for evaluating the alternatives for all the sectors. The ranking results of the alternatives based on the sub-criteria weights for each sector are given in the table below.

Table 39: Ranking the Alternatives Based on the Sectors

Sector/Rank	Metal Production Sector	Automotive Sector	Petrochemical Industry	Textile Sector	Food Sector
Alternative 1	5	6	3	8	7
Alternative 2	10	1*	8	10	6
Alternative 3	2	8	4	3	2
Alternative 4	8	9	7	6	1*
Alternative 5	9	5	9	7	5
Alternative 6	4	10	6	9	8
Alternative 7	3	7	10	5	10
Alternative 8	7	4	2	2	4
Alternative 9	6	3	5	4	9
Alternative 10	1*	2	1*	1*	3

Source: Created by the author.

According to the table, the smart factory is the alternative that best meets the social, economic, and environmental sustainability criteria for companies operating in the metal production sector, petrochemical industry, and textile sector. Furthermore, for the metal production sector alternative 3 (autonomous robots) and alternative 7 (cyber-physical systems) are among the other potential options though alternative 2 augmented reality appears to be the last alternative.

As for the automotive sector, the best possible alternative is augmented reality that is followed by alternative 10 (smart factory) and alternative 9 (simulation). However, alternative 6 (cloud computing) is the least preferred technology.

Apart from the smart factory, alternative 8 (system integration) and alternative 1 (additive manufacturing) are also considered to be potential choices for the petrochemical industry but alternative 7 (cyber-physical systems) is the last option.

According to this ranking, it can be said that alternative 10 (smart factory) is the best alternative for the chosen textile sector out of the set of feasible Industry 4.0 technology alternatives. Then, alternative 8 (system integration) and alternative 3 (autonomous robots) have the highest scores when taking into sub-criteria consideration. However, alternative 2 (augmented reality) has the least score among the other alternatives.

Lastly, for the food sector alternative 4 (big data analytics) is considered to be the most effective Industry 4.0 technology alternative while creating a sustainable working environment, and that is followed by alternative 3 (autonomous robots) and alternative 10 (smart factory). In parallel with the results of the petrochemical industry, alternative 7 (cyber-physical systems) is among the last preferences.

Overall it can be said that, although the best technology selection decision is similar among the specified sectors, that is smart factory for three sectors out of five, other alternatives' ranking differs from sector to sector.

In order to validate and reinforce the fuzzy TOPSIS method results for the ranking and selection of alternatives, another MCDM that is Multi-Attribute Utility Theory (MAUT) was employed and the fuzzy version of this method was preferred. MAUT method interprets a number of alternatives in terms of a number of decision criteria (Shanmuganathan et al., 2018) and the process of the method is based on the expected utility theory (von Winterfeldt and Edwards, 1986; French, 1988). The table below represents the results of the fuzzy MAUT for the textile sector and clarifies the comparison of these two methods.

Table 40: A Comparison of Ranking the Alternatives

Alternatives	Textile Sector/Fuzzy TOPSIS Results	Textile Sector/Fuzzy MAUT Results
Alternative 1	8	8
Alternative 2	10	10
Alternative 3	3	3
Alternative 4	6	6
Alternative 5	7	7
Alternative 6	9	9
Alternative 7	5	5
Alternative 8	2	2
Alternative 9	4	4
Alternative 10	1*	1*

Source: Created by the author.

As it is evident from the table above our results regarding the ranking and selection of the alternatives are consistent with the results of the other method chosen. According to the results of the fuzzy MAUT method smart factory is the best alternative. Thereafter, system integration and autonomous robots have the highest scores when taking into sub-criteria consideration. However, augmented reality is regarded as the last option among the other alternatives.

2.3.6. Evaluation of the In-Depth Interviews and Open-Ended Questions

In this study, in order to apprehend decision-makers` perceptions and tendencies towards sustainability and Industry 4.0 notions as well as enhance the validity of the analysis results open-ended questions are prepared and gathered through both in-depth interviews and from the questionnaire forms. Open-ended questions include questions regarding the business size, personal information such as respondents' roles experience in their working environment, technical information within the scope of sustainability and Industry 4.0 as well as the general views on the predictions about sustainability and Industry 4.0 technologies and applications.

Using the expert sampling technique of purposive sampling approach, interviews were conducted with competent sources including managers from production, marketing, R&D, quality, and human resources departments as they are equipped with sufficient knowledge and expertise in the field. The characteristics and demographic features of decision-makers in this study are depicted in Table 40.

Table 41: Demographic Profile of the Decision-Makers

Decision-Makers	**Sectors**	**Departments**	**Job Titles**	**Experience (Years)**
1	Petrochemical	Production	Production Manager	2
2	Petrochemical	Production	Supply Chain Planning and Logistics Manager	4
3	Petrochemical	Production	Planning Specialist	1
4	Metal Production	Marketing	Corporate Communications and Brand Manager	1
5	Metal Production	Top Management	Chief Executive Officer	21

Decision-Makers	Sectors	Departments	Job Titles	Experience (Years)
6	Metal Production	Quality	Quality, Environment and Occupational Safety and Health Coordinator	16
7	Textile	R&D	R&D and Innovation Center Manager	4
8	Textile	Top Management	Executive Board Member	3
9	Textile	R&D	R&D and Innovation Center Manager	4
10	Automotive	R&D	Technology and Intellectual Property Officer	4
11	Automotive	R&D	R&D Specialist	2
12	Automotive	R&D	R&D Manager	15
13	Food	Production	Production Manager	6
14	Food	Human Resource	Human Resource Manager	1
15	Food	R&D	R&D Manager	5

Source: Created by the author.

In-depth interviews were conducted via phone and lasted approximately 30 minutes and interviews are noted verbatim simultaneously. Additionally, questionnaire forms were sent via e-mail and then was merged with the results of the in-depth interviews. Based on the data collected through both in-depth interviews and questionnaire forms, a tag cloud is prepared by using an open-source Edwordle.net (2021), one of the visualization tools. Thereby, a visual analysis of the data was achieved and depicted in the figure below.

Figure 12: A Visual Representation of Word Cloud

Source: Edwordle.net, 2021.

Thereafter rendering the data gathered, the most highlighted terms include sustainability, technologies, production, generations, digitalization, development, processes, industry, competitiveness, change, efficiency, production, resources, and profitability throughout the in-depth interviews and questionnaire forms. In addition, decision-makers overwhelmingly highlighted that Industry 4.0 and sustainability are not adequately understood and applied in our country, but that they have awareness of these concepts. Furthermore, the decision-makers acknowledged that having a mindset of sustainability is essential to stimulate businesses operations and to leave a better future for the next generations as indicated in the quotes below:

> *In today's world, waste and resource management have been occupying the agenda and become a topical instance on account of global warming and climate change threats. For this reason, businesses should reorganize their structures with a holistic approach and with a sense of responsibility for the future while creating their goals.* (Decision-maker 4)

> *The future of the world depends on our natural resources. Our natural resources are unfortunately not inexhaustible. This is where the concept of sustainability comes into play. The sustainability phenomenon can be used as a shield and/or a protection approach to the effective environmental and economic use of resources. Thus, cultivating a sustainable frame of mind makes it possible for us to leave a more livable world to future generations.* (Decision-maker 5)

> *In order to leave tomorrow's resources to future generations, we have to act upon them today. Limiting the increase in world temperature to below 2 degrees and 1.5 degrees that was mentioned in the 2015 Paris Agreement is the least we can do for climate change instead we need to work harder to create a sustainable world for both our businesses and our future.* (Decision-maker 7)

> *Organizations should scrutinize and if necessary regulate their mechanisms to leave a sustainable life with ecological, economic, and social conditions for future generations.* (Decision-maker 11)

It is evident from the statements that there is an awareness among the decision-makers regarding the sustainability issue and a necessity of taking steps towards sustainability at both the businesses level and individually. Moreover, decision-makers also stated their views on Industry 4.0 and its revolving technologies as appeared in the quotes below:

> *Although we call it the 4th Industrial Revolution, it is actually a change and development process that includes the increase in the applications of new digital technologies in production and the development of business models, rather than*

a radical change that comes suddenly. In the global competitive environment, it has become a necessity for every manufacturer who aims to maintain their market share, drive down their costs, and increase their profitability in the future. In this changing environment, inevitably, companies that cannot adapt new technologies to production and even develop these technologies will lag behind the race in the future. The competitiveness of our country and domestic producers in 10 years will be determined by our perspective on the technologies presented under the title of Industry 4.0 today. It is of great importance to develop policies that will support the production of these technologies in our country, especially on a macro scale, instead of buying and consuming them from abroad. (Decision-maker 9)

Instant tracking, digitalization, efficiency, traceability, and competitiveness will be possible for manufacturers in the coming periods with the use of Industry 4.0 technologies. For this reason, developing investments and projects from today will make a difference (Decision-maker 3)

It is the 4th generation industrial revolution that aims to bring a new horizon to the industry together with an emerging generation of technologies. (Decision-maker 8)

...very comprehensive work is being carried out globally towards Industry 4.0. In order to survive and compete, we also need to develop a vision and goals towards Industry 4.0. It is one of the areas open to development in our country. It is a process that depends primarily on human resources. (Decision-makers 1, 2, and 12)

Based on the views of the decision-makers regarding Industry 4.0 and its technologies, although the decision-makers are familiar with the terms they worry about the necessity for taking tactical and strategical attempts in order not to lag behind the competitors. Furthermore, in line with the research question of this study that is whether the Industry 4.0 technologies play a role in creating a sustainable working environment, decision-makers also delivered their perspectives on both sustainability and Industry 4.0 technologies.

Lights-out manufacturing as a reflection of Industry 4.0 and smart factories will bring various advantages however the question of what will happen to blue collars is yet agitative and intriguing. (Decision-maker 5)

The development of new job disciplines is particularly necessary for this area. (Decision-maker 6)

It is one of the most important issues for both our country and our world. In the medium and long term, digitalization in production will have a high impact on sustainability. (Decision-maker 3)

Profitability alone does not enable companies to achieve their future goals, for this, studies on the combination of sustainability and Industry 4.0 technologies and applications must be carried out. (Decision-maker 1)

It is an important process of change for the whole world to standardize, improve and adapt their services and production processes to the needs of this century and to do this with a joint effort. Applying the concept and practices of change management, which are used for the changes that occur in the internal and external processes of the companies from time to time, is required however, for such big alteration governments should play the key role and support organizations throughout this change process. (Decision-maker 7)

I think it is important to use Industry 4.0 technologies in our production processes for the spread and advancement of digitalization and technology. It is an exciting process to be able to devote more time to work with added value for myself and to be able to do routine and non-value-added work by robots. (Decision-maker 2)

Companies have turned to sustainability and Industry 4.0 technologies and practices in order to reduce the risks of fulfilling their environmental and social responsibilities beyond increasing their efficiency and profitability. Companies can only make a difference when profitability, efficiency, productivity, continuous improvement activities are integrated with sustainability and Industry 4.0 technologies and practices. (Decision-maker 11)

Sustainability is one of the most important issues for both our country and our world. In the medium and long term, digitalization in production will have a high impact on environmental, social, and economic sustainability. (Decision-maker 9)

…all companies should develop applications on the way to digitization and sustainability as quickly as possible however economic concerns regarding the implementation of these technologies. (Decision-maker 4)

Overall, it can be deduced from the expressions of the decision-makers that although Industry 4.0 technologies are deemed to effectuate a blend of various opportunities on the way to enrich the sustainability pillars there are some concerns and drawbacks regarding the adaptation process.

CONCLUSION

Throughout the first three industrial revolutions, productivity accelerated in the light of developments such as the steam engine, electricity, and digital technology however, the Industry 4.0 paradigm is rather a complex and widely-discussed set of systems incorporating various technologies such as CPSs, smart factories, autonomous robots, simulation, system integration, IoT, cloud computing, additive manufacturing, augmented reality, big data analytics. Furthermore, Industry 4.0 creates faster, more flexible, more efficient production processes and low-cost industrial value, enhances high-quality customized products, productivity, revenue growth, and competitiveness, optimizes decision-making processes, provides with effective and efficient use of resources, and alters conventional production systems into fully integrated and automated systems (Almada-Lobo, 2015; Kusmin, 2018; Wichmann et al., 2019, Strandhagen et al., 2017; Agostini and Filippini, 2019).

Factors that constitute the ground of the Industry 4.0 manufacturing paradigm such as artificial intelligence-based, self-optimizing, configuring, constantly interacting industrial robots and machines, smart factories and system integration ensuring automation and digitalization across the value chains with real-time data flow, cyber-physical systems, and internet of things provide the basis for more productive, flexible, high quality, versatile, safer and collaborative working ecosystems (Martín et al., 2017). Accordingly, while Industry 4.0 applications overcome challenges such as global competition, volatile markets, declining product life cycles, desire for high quality, and customized products it also provides opportunities such as industrial value creation, productivity, revenue growth, and competitiveness at low costs (Ardito et al., 2019). Moreover, Industry 4.0 technologies and applications also improve living standards for future generations, take steps towards depletion of non-renewable resources, elimination of environmental problems such as climate change, loss of biodiversity, carbon footprint, energy and water consumption per capita, waste and pollution. That is to say, keeping in mind creation of a sustainable industrial value in social, environmental, and economic dimensions is of great importance for today's business environments Industry 4.0 technologies are assumed to have significant effects within the scope of creating opportunities for sustainability (Nagasawa et al., 2017).

Regarding the social sustainability aspect of Industry 4.0, thanks to technologies such as smart production infrastructures and advanced machine learning through human-machine interfaces, new job profiles are anticipated to emerge, such as robot engineering, network development engineering, big data specialist, data security analyst, artificial intelligence and machine learning specialists so industrial workplaces are expected to transform into innovative workplaces in which brainpower is used instead of muscle power. In addition, dangerous and/or repetitive, monotonous tasks within production, maintenance, logistics operations are thought to be taken from the employees and left to robots and robotic systems which in turn will increase social welfare, eliminate human-induced error margins, increase quality and flexibility, reduce physical fatigue, reduce working times, and accelerate decision-making processes (Prause, 2015; Cohen et al., 2019).

In the environmental dimension of sustainability, factors such as the constantly accelerating population growth, the intensification of global industrialization with high production levels and excessive consumption, climate change, global warming, and environmental degradation of ecosystems were shown as the starting point of the study. Industry 4.0 and the technologies it brings are expected to lead to factors such as increasing transparency and traceability in both demand and processes, intelligent planning of processes, thus reducing energy and material consumption. Moreover, with the use of smart factories, cloud computing, the internet of things, and system integration immediate interventions for such indicators as greenhouse gas emissions, wastes, environmental pollution, and excessive resource consumption can be acted upon, managed, and controlled effectively (Valdez et al., 2015; Posada et al., 2015; Burritt and Christ, 2016).

As for the economic sustainability dimension of Industry 4.0, technological developments in manufacturing have played and been continuing to play a vital role in supporting economic growth and generating financial benefits for decades. The sustainable factories of the future lay the foundations for industrial growth and economic and social well-being. New technologies that emerged with Industry 4.0, enabling faster and cheaper R&D processes, such as simulation, simultaneous engineering, or rapid prototyping, can radically drive down product time to market, and being the first supplier in the market with a new product can provide businesses with a competitive advantage. In addition, the technologies such as smart production brought by Industry 4.0 can provide efficiency, flexibility, reliability, transparency, traceability of processes, optimization of quality problems and resource use, minimization of waste, and early detection of errors, increase a company's competitiveness and drive down its costs (de Man and Strandhagen, 2017).

Considering the studies carried out within the systematic literature review, although there has been a deep interest in the concepts of Industry 4.0 and sustainability globally, these paradigms has been conceptually discussed in the literature and there was no definitive consensus on the reflection of this new manufacturing paradigm into sustainability within the applicability framework. Therefore, it was seen that there were deficiencies in the analysis and applications related to this study area in the literature. Moreover, these concepts have not been adequately assessed within both conceptual and applicability frameworks in Turkey. That is to say, there were limited resources both in the application and theoretical aspects in Turkey regarding the combination of this manufacturing approach and sustainability pillars. Thus, this thesis aimed to contribute to the literature in this context by eliminating the application and analysis deficiencies regarding social, environmental, and economic sustainability benefits which were thought to be realized by the integration of Industry 4.0 technologies in the literature. This thesis also differed from the theoretical studies in the literature as it deals with all three dimensions of sustainability together. Within the scope of this thesis, it was planned to determine which Industry 4.0 technologies contribute to the social, environmental, and economic dimensions of sustainability by sorting and selecting the Industry 4.0 technologies that best meet the determined sustainability sub-criteria. In order to achieve this goal, firstly a focus group study was done for specifying the criteria and alternatives that were used in the analysis with the help of brainstorming and mind mapping techniques and finalized after the feedbacks of some academics with various backgrounds.

Thereafter designating the proposed model owing to the complex nature of technology selection decisions, the MCDM process was employed. In the proposed model, as there are relationships and ties among main criteria and sub-criteria and in an attempt to eliminate ambiguity and vagueness derived from the qualitative evaluations of the decision-makers the fuzzy DEMATEL method was used in the weighting process of the criteria to obtain accurate results with fuzzy set theory. As for the ranking and selection process of the alternatives, the fuzzy TOPSIS method was utilized as this method enables the evaluation of all sub-criteria to determine the most suitable and feasible alternative solution, proceeds directly on the data set without requiring a numerical conversion, and also calculates both the negative and positive distances to the solution. Overall, an integrated or mixed-method consisting of fuzzy DEMATEL and fuzzy TOPSIS was used to solve the proposed research problem. This integrated methodology was applied with the convenience and purposive sampling constituting fifteen decision-makers from various sectors include metal production, petrochemical, textile, automotive, and food, where the importance of Industry 4.0 and sustainability purports have been appreciated and in an effort to reveal if there were any differences of Industry 4.0 technologies on a sectoral basis in creating a sustainable production ecosystem as it is known, the requirements might vary from sector to sector.

According to the results of the fuzzy DEMATEL used for weighting the main and sub-criteria, the metal production sector regarded environmental sustainability as the most important sustainability dimension, and enhancing workplace safety is the most important criterion while the least important one is cost reductions. For the automotive sector, environmental sustainability is slightly more significant than the other sustainability pillars and the least important criterion is process optimization and the most important one is workplace safety. Based on the data gathered from the decision-makers working in the petrochemical industry, it was implied that the most critical sustainability dimension was social and improvement in the working standards and conditions and increase in social welfare were the most important criteria though the transparency and monitoring in production, flexibility in production, and delivery and lead time reductions are the least important ones. Textile sector's data showed that the most significant sustainability dimension was the economic and improvement in the working standards and conditions was the most significant and quality control and assurance was the least significant criterion. Lastly, for the food sector, social sustainability was the most crucial sustainability dimension, and demand for a qualified workforce was the leading criterion whereas flexibility in production can be considered as the least important criterion.

These results show that overall, social and environmental sustainability were given the most importance under the umbrella of sustainability. This is a confounding however a favorable situation for the firms located in Turkey as they ordinarily struggle with economic concerns and neglect the social and environmental issues. Furthermore, enhancing workplace safety along with working standards and conditions were considered to be among the most important criteria as out of five, four sectors opted for these criteria.

Based on the results of the sub-criteria weights fuzzy TOPSIS was applied for ranking and selecting the alternatives. For the metal production, petrochemical, and textile sector smart factory appeared to be the alternative that best meets the social, economic, and environmental sustainability criteria. Furthermore, for the metal production sector, autonomous robots can be also the second potential alternative. This might be because of the elimination of hazardous tasks such as welding, extrusion, and casting within the production processes, thus enhancing workplace safety. Moreover, the application of autonomous robots in the metal sector provides flexibility, reduced labor costs and waste, resource efficiency, and improved quality of products, thus leading to the creation of a sustainable working environment.

As for the automotive sector, the best possible alternative was augmented reality that was followed by the smart factory. The reasons for selecting augmented reality among the other technology alternatives lie behind the idea of augmented reality offers various benefits especially in assembly, maintenance, diagnostics, inspection, and after-sales operations. Moreover, with the augmented reality applications, the visibility of information, improvements in safety, efficiency, ergonomics aspects, and designing of customized products could be provided (Boboc et al., 2020; Himperich, 2007). Therefore, as the firm operating in the automotive sector produces customized products for both logistics and defence industries and offers after-sales services augmented reality could provide a sustainable working environment for its operations.

Apart from the smart factory, system integration was regarded as a second preference for both the petrochemical industry and the textile sector. Having the management, control, and integration within the organization operations including production, R&D, marketing, purchasing, sourcing, product design and development, scheduling, warehousing, delivery and transportation, after-sales services, reverse logistics as well as across the entire supply chains ensure a reliable and visible working environment, flexibility, real-time inventory control, cost-effectiveness, and transparency, (Zhou and Zhou, 2015), thus providing a sustainable working environment for their operations.

Lastly, for the food sector, big data analytics seemed to be the most important Industry 4.0 technology alternative when taking sustainability criteria into consideration. Surrounded by a wide range of distributors, vendors, and customers, the firm functioning in the food sector can collect operational logs, feedback data, and social network data and analyze them through big data analytics. By doing so, the firm can have opportunities such as understanding its customers' shopping habits and behaviors and hence increasing customer satisfaction. Moreover, the firm can flexibly change its order priorities, monitor, and control its production performance and processes, improve its logistics routes, and optimize its operations with effective decision-making processes (Wang et al., 2018; Belhadi et al., 2019), thus leading to a sustainable working environment for its operations.

In order to validate and reinforce the fuzzy TOPSIS method results for the ranking and selection of alternatives, another MCDM that is Multi-Attribute Utility Theory (MAUT) was employed and the fuzzy version of this method was preferred. As a result, the fuzzy MAUT outputs regarding the ranking and selection of the alternatives were consistent with the results of the fuzzy TOPSIS.

Overall it can be deduced that decision-makers from each sector had made their preferences based on their sectors requirements and needs. Smart factory alternative obtained the highest score compared to other alternatives, considering it was the best alternative in creating a sustainable working environment as three sectors out of five ranked the smart factory the highest. In fact, the smart factory can be perceived as a reflection of Industry 4.0 as a whole as it consists of a bunch of technologies including CPSs, data handling, information technologies, human-machine interaction, IoT, and cloud systems. Therefore, it is possible with the smart factories to ensure visibility and transparency of manufacturing operations, having real-time information thus achieving on-time delivery, resource utilization, energy efficiency, reduction in costs, customer satisfaction, enhanced output quality as well as flexibility (Radziwon et al., 2014; Mabkhot et al., 2018; Strozzi et al., 2017).

As a result, using mixed-method consisting of fuzzy DEMATEL and fuzzy TOPSIS has brought a scientific approach to the solution of a technology decision problem based on sustainability criteria as well as contributed to the literature with the outputs.

Furthermore, coping with increasingly personalized demands of customers and shortened product life cycles while seeking out answers to problems such as a chain of high costs ranging from design to logistics, manufacturing in a more economical, faster, and higher quality manner forces organizations to embrace and adapt to innovative solutions brought by Industry 4.0 technologies, and undergo radical changes within business processes to keep up with these changes, from the top management level to the bottom level. However, as the in-depth interviews and results of the open-ended questions suggested organizations operating in Turkey have remained in the shadow of Industry 2.0 and Industry 3.0 applications regardless of their sizes and organizational structures. Furthermore, most organizations in Turkey have a lack of comprehending Industry 4.0 and accompanying technologies as well as the sustainability dimensions. Therefore, the results of the study have practical and managerial implications and particularly were intended to set an example to organizations that might go through Industry 4.0 transformation process and are interested in creating a sustainable working environment as well as seeing these concepts as a necessity in today's globally competitive environment. That is to say, implications of the study are aimed to use as a road map that could be benefitted by the Ministry of Industry and Technology, Small and Medium Industry Development Organization, R&D and Innovation directional institutions as well as organisations located in Turkey planning to go through an adaptation and/or a transformation process to Industry 4.0 but having some concerns regarding the social, economic and environmental impacts of these technologies. Moreover, it is also planned to contribute to the literature with the academic outcomes of this research, which covers Industry 4.0 and all three dimensions of sustainability.

The findings of this study have several limitations. First, this study was carried out within organizations located in Turkey which restricts the representativeness of the sample even though the use of various sectors elicits fructuous ground for the research of revealing the differences in the selection of Industry 4.0 technology alternatives. Secondly, with the purposive sampling procedure, a focus was only given to the experts in the field and this may lead to a failure to grab the insights and experiences of other sectors and for future research suggestions including other sectors like logistics, construction, and agriculture would enhance the breadth and generalizability of the existing results. Moreover, apart from the expert perspectives on the topic of interest, other working groups like blue-collar employees can be also interviewed as there is an ongoing debate regarding the emergence of job definitions and the fear of losing occupations with the Industry 4.0 technologies. Hence, hence these issues can be treated under social sustainability. Additionally, since the organizations functioning in Turkey are still struggling between Industry 2.0 and Industry 3.0, this study should be replicated in countries and/or organizations that have already applied Industry 4.0 applications and technologies within their manufacturing environments to reveal the effectiveness of these applications and technologies in creating a sustainable working environment.

REFERENCES

Agostini, L., & Filippini, R. (2019). Organizational and managerial challenges in the path toward Industry 4.0. *European Journal of Innovation Management*, *22*(3), 406-421.

Albertos, P., Sala, A., & Olivares, M. (1998). Fuzzy logic controllers. Advantages and drawbacks. In *VIII international congress of automatic control*, 14.09.1998, 833-844.

Alguliyev, R., Imamverdiyev, Y., & Sukhostat, L. (2018). Cyber-physical systems and their security issues. *Computers in Industry*, *100*, 212-223.

Allen, R. C. (2009). The British Industrial Revolution in Global Perspective. Cambridge: Cambridge University Press.

Almada-Lobo, F. (2015). The Industry 4.0 revolution and the future of Manufacturing Execution Systems (MES). Journal of innovation management, 3(4), 16-21.

Altan, Ş., & Karaş Aydin, E. (2015). Bulanık DEMATEL ve Bulanık TOPSIS Yöntemleri ile Üçüncü Parti Lojistik Firma Seçimi için Bütünleşik bir Model Yaklaşımı. Suleyman Demirel University Journal of Faculty of Economics & Administrative Sciences, 20(3).

Amadeo, K.. (2020) Vertical Integration: Pros, Cons, Examples. Retrieved from: https://www.thebalance.com/what-is-vertical-integration-3305807, (28.05. 2020).

Anderl, R., Haag, S., Schützer, K., & Zancul, E. (2018). Digital twin technology–Anapproach for Industrie 4.0 vertical and horizontal lifecycle integration. *it-Information Technology*, *60*(3), 125-132.

Ardito, L., Petruzzelli, A. M., Panniello, U., & Garavelli, A. C. (2019). Towards Industry 4.0: Mapping digital technologies for supply chain management-marketing integration. *Business Process Management Journal*, *25*(2), 323-346.

Aria, M. & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis, Journal of Informetrics, 11(4), 959-975.

Arowoshegbe, A. O., Emmanuel, U. (2016). Sustainability and triple bottom line: An overview of two interrelated concepts. *Igbinedion University Journal of Accounting*, *2*(16), 88-126.

Atkeson, A., & Kehoe, P. J. (2001). The transition to a new economy after the second industrial revolution. *National Bureau of Economic Research*., 1-55.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer networks*, *54*(15), 2787-2805.

Awasthi, A., Chauhan, S. S., & Omrani, H. (2011). Application of fuzzy TOPSIS in evaluating sustainable transportation systems. *Expert systems with Applications*, *38*(10), 12270-12280.

Ayres, R. U. (1989). Industrial metabolism. *Technology and environment*, *1989*, 23-49.

Azuma, R., Baillot, Y., Behringer, R., Feiner, S., Julier, S., & MacIntyre, B. (2001). Recent advances in augmented reality. *IEEE computer graphics and applications*, *21*(6), 34-47.

Baheti, R., & Gill, H. (2011). Cyber-physical systems. *The impact of control technology*, *12*(1), 161-166.

Bahrin, M. A. K., Othman, M. F., Azli, N. N., & Talib, M. F. (2016). Industry 4.0: A review on industrial automation and robotic. Jurnal Teknologi, 78(6-13), 137-143.

Bakkari, M., & Khatory, A. (2017). Industry 4.0: Strategy for more sustainable industrial development in SMEs. In Proceedings of the IEOM 7th International Conference on Industrial Engineering and Operations Management, Rabat, Morocco (pp. 11-13).

Balasooriya, P. N., Wibowo, S., & Wells, M. (2016). Green cloud computing and economics of the cloud: Moving towards sustainable future. *GSTF Journal on Computing (JoC)*, *5*(1), 15.

Bandyopadhyay, D., & Sen, J. (2011). Internet of things: Applications and challenges in technology and standardization. *Wireless personal communications*, *58*(1), 49-69.

Banerjee, A., Venkatasubramanian, K. K., Mukherjee, T., & Gupta, S. K. S. (2011). Ensuring safety, security, and sustainability of mission-critical cyber–physical systems. *Proceedings of the IEEE*, *100*(1), 283-299.

Banks, J. (1999). Introduction to simulation. In *Proceedings of the 31st conference on Winter simulation: Simulation---a bridge to the future-Volume 1* (pp. 7-13).

Barbier, E. B. (1987). The concept of sustainable economic development. *Environmental conservation*, *14*(2), 101-110.

Barzilay, M. (2013). A simple definition of cybersecurity. Retrieved from: http://www.isaca.org/Knowledge-Center/Blog/Lists/Posts/Post.aspx?ID=296, (01.06. 2020).

Bashar, D. A. (2020). Review on sustainable green Internet of Things and its application. *J. Sustain. Wireless Syst*, *1*(4), 256-264.

Bausys, R., Cavallaro, F., & Semenas, R. (2019). Application of sustainability principles for harsh environment exploration by autonomous robot. *Sustainability*, *11*(9), 2518.

Bekey, G. A. (2005). *Autonomous robots: from biological inspiration to implementation and control*. MIT press.

Belhadi, A., Zkik, K., Cherrafi, A., & Sha'ri, M. Y. (2019). Understanding big data analytics for manufacturing processes: insights from literature review and multiple case studies. *Computers & Industrial Engineering*, *137*, 106099.

Berman, B. (2012). 3-D printing: The new industrial revolution. Business horizons, 55(2), 155-162.

Bernard, H. R. (2017). *Research methods in anthropology: Qualitative and quantitative approaches*. Rowman & Littlefield.

Berryman, D. R. (2012). Augmented reality: a review. *Medical reference services quarterly*, *31*(2), 212-218.

Biocca, F. A., & Rolland, J. P. (1998). Virtual eyes can rearrange your body: Adaptation to visual displacement in see-through, head-mounted displays. *Presence*, *7*(3), 262-277.

Blunck, E., & Werthmann, H. (2017). Industry 4.0–An opportunity to realize sustainable manufacturing and its potential for a circular economy. In DIEM: Dubrovnik International Economic Meeting (Vol. 3, No. 1, pp. 644-666). Sveučilište u Dubrovniku.

Boboc, R. G., Gîrbacia, F., & Butilă, E. V. (2020). The application of augmented reality in the automotive industry: A systematic literature review. *Applied Sciences*, *10*(12), 4259.

Bock, T., Linner, T., (2012). Evolution of large-scale industrialization and Service - innovation in Japanese prefabrication industry. Construction Innovation.

Bonilla, S., Silva, H., Terra da Silva, M., Franco Gonçalves, R., & Sacomano, J. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability*, *10*(10), 3740.

Bottani, E., & Vignali, G. (2019). Augmented reality technology in the manufacturing industry: A review of the last decade. *IISE Transactions*, *51*(3), 284-310.

Brockett A, & Rezaee Z. (2012). Brief history of sustainability reporting. In *Corporate Sustainability: Integrating Performance and Reporting.* Hoboken NJ: John Wiley & Sons, Inc.: 27-35.

Brundtland, G.H. (1987). The United Nations World Commission on Environment and Development: Our Common Future, Oxford, UK.

Büchi, G., Cugno, M., & Castagnoli, R. (2020). Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, *150*, 119790.

Bugmann, G., Siegel, M., & Burcin, R. (2011). A role for robotics in sustainable development?. In *IEEE Africon'11* (pp. 1-4). IEEE.

Burinskiene, A., Lorenc, A., & Lerher, T. (2018). A simulation study for the sustainability and reduction of waste in warehouse logistics. *International Journal of Simulation Modelling*, *17*(3), 485-497.

Burke, R., Mussomeli, A., Laaper, S., Hartigan, M. Sniderman, B. (2017). The smart factory Responsive, adaptive, connected manufacturing A Deloitte series on Industry 4.0, digital manufacturing enterprises, and digital supply networks. Retrieved from: https://www2.deloitte.com/content/dam/insights/us/articles/4051_The-smart factory/DUP_The-smart-factory.pdf, (25.07. 2020).

Burritt, R., & Christ, K. (2016). Industry 4.0 and environmental accounting: a new revolution?. *Asian Journal of Sustainability and Social Responsibility*, *1*(1), 23.

Butt, J. (2020). Exploring the interrelationship between additive manufacturing and Industry 4.0. *Designs*, *4*(2), 13.

Büyüközkan, G., & Çifçi, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. *Expert Systems with Applications*, *39*(3), 3000-3011.

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

Büyüközkan, G., Çifçi, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Systems with Applications, 39(3), 3000-3011.

Calace, D. (2016). Battle of giants: GRI vs SASB vs IR. Retrieved from: https://www.greenbiz.com/article/battle-giants-gri-vs-sasb-vs-ir, (01.10. 2020).

Calace, D. (2017). The battle continues: GRI vs SASB vs IR. Retrieved from: https://www.greenbiz.com/article/battle-continues-gri-vs-sasb-vs-ir., (01.10. 2020).

Can, M. (2015). Karar Teorisi In Operasyonel, yönetsel ve stratejik problemlerin çözümünde çok kriterli karar verme yöntemleri. Editors Yıldırım, B. F., Önder, E. Dora Yayıncılık, 2, 15.

Carmigniani, J., Furht, B., Anisetti, M., Ceravolo, P., Damiani, E., & Ivkovic, M. (2011). Augmented reality technologies, systems and applications. *Multimedia tools and applications*, *51*(1), 341-377.

Carvalho, N., Chaim, O., Cazarini, E., & Gerolamo, M. (2018). Manufacturing in the fourth industrial revolution: A positive prospect in sustainable manufacturing. Procedia Manufacturing, 21, 671-678.

Caudell, T. & Mizell, D. (1992). Augmented reality: An application of heads-up display technology to manual manufacturing processes. In Hawaii international conference on system sciences (pp. 659-669).

Çengelci, B., & Çimen, H. (2005). Endüstriyel robotlar. *Makine Teknolojileri Elektronik Dergisi*, *2*(2), 69-78.

Ceruti, A., Marzocca, P., Liverani, A., & Bil, C. (2019). Maintenance in aeronautics in an Industry 4.0 context: The role of Augmented Reality and Additive Manufacturing. *Journal of Computational Design and Engineering*, *6*(4), 516-526.

Chandler, A. D. (1993). The Visible Hand: The Management Revolution in American Business. Belknap Press of Harvard University Press.

Chang, B., Chang, C. W., & Wu, C. H. (2011). Fuzzy DEMATEL method for developing supplier selection criteria. Expert systems with Applications, 38(3), 1850-1858.

Chang, M. H., Liou, J. J., & Lo, H. W. (2019). A hybrid MCDM model for evaluating strategic alliance partners in the green biopharmaceutical industry. *Sustainability*, *11*(15), 4065.

Chang, V., Issa, T., & Issa, T. (2011). Cloud computing and sustainability: an Australian public sector perspective. In *Proceedings of the XXII ISPIM conference*. International Society for Professional Innovation Management (ISPIM).

Chang, V., Wills, G., & De Roure, D. (2010). A review of cloud business models and sustainability. In *2010 IEEE 3rd International Conference on Cloud Computing* (pp. 43-50). IEEE.

Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M., & Yin, B. (2017). Smart factory of industry 4.0: Key technologies, application case, and challenges. *IEEE Access*, *6*, 6505-6519.

Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. International journal of production economics, 102(2), 289-301.

Chen, D., Heyer, S., Ibbotson, S., Salonitis, K., Steingrímsson, J. G., & Thiede, S. (2015). Direct digital manufacturing: definition, evolution, and sustainability implications. Journal of Cleaner Production, 107, 615-625.

Chen, M. F., & Tzeng, G. H. (2004). Combining grey relation and TOPSIS concepts for selecting an expatriate host country. Mathematical and computer modelling, 40(13), 1473-1490.

Chen, X. Y., & Jin, Z. G. (2012). Research on key technology and applications for internet of things. *Physics Procedia*, *33*, 561-566.

Chen-Yi, H., Ke-Ting, C., & Gwo-Hshiung, T. (2007). FMCDM with Fuzzy DEMATEL Approach for Customers' Choice Behavior Model. *International Journal of Fuzzy Systems*, *9*(4).

Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. *Production and Operations Management*, *27*(10), 1868-1883.

Chou, D. C. (2015). Cloud computing: A value creation model. *Computer Standards & Interfaces*, *38*, 72-77.

Christofi A, Christofi P, Sisaye S. (2012). Corporate sustainability: Historical development and reporting practices. Management Research Review 25(2): 157-172.

Chu, T. C. (2002). Selecting plant location via a fuzzy TOPSIS approach. The International Journal of Advanced Manufacturing Technology, 20(11), 859-864.

Chu, T. C., & Lin, Y. C. (2003). A fuzzy TOPSIS method for robot selection. *The International Journal of Advanced Manufacturing Technology*, *21*(4), 284-290.

Clark II, W. W., & Cooke, G. (2014). The Green industrial revolution. In *Global Sustainable Communities Handbook* (pp. 13-39). Butterworth-Heinemann.

Clemons, E. K., Wilson, J., & Jin, F. (2014). Investigations into consumers preferences concerning privacy: an initial step towards the development of modern and consistent privacy protections around the globe. In *2014 47th Hawaii International Conference on System Sciences* (pp. 4083-4092). IEEE.

Cohen, Y., Naseraldin, H., Chaudhuri, A., & Pilati, F. (2019). Assembly systems in Industry 4.0 era: a road map to understand Assembly 4.0. *The International Journal of Advanced Manufacturing Technology*, *105*(9), 4037-4054.

Cooper, C., & Kaplinsky, R. (Eds.). (2005). Technology and development in the third industrial revolution. Routledge.

Daunton, M. J. (1995). Progress and Poverty: An Economic and Social History of Britain, 1700–1850. Oxford University Press, Oxford.

de Man, J. C., & Strandhagen, J. O. (2017). An Industry 4.0 research agenda for sustainable business models. *Procedia Cirp*, *63*, 721-726.

De Pace, F., Manuri, F., & Sanna, A. (2018). Augmented reality in industry 4.0. *Am J ComptSci Inform Technol*, *6*(1), 17.

Deane, P. M., & Deane, P. M. (1979). The first industrial revolution. Cambridge University Press.

Dell, J, T Greiner and W Rosenstiel (2014). Model-based platform design and evaluation of cloud-based cyber-physical systems (CCPS). In 2014 12th IEEE Int. Conf. Industrial Informatics (INDIN), November 3, 2014, Porto Alegre, Brazil, pp. 376–381. IEEE.

Diesendorf, M. (2000). Sustainability and sustainable development. Sustainability: The corporate challenge of the 21st century, 2, 19-37.

Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., & Dolen, M. (2017). The role of additive manufacturing in the era of industry 4.0. *Procedia Manufacturing*, *11*, 545-554.

Dillon, T., Wu, C., & Chang, E. (2010). Cloud computing: issues and challenges. In *2010 24th IEEE international conference on advanced information networking and applications* (pp. 27-33).

Dinwiddy, J. (1979). Luddism and politics in the northern counties. *Social History*, *4*(1), 33-63.

Dornyei, Z. (2007). Research Methods in Applied Linguistics Oxford University Press. New York, 748.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability?. *Technological Forecasting and Social Change*, *144*, 534-545.

Dyllick, T., & Hockerts, K. (2002). Beyond the business case for corporate sustainability. *Business strategy and the environment*, *11*(2), 130-141.

Eden, L. (2018). The fourth industrial revolution: Seven lessons from the past. *International Business in the Information and Digital Age (Progress in International Business Research, Vol. 13), Emerald Publishing Limited*, 15-35.

Edwordle.net (2021). Retrieved from: http://www.edwordle.net/create.html#, (10.10. 2021).

Eizenberg, E., & Jabareen, Y. (2017). Social sustainability: A new conceptual framework. *Sustainability*, *9*(1), 68.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American journal of theoretical and applied statistics, 5(1), 1-4.

Elgendy, N., & Elragal, A. (2014). Big data analytics: a literature review paper. In *Industrial conference on data mining* (pp. 214-227). Springer, Cham.

Elkington, J. (1997). The triple bottom line. Environmental management: Readings and cases, 2.

Elliott, S. R. (2005). Sustainability: an economic perspective. *Resources, Conservation and Recycling*, *44*(3), 263-277.

Ellis, S. R., Breant, F., Manges, B., Jacoby, R., & Adelstein, B. D. (1997). Factors influencing operator interaction with virtual objects viewed via head-mounted see-through displays: viewing conditions and rendering latency. In *Proceedings of IEEE 1997 Annual International Symposium on Virtual Reality* (pp. 138-145). IEEE.

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of Manufacturing Systems*, *39*, 79-100.

Fahimi, F. (2009). Autonomous robots. Modeling, Path Planning and Control. Springer, New York.

Fahrner, W. R., Werner, M., & Job, R. (2001). Sensors and smart electronics in harsh environment applications. *Microsystem Technologies*, *7*(4), 138–144.

Finkelstein, J., & Newman, D. (1984). The third industrial revolution: a special challenge to managers. *Organizational Dynamics*, *13*(1), 53-65.

Fisher, T. (2015). Welcome to the Third Industrial Revolution: The Mass-Customisation of Architecture, Practice and Education. *Architectural Design*, *85*(4), 40-45.

Fite-Georgel, P. (2011). Is there a reality in industrial augmented reality?. In *2011 10th ieee international symposium on mixed and augmented reality* (pp. 201-210). IEEE.

Fitzgerald, J., & Quasney, E. (2017). Using Autonomous Robots to Drive Supply Chain Innovation. *Deloitte Perspectives*.

Fitzsimmons, J. (1994). Information technology and the third industrial revolution. *The Electronic Library*.

Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: an exploratory study of the advantages and challenges. Journal of cleaner Production, 137, 1573-1587.

Fortino, G., & Trunfio, P. (Eds.). (2014). *Internet of things based on smart objects: Technology, middleware and applications*. Springer Science & Business Media.

Fraga-Lamas, P., Fernández-Caramés, T. M., Blanco-Novoa, Ó., & Vilar-Montesinos, M. A. (2018). A review on industrial augmented reality systems for the industry 4.0 shipyard. *Ieee Access*, *6*, 13358-13375.

French, S. (1988). Reading in Decision Analysis. Chapman and Hall: London.

Freund, E., & Rossmann, J. (1994). Intelligent autonomous robots for industrial and space applications. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'94)* (Vol. 2, pp. 1072-1079). IEEE.

Gabus, A., & Fontela, E. (1972). World problems, an invitation to further thought within the framework of DEMATEL. Battelle Geneva Research Center, Geneva, Switzerland, 1-8.

Gabus, A., & Fontela, E. (1973). Perceptions of the world problematique: Communication procedure, communicating with those bearing collective responsibility. (DEMATEL report no. 1). Switzerland Geneva: Battelle Geneva Research Centre.

Galbi, D. A. (1994). Child Labor and the Division of Labor in the Early English Cotton Mills. Journal of Population Economics, 10 (4), 357–375.

Gao, W., Zhang, Y., Ramanujan, D., Ramani, K., Chen, Y., Williams, C. B., Wang, C.C.L., Shin, Y.C., Zhang, S, Zavattieri, P.D. (2015). The status, challenges, and future of additive manufacturing in engineering. *Computer-Aided Design*, *69*, 65-89.

Garg, S. K., & Buyya, R. (2012). Green cloud computing and environmental sustainability. *Harnessing Green IT: Principles and Practices*, *2012*, 315-340.

Garza, H., & Kurfess, T. (2018). A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing. *Manufacturing Letters*, *15,* 60-63.

Gattullo, M., Scurati, G. W., Fiorentino, M., Uva, A. E., Ferrise, F., & Bordegoni, M. (2019). Towards augmented reality manuals for industry 4.0: A methodology. *Robotics and Computer-Integrated Manufacturing*, *56,* 276-286.

Gibson, I., Rosen, D.W., & Stucker, B. (2010). Additive manufacturing technologies: Rapid prototyping to direct digital manufacturing (pp. 1–459).

Gillis, A. S. (2021). Triple Bottom Line. Retrieved from: https://whatis.techtarget.com/definition/triple-bottom-line-3BL, (05.10.2020)

Global Reporting Initiative (GRI). (2006). Sustainability reporting guidelines. Retrieved from: https://www.globalreporting.org/, (11.10.2020)

Goel, P. (2010). Triple bottom line reporting: An analytical approach for corporate sustainability. *Journal of Finance, Accounting, and Management*, *1*(1), 27-42.

Gong, C., Liu, J., Zhang, Q., Chen, H., & Gong, Z. (2010). The characteristics of cloud computing. In *2010 39th International Conference on Parallel Processing Workshops* (pp. 275-279). IEEE.

Goodland, R. (1995). The concept of environmental sustainability. *Annual review of ecology and systematics*, *26*(1), 1-24.

Gordon, R. J. (2012). Is US Economic Growth Over? Faltering Innovation Confronts the Six Headwinds. The Centre for Economic Policy Research, Policy Insight No. 63. North-western University, London.

Govindan, K., Sarkis, J., Jabbour, C. J. C., Zhu, Q., & Geng, Y. (2014). Eco-efficiency based green supply chain management: Current status and opportunities. *European Journal of Operational Research*, *233*(2), 293-298.

GRI (2016). Consolidated set of GRI Sustainability reporting standards 2016 Retrieved from: http://www.ekvilib.org/wp-content/uploads/2018/03/GRI-standardi-2016.pdf, (11.10.2020)

Grieves, M. (2014). Digital twin: manufacturing excellence through virtual factory replication. *Florida Institute of Technology, Tech. Rep.*, *1*, 1-7.

Griffin, E. (2010). Short History of the British Industrial Revolution. Palgrave Macmillan, New York, NY.

Gümüşoğlu, Ş. (2018). Bilimsel Yaklaşımlarla Değişim, Dönüşüm ve Kalite 4.0. *Dokuz Eylül Üniversitesi İktisadi İdari Bilimler Fakültesi Dergisi*, *33*(2), 543-568.

Gunal, M. M. (2019). Simulation for the Better: The Future in Industry 4.0. In *Simulation for Industry 4.0* (pp. 275-283). Springer, Cham.

Gunal, M. M., & Karatas, M. (2019). Industry 4.0, Digitisation in Manufacturing, and Simulation: A Review of the Literature. *Simulation for Industry 4.0*, 19-37.

Gunes, V., Peter, S., Givargis, T., & Vahid, F. (2014). A survey on concepts, applications, and challenges in cyber-physical systems. *KSII Transactions on Internet & Information Systems*, *8*(12).

Gupta, S. K., Mukherjee, T., Varsamopoulos, G., & Banerjee, A. (2011). Research directions in energy-sustainable cyber–physical systems. *Sustainable Computing: Informatics and Systems*, *1*(1), 57-74.

Gürdür, D., & Gradin, K. T. (2017). Interoperable toolchains in cyber-physical systems with a sustainability perspective. In *2017 IEEE conference on technologies for sustainability (SusTech)* (pp. 1-8). IEEE.

Haleem, A., & Javaid, M. (2019). Additive manufacturing applications in industry 4.0: a review. *Journal of Industrial Integration and Management*, *4*(04), 1930001.

Hansmann, R., Mieg, H. A., & Frischknecht, P. (2012). Principal sustainability components: empirical analysis of synergies between the three pillars of sustainability. *International Journal of Sustainable Development & World Ecology*, *19*(5), 451-459.

Hermann, M., Pentek, T., & Otto, B. (2015). Design principles for Industrie 4.0 scenarios: A literature review. Dortmund: Technische Universität Dortmund.

Himperich, F. (2007). Applications in Augmented Reality in the Automotive Industry. *Fachgebiet Augmented Reality, Department of Informatics*, 1-21.

Hozdić, E. (2015). Smart factory for industry 4.0: A review. *International Journal of Modern Manufacturing Technologies*, *7*(1), 28-35.

Holmström, J., Holweg, M., Khajavi, S.H., Partanen, J., (2016). The direct digital manufacturing (r)evolution: definition of a research agenda. Oper. Manag. Res. 9 (1–2), 1–10.

Hong, J., Shen, G. Q., Feng, Y., Lau, W. S. T., & Mao, C. (2015). Greenhouse gas emissions during the construction phase of a building: a case study in China. Journal of cleaner production, 103, 249-259.

Horcas, J. M., Pinto, M., & Fuentes, L. (2019). Context-aware energy-efficient applications for cyber-physical systems. *Ad Hoc Networks*, *82*, 15-30.

Huang, B. X. (2008). Cyber physical systems: a survey. *Presentation Report.*

Huang, Y., Leu, M. C., Mazumder, J., & Donmez, A. (2015). Additive manufacturing: current state, future potential, gaps and needs, and recommendations. *Journal of Manufacturing Science and Engineering*, *137*(1).

Huth, A., & Cebula, J. (2011). The basics of cloud computing. *United States Computer*.

Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58-191). Springer, Berlin, Heidelberg.

İpek, İ. & Hızarcı-Payne, A. (2020). Sorumlu Tüketim ve Üretim. In Madran C. & Tanyeri M. (Eds.) Sürdürülebilir Kalkınma Amaçları ile Kurumsal Dönüşüm (p 279-299) Akademisyen Kitabevi, Ankara.

Isaias, P., Issa, T., Chang, V., & Issa, T. (2015). Outlining the issues of cloud computing and sustainability opportunities and risks in European organizations: a SEM study. *Journal of Electronic Commerce in Organizations (JECO)*, *13*(4), 1-25.

ITU (2012). New ITU standards define the internet of things and provide the blueprints for its development. Retrieved from : https://www.itu.int/en/I TU-T/gsi/iot/Pages/default.aspx., (05.10.2020)

Jacob, M. C. (1997). Scientific Culture and the Making of the Industrial West. Oxford: Oxford University Press.

Jacobs, P., Gardner, J., & Munro, D. (1987). Sustainable and equitable development: An emerging paradigm. *Conservation with Equity: Strategies for Sustainable Development, International Union for Conservation of Nature and Natural Resources, Cambridge, UK*, 17-29.

Jadeja, Y., & Modi, K. (2012). Cloud computing-concepts, architecture and challenges. In *2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET)* (pp. 877-880). IEEE.

Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., & Young, T. (2010). Simulation in manufacturing and business: A review. *European journal of operational research*, *203*(1), 1-13.

Jänicke, M., & Jacob, K. (2009). A Third Industrial Revolution? Solutions to the crisis of resource-intensive growth. *Solutions to the Crisis of Resource-Intensive Growth*.

Jevons, H. (1931). The Second Industrial Revolution. *The Economic Journal, 41*(161), 1-18.

Kabir, G., & Hasin, M. (2012). Comparative Analysis Of TOPSIS and FUZZY TOPSIS for the Evaluation of Travel Website Service Quality. *International Journal for Quality Research*, *6*(3).

Kagermann, H., Helbig, J., Hellinger, A., & Wahlster, W. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group. *Forschungsunion.*

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. Process Safety and Environmental Protection, 117, 408-425.

Karvonen, E. (2001). *Informational societies: understanding the third industrial revolution*. Tampere University Press.

Kaya, T., & Kahraman, C. (2011). Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. *Expert Systems with Applications*, *38*(6), 6577-6585.

Khatua, P. K., Ramachandaramurthy, V. K., Kasinathan, P., Yong, J. Y., Pasupuleti, J., & Rajagopalan, A. (2020). Application and assessment of internet of things toward the sustainability of energy systems: Challenges and issues. *Sustainable Cities and Society*, *53*, 101957.

Kiel, D., Müller, J. M., Arnold, C., & Voigt, K. I. (2017). Sustainable industrial value creation: Benefits and challenges of industry 4.0. *International Journal of Innovation Management*, *21*(08), 1740015.

Kim, S. (2007). Immigration, Industrial Revolution and Urban Growth in the United States, 1820–1920: Factor Endowments, Technology and Geography. NBER Working Paper Series, Working Paper 12900, Washington, DC.

Kim, W. (2009). Cloud computing: Today and tomorrow. *J. Object Technol.*, *8*(1), 65-72.

Knorr, E., & Gruman, G. (2008). What cloud computing really means. *InfoWorld*, *7*(20-20), 1-17.

Kobryn, P.A., Ontko, N.R., Perkins, L.P., Tiley, J.S. (2006). Additive Manufacturing of Aerospace Alloys for Aircraft Structures. Air Force Research Lab Wright-Patterson AFB OH Materials and Manufacturing Directorate.

Koca, K. C. (2018). Industry 4.0: Chances and threats from the point of Turkey. Sosyoekonomi Journal, (26 (36)).

Kohl, J. L., van der Schoor, M. J., Syré, A. M., & Göhlich, D. (2020). Social Sustainability in the Development of Service Robots. In *Proceedings of the Design Society: DESIGN Conference* (Vol. 1, pp. 1949-1958). Cambridge University Press.

Kohtala, C. (2015). Addressing sustainability in research on distributed production: an integrated literature review. Journal of Cleaner Production, 106, 654-668.

Kopetz, H. (2011). Internet of things. In *Real-time systems* (pp. 307-323). Springer, Boston, MA.

Koren, Y., Gu, X., Badurdeen, F., & Jawahir, I. S. (2018). Sustainable living factories for next generation manufacturing. Procedia Manufacturing, 21, 26.

Korkmaz, E. (2020). İnsana Yakışır İş ve Ekonomik Büyüme. In Madran C. & Tanyeri M. (Eds.) Sürdürülebilir Kalkınma Amaçları ile Kurumsal Dönüşüm (pp. 185-207) Akademisyen Kitabevi, Ankara.

Kremer, H. (2021). End-to-end Supply Chain Management. Retrieved from: https://inchainge.com/knowledge/supply-chain/end-to-end/, (07.08.2020)

Kubick, W. R. (2012). Big data, information and meaning. *Applied Clinical Trials*, *21*(2), 26.

Kumar, V., & Vidhyalakshmi, P. (2012). Cloud computing for business sustainability. *Asia-Pacific Journal of Management Research and Innovation*, *8*(4), 461-474.

Kusmin, K. L. (2018). Industry 4.0. IFI8101-Information Society Approaches and ICT Processes.

Lee, E. A. (2015). The past, present and future of cyber-physical systems: A focus on models. *Sensors*, *15*(3), 4837-4869.

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing letters*, *3*, 18-23.

Leitao, P., Karnouskos, S., Ribeiro, L., Lee, J., Strasser, T., & Colombo, A. W. (2016). Smart agents in industrial cyber–physical systems. *Proceedings of the IEEE*, *104*(5), 1086-1101.

Li, G., Hou, Y., Wu, A., (2017). Fourth industrial revolution: technological drivers, impacts and coping methods. Chin. Geogr. Sci. 27 (4), 626–637.

Lin, K. P., Tseng, M. L., & Pai, P. F. (2018). Sustainable supply chain management using approximate fuzzy DEMATEL method. *Resources, Conservation and Recycling*, *128*, 134-142.

Lin, R. J. (2013). Using fuzzy DEMATEL to evaluate the green supply chain management practices. *Journal of Cleaner Production*, *40*, 32-39.

Liu, Y., & Xu, X. (2017). Industry 4.0 and cloud manufacturing: A comparative analysis. *Journal of Manufacturing Science and Engineering*, *139*(3).

Liu, Y., Peng, Y., Wang, B., Yao, S., & Liu, Z. (2017). Review on cyber-physical systems. *IEEE/CAA Journal of Automatica Sinica*, *4*(1), 27-40.

Lowrey, A. (2018). *Give People Money - How a Universal Basic Income Would End Poverty, Revolutionize Work, and Remake the World*, Crown, New York City.

Lucke, D., Constantinescu, C., & Westkämper, E. (2008). Smart factory-a step towards the next generation of manufacturing. In *Manufacturing systems and technologies for the new frontier* (pp. 115-118). Springer, London.

Lv, Z., Iqbal, R., & Chang, V. (2018). Big data analytics for sustainability. Future Generation Computer Systems, 86, 1238-1241.

Mabkhot, M. M., Al-Ahmari, A. M., Salah, B., & Alkhalefah, H. (2018). Requirements of the smart factory system: a survey and perspective. *Machines*, *6*(2), 23.

Madran, C. (2020). İklim Eylemi. In Madran C. & Tanyeri M. (Eds.) Sürdürülebilir Kalkınma Amaçları ile Kurumsal Dönüşüm (pp. 299-331) Akademisyen Kitabevi, Ankara.

Maksimovic, M. (2018). Greening the future: Green Internet of Things (G-IoT) as a key technological enabler of sustainable development. In *Internet of things and big data analytics toward next-generation intelligence* (pp. 283-313). Springer, Cham.

Maldonado-Macías, A., Alvarado, A., García, J. L., & Balderrama, C. O. (2014). Intuitionistic fuzzy TOPSIS for ergonomic compatibility evaluation of advanced manufacturing technology. *The International Journal of Advanced Manufacturing Technology*, *70*(9-12), 2283-2292.

Mani, M., Lyons, K. W., & Gupta, S. K. (2014). Sustainability characterization for additive manufacturing. Journal of research of the National Institute of Standards and Technology, 119, 419.

Mani, V., Delgado, C., Hazen, B. T., & Patel, P. (2017). Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain. *Sustainability*, *9*(4), 608.

Marjani, M., Nasaruddin, F., Gani, A., Karim, A., Hashem, I. A. T., Siddiqa, A., & Yaqoob, I. (2017). Big IoT data analytics: architecture, opportunities, and open research challenges. *IEEE Access*, *5*, 5247-5261.

Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., & Ghalsasi, A. (2011). Cloud computing—The business perspective. *Decision support systems*, *51*(1), 176-189.

Martín, A. M., Marcos, M., Aguayo, F., & Lama, J. R. (2017). Smart Industrial Metabolism: a literature review and future directions. Procedia Manufacturing, 13, 1223-1228.

Masood, T., & Egger, J. (2019). Augmented reality in support of Industry 4.0—Implementation challenges and success factors. *Robotics and Computer-Integrated Manufacturing*, *58*, 181-195.

Mattern, F., & Floerkemeier, C. (2010). From the Internet of Computers to the Internet of Things. In *From active data management to event-based systems and more* (pp. 242-259). Springer, Berlin, Heidelberg.

McKinsey and Company (2017). *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, McKinsey & Company, New York City.

Mehrpouya, M., Dehghanghadikolaei, A., Fotovvati, B., Vosooghnia, A., Emamian, S. S., & Gisario, A. (2019). The potential of additive manufacturing in the smart factory industrial 4.0: A review. *Applied Sciences*, *9*(18), 3865.

Mell, P., & Grance, T. (2009). Draft nist working definition of cloud computing-v15. *21. Aug 2009*, *2*, 123-135.

Mellos, K. (1988). Theory of eco-development. In *Perspectives on ecology* (pp. 59-74). Palgrave Macmillan, London.

Meseguer-Sánchez, V., Gálvez-Sánchez, F. J., López-Martínez, G., & Molina-Moreno, V. (2021). Corporate Social Responsibility and Sustainability. A Bibliometric Analysis of Their Interrelations. *Sustainability*, *13*(4), 1636.

Milgram, P., & Kishino, F. (1994). A taxonomy of mixed reality visual displays. *IEICE TRANSACTIONS on Information and Systems*, *77*(12), 1321-1329.

Mills, S., Lucas, S., Irakliotis, L., Rappa, M., Carlson, T., & Perlowitz, B. (2012). Demystifying big data: a practical guide to transforming the business of government. *TechAmerica Foundation, Washington*.

Mitchell, W. J., Borroni-Bird, C. E., & Burns, L. D. (2010). *Reinventing the automobile: Personal urban mobility for the 21st century*. Cambridge: MIT Press.

Mohajan, H. K. (2013). Global Greenhouse Gas Emissions and Climate Change. Lambert Academic Publishing, Germany.

Mohamed, A. M. O., & Antia, H. E. (1998). *Geoenvironmental engineering*. Elsevier.

Mokyr, J. (1998). The second industrial revolution, 1870-1914. *Storia dell'economia Mondiale, 21945*.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W. & Ueda, K. (2016). Cyber-physical systems in manufacturing. *Cirp Annals, 65*(2), 621-641.

Moon, Y. B. (2017). Simulation modelling for sustainability: a review of the literature. *International Journal of Sustainable Engineering*, *10*(1), 2-19.

Morrar, R., Arman, H., & Mousa, S. (2017). The fourth industrial revolution (Industry 4.0): A social innovation perspective. Technology Innovation Management Review, 7(11), 12-20.

Morrow,W.R., Qi, H., Kim, I., Mazumder, J., Skerlos, S.J. (2007). Environmental aspects of laser-based and conventional tool and die manufacturing. J. Clean. Prod. 15 (10), 932-943.

Moyne, J., & Iskandar, J. (2017). Big data analytics for smart manufacturing: Case studies in semiconductor manufacturing. *Processes*, *5*(3), 39.

Mukhopadhyay, S. C., & Suryadevara, N. K. (2014). Internet of things: Challenges and opportunities. In *Internet of Things* (pp. 1-17). Springer, Cham.

Müller, J. M., Kiel, D., & Voigt, K. I. (2018). What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability*, *10*(1), 247.

Mulliner, E., Smallbone, K., & Maliene, V. (2013). An assessment of sustainable housing affordability using a multiple criteria decision making method. *Omega, 41*(2), 270-279.

Munier, N. (2005). Introduction to sustainability: road to a better future. Springer, Netherlands.

Nădăban, S., Dzitac, S., & Dzitac, I. (2016). Fuzzy TOPSIS: a general view. Procedia computer science, 91, 823-831.

Nagasawa, T., Pillay, C., Beier, G., Fritzsche, K., Pougel, F., Takama, T., & Bobashev, I. (2017). Accelerating Clean Energy through Industry 4.0: Manufacturing the Next Revolution. *A Report of the United Nations Industrial Development Organization*.

Nahavandi, S. (2019). Industry 5.0—A human-centric solution. *Sustainability, 11*(16), 4371.

Naik, S. S., Chakravorty, S., & Kulkarni, N. (2010). A review of vertical and horizontal integration in a manufacturing environment. In *IIE Annual Conference. Proceedings* (p. 1). Institute of Industrial and Systems Engineers (IISE).

Ngo, T. D., Kashani, A., Imbalzano, G., Nguyen, K. T., & Hui, D. (2018). Additive manufacturing (3D printing): A review of materials, methods, applications and challenges. *Composites Part B: Engineering*, *143*, 172-196.

Nižetić, S., Šolić, P., González-de, D. L. D. I., & Patrono, L. (2020). Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future. *Journal of Cleaner Production*, *274*, 122877.

North, D. W. (1968). A tutorial introduction to decision theory. IEEE transactions on systems science and cybernetics, 4(3), 200-210.

O. Nyumba, T., Wilson, K., Derrick, C. J., & Mukherjee, N. (2018). The use of focus group discussion methodology: Insights from two decades of application in conservation. *Methods in Ecology and evolution*, *9*(1), 20-32.

Ocampo, L., Deiparine, C. B., & Go, A. L. (2020). Mapping strategy to best practices for sustainable food manufacturing using fuzzy DEMATEL-ANP-TOPSIS. *Engineering Management Journal*, *32*(2), 130-150.

Organ, A. (2013). Bulanık DEMATEL yöntemiyle makine seçimini etkileyen kriterlerin değerlendirilmesi. Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 22(1), 157–172.

Osterrieder, P., Budde, L., & Friedli, T. (2020). The smart factory as a key construct of industry 4.0: A systematic literature review. *International Journal of Production Economics*, *221*, 107476.

Özbek, A. (2017). Çok kriterli karar verme yöntemleri ve excel ile problem çözümü. Seçkin Yayıncılık, Ankara.

Özbekler, T. M., & Akgül, A. K. (2020). An Ex-Ante Assessment of City Distribution Alternatives Based on Multi Actor Multi Criteria Framework. *Business & Management Studies: An International Journal*, *8*(5), 4241-4272.

Özdağoğlu A. & Yılmaz, K. (2020). Erişilebilir ve Temiz Enerji. In Madran C. & Tanyeri M. (Eds.) Sürdürülebilir Kalkınma Amaçları ile Kurumsal Dönüşüm (p 207-231). Akademisyen Kitabevi, Ankara.

Özdağoğlu, A., & Güler, M. E. (2016). E-Service Quality of Internet Based Banking Using Combined Fuzzy Ahp and Fuzzy Topsis. *Tehnicki vjesnik/Technical Gazette*, *23*(4).

Özdağoğlu, A., Keleş, M. K., & Işıldak, B. (2021). Havalimanlarının Bulanık Dematel ve Mabac Yöntemleri ile Sıralanması. Omer Halisdemir Universitesi Iktisadi ve Idari Bilimler Fakültesi Dergisi, 14(1).

Özdoğan, O. (2017). Endüstri 4.0: Dördüncü Sanayi Devrimi ve Endüstriyel Dönüşümün Anahtarları. Pusula.

Palczewski, K., & Sałabun, W. (2019). The fuzzy TOPSIS applications in the last decade. Procedia Computer Science, 159, 2294-2303.

Pan, M., Linner, T., Pan, W., Cheng, H., & Bock, T. (2018). A framework of indicators for assessing construction automation and robotics in the sustainability context. *Journal of Cleaner Production*, *182*, 82-95.

Paris, H., Mokhtarian, H., Coatanéa, E., Museau, M., & Ituarte, I. F. (2016). Comparative environmental impacts of additive and subtractive manufacturing technologies. *CIRP Annals*, *65*(1), 29-32.

Patton, M. Q. (2014). *Qualitative research & evaluation methods: Integrating theory and practice*. Sage publications.

Peng, T., Kellens, K., Tang, R., Chen, C., & Chen, G. (2018). Sustainability of additive manufacturing: An overview on its energy demand and environmental impact. *Additive Manufacturing*, *21*, 694-704.

Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. Procedia Manufacturing, 13, 1206-1214.

Pérez-Lara, M., Saucedo-Martínez, J. A., Marmolejo-Saucedo, J. A., Salais-Fierro, T. E., & Vasant, P. (2018). Vertical and horizontal integration systems in Industry 4.0. *Wireless Networks*, 1-9.

Perner, P. (Ed.). (2014). Advances in Data Mining: Applications and Theoretical Aspects: 14th Industrial Conference, *ICDM 2014, St. Petersburg, Russia, July 16-20, 2014, Proceedings* (Vol. 8557). Springer.

Petrovic, I., & Kankaras, M. (2020). A hybridized IT2FS-DEMATEL-AHP-TOPSIS multicriteria decision making approach: Case study of selection and evaluation of criteria for determination of air traffic control radar position. *Decision Making: Applications in Management and Engineering*, *3*(1), 146-164.

Pinzone, M., Albe, F., Orlandelli, D., Barletta, I., Berlin, C., Johansson, B., & Taisch, M. (2020). A framework for operative and social sustainability functionalities in Human-Centric Cyber-Physical Production Systems. *Computers & Industrial Engineering*, *139*, 105132.

Popovic, T., Kraslawski, A., & Avramenko, Y. (2013). Applicability of sustainability indicators to wastewater treatment processes. In *Computer Aided Chemical Engineering* (Vol. 32, pp. 931-936). Elsevier.

Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., De Amicis, R. et al. (2015). Visual computing as a key enabling technology for industrie 4.0 and industrial internet. Computer Graphics and Applications, IEEE, 35(2), 26-40.

Prakash, K. S., Nancharaih, T., & Rao, V. S. (2018). Additive manufacturing techniques in manufacturing-an overview. *Materials Today: Proceedings*, *5*(2), 3873-3882.

Prause, G. (2015). Sustainable business models and structures for Industry 4.0. *Journal of Security & Sustainability Issues*, *5*(2).

Purvis, B., Mao, Y., & Robinson, D. (2019). Three pillars of sustainability: in search of conceptual origins. *Sustainability science*, *14*(3), 681-695.

Qin, S. J. (2014). Process data analytics in the era of big data. AIChE Journal, 60(9), 3092-3100.

Radziwon, A., Bilberg, A., Bogers, M., & Madsen, E. S. (2014). The smart factory: exploring adaptive and flexible manufacturing solutions. *Procedia engineering*, *69*, 1184-1190.

Rahman, S. M., Perry, N., Müller, J. M., Kim, J., & Laratte, B. (2020). End-of-life in industry 4.0: ignored as before?. *Resources, Conservation and Recycling*, *154*, 104539.

Rajak, M., & Shaw, K. (2019). Evaluation and selection of mobile health (mHealth) applications using AHP and fuzzy TOPSIS. Technology in Society, 59, 101186.

Rajkumar, R., Lee, I., Sha, L., & Stankovic, J. (2010). Cyber-physical systems: the next computing revolution. In *Design automation conference* (pp. 731-736). IEEE.

Rapoport, A. (1998). Decision theory and decision behaviour. Springer.

Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P., & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of cleaner production*, *224*, 10-24.

Reeves, P. (2009). Additive Manufacturingea Supply Chain Wide Response to Economic Uncertainty and Environmental Sustainability. Econolyst Limited, The Silversmiths, Crown Yard, Wirksworth, Derbyshire, DE4 4ET, UK.

Rifkin, J. (2011). The third industrial revolution: how lateral power is transforming energy, the economy, and the world. Macmillan.

Rifkin, J. (2012). The third industrial revolution: How the internet, green electricity, and 3-d printing are ushering in a sustainable era of distributed capitalism. *World Financial Review*, *1*(1), 4052-4057.

Rose, K., Eldridge, S., & Chapin, L. (2015). The internet of things: An overview. *The internet society (ISOC)*, *80*, 1-50.

Russel, R. S., & Taylor III, B. W. (2003). *Operations management: focusing on quality and competitiveness*.

Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). *Industry 4.0: The future of productivity and growth in manufacturing industries.* Boston Consulting Group, 9.

Russom, P., & Analytics, B. D. (2011). TDWI best practices report. *Fourth quarter*, *19*(4), 1-34.

Saidani, M., Pan, E., Kim, H., Greenlee, A., Wattonville, J., Yannou, B., ... & Cluzel, F. (2020). Assessing the environmental and economic sustainability of autonomous systems: A case study in the agricultural industry. *Procedia CIRP*, *90*, 209-214.

Salah, B., Abidi, M. H., Mian, S. H., Krid, M., Alkhalefah, H., & Abdo, A. (2019). Virtual reality-based engineering education to enhance manufacturing sustainability in industry 4.0. *Sustainability*, *11*(5), 1477.

Sangaiah, A. K., Gopal, J., Basu, A., & Subramaniam, P. R. (2017). An integrated fuzzy DEMATEL, TOPSIS, and ELECTRE approach for evaluating knowledge transfer effectiveness with reference to GSD project outcome. *Neural Computing and Applications*, *28*(1), 111-123.

Savitz, A. (2013). The triple bottom line: how today's best-run companies are achieving economic, social and environmental success-and how you can too. John Wiley & Sons.

Schmidheiny, S., & Timberlake, L. (1992). *Changing course: A global business perspective on development and the environment* (Vol. 1). MIT press.

Schneider, S. (2019). The impacts of digital technologies on innovating for sustainability. In *Innovation for sustainability* (pp. 415-433). Palgrave Macmillan, Cham.

Schwab, K. (2016). The Fourth Industrial Revolution, World Economic Forum.

Şengül, Ü., Eren, M., Shiraz, S. E., Gezder, V., & Şengül, A. B. (2015). Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. Renewable energy, 75, 617-625.

Shanmuganathan, M., Kajendran, K., Sasikumar, A. N., & Mahendran, M. (2018). Multi Attribute Utility Theory–An Over View. International Journal of Scientific & Engineering Research Volume 9, Issue 3.

Serpanos, D. (2018). The cyber-physical systems revolution. *Computer*, *51*(3), 70-73.

Shi, Z., Xie, Y., Xue, W., Chen, Y., Fu, L., & Xu, X. (2020). Smart factory in Industry 4.0. *Systems Research and Behavioral Science*, *37*(4), 607-617.

Six, L., Velghe, F., Verstichel, S., & De Meester, S. (2016). Sustainability considerations on the valorization of organic waste. In *Biotransformation of agricultural waste and by-products* (pp. 287-307). Elsevier.

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

Stock, T., Obenaus, M., Kunz, S., & Kohl, H. (2018). Industry 4.0 as enabler for a sustainable development: A qualitative assessment of its ecological and social potential. Process Safety and Environmental Protection, 118, 254-267.

Strandhagen, J. W., Alfnes, E., Strandhagen, J. O., & Vallandingham, L. R. (2017). The fit of Industry 4.0 applications in manufacturing logistics: a multiple case study. *Advances in Manufacturing*, *5*(4), 344-358.

Strozzi, F., Colicchia, C., Creazza, A., & Noè, C. (2017). Literature review on the 'Smart Factory'concept using bibliometric tools. *International Journal of Production Research*, *55*(22), 6572-6591.

Tonge, A. M., Kasture, S. S., & Chaudhari, S. R. (2013). Cyber security: challenges for society-literature review. *IOSR Journal of computer Engineering*, *12*(2), 67-75.

Tsai, C. W., Lai, C. F., Chao, H. C., & Vasilakos, A. V. (2015). Big data analytics: a survey. *Journal of Big data*, *2*(1), 1-32.

TÜSİAD (2016). *Türkiye'nin Küresel Rekabetçiliği İçin Bir GereklilikOlarak Sanayi 4.0 – Gelişmekte Olan Ekonomi*. Retrieved from: http://tusiad.org/tr/tum/item/8671-turkiyenin-sanayi-40-donusumu, (09.05.2018)

UNDP (2021). Sustainable Development Goals. Retrieved from: https://sdgs.un.org/goals, (21.05.2020)

Usher, A. P. (1920). An Introduction to the Industrial History of England. Michigan: University of Michigan Press.

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

Valdez, A. C., Brauner, P., Schaar, A. K., Holzinger, A., & Zieflea, M. (2015). Reducing Complexity with simplicity-Usability Methods for Industry 4.0. Proceedings 19th Triennial Congress of the IEA. Melbourne, Australia, RWTH Publications, Germany. 9-14.

Vallance, S., Perkins, H. C., & Dixon, J. E. (2011). What is social sustainability? A clarification of concepts. *Geoforum*, *42*(3), 342-348.

Vinodh, S., & Swarnakar, V. (2015). Lean Six Sigma project selection using hybrid approach based on fuzzy DEMATEL–ANP–TOPSIS. *International Journal of Lean Six Sigma*.

Vinodh, S., Balagi, T. S., & Patil, A. (2016). A hybrid MCDM approach for agile concept selection using fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS. *The International Journal of Advanced Manufacturing Technology*, *83*(9-12), 1979-1987.

Von Winterfeldt, D. and W. Edwards (1986). Decision Analysis and Behavioural Research. Cambridge University Press: Cambridge.

Voss, A. (2010). Cloud computing. Retrieved from: https://www.itapa.sk/data/att/628.pdf, (11.04.2020)

Walls, A., Perkins, E., & Weiss, J. (2013). Definition: Cybersecurity, 5. Retrieved from: https://www.gartner.com/doc/2510116/definition cybersecurity, (06.03.2020)

Wamala, F. (2011). *ITU National Cybersecurity Strategy Guide*. Retrieved from: http://www.itu.int/ITUD/cyb/cybersecurity/docs/itu-nationalcybersecurity-guide.pdf, (06.03.2020)

Wang, L., Von Laszewski, G., Younge, A., He, X., Kunze, M., Tao, J., & Fu, C. (2010). Cloud computing: a perspective study. *New generation computing*, *28*(2), 137-146.

Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016a). Implementing smart factory of industrie 4.0: an outlook. *International journal of distributed sensor networks*, *12*(1), 3159805.

Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016b). Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. *Computer Networks*, *101*, 158-168.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3-13.

Wang, Z., Song, H., Watkins, D. W., Ong, K. G., Xue, P., Yang, Q., & Shi, X. (2015). Cyber-physical systems for water sustainability: challenges and opportunities. *IEEE Communications Magazine*, *53*(5), 216-222.

Watson, D. P., & Scheidt, D. H. (2005). Autonomous systems. *Johns Hopkins APL technical digest*, *26*(4), 368-376.

Watson, H. J. (2014). Tutorial: Big data analytics: Concepts, technologies, and applications. *Communications of the Association for Information Systems*, *34*(1), 65.

Watson, J. K., & Taminger, K. M. B. (2018). A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption. *Journal of Cleaner Production*, *176*, 1316-1322.

Wichmann, R. L., Eisenbart, B., & Gericke, K. (2019). The Direction of Industry: A Literature Review on Industry 4.0. In *Proceedings of the Design Society: International Conference on Engineering Design* (Vol. 1, No. 1, pp. 2129-2138). Cambridge University Press.

Widok, A. H., & Wohlgemuth, V. (2011). Simulation and Sustainability Enhancing Event-Discrete-Simulation Software with Sustainability Criteria.

Wong, C., Yang, E., Yan, X.-T., & Gu, D. (2018). Autonomous robots for harsh environments: a holistic overview of current solutions and ongoing challenges. *Systems Science & Control Engineering*, *6*(1), 213–219.

Wortmann, F., & Flüchter, K. (2015). Internet of things. *Business & Information Systems Engineering*, *57*(3), 221-224.

Wu, W. W., & Lee, Y. T. (2007). Developing global managers' competencies using the fuzzy DEMATEL method. Expert systems with applications, 32(2), 499-507.

Xiaojiang, X., Jianli, W., & Mingdong, L. (2020). Services and key technologies of the Internet of Things. *ZTE Communications*, *8*(2), 26-29.

Xu, M., Gao, D., Chao Deng, Zhiguo Luo, and Shaoling Sun. (2009). Cloud Computing Boosts Business Intelligence of Telecommunication Industry. *Cloud Computing: First International Conference, CloudCom 2009, Beijing, China, December 1-4, 2009, Proceedings* (Vol. 5931). Springer.

Yang, J. L., & Tzeng, G. H. (2011). An integrated MCDM technique combined with DEMATEL for a novel cluster-weighted with ANP method. *Expert Systems with Applications*, *38*(3), 1417-1424.

Yelis, B. (2021). Yatay ve Dikey Entegrasyon Nedir? Retrieved from: https://www.endustri40.com/yatay-ve-dikey-entegrasyon-nedir/, (13.06.2020).

Yılmaz, F. (2018). Robotlar Hayatımızda. *FSM İlmî Araştırmalar İnsan ve Toplum Bilimleri Dergisi*, (12), 109-120.

Yılmaz, K. & Özdağoğlu A (2020). Sanayi, Yenilikçilik ve Altyapı. In Madran C. & Tanyeri M. (Eds.) Sürdürülebilir Kalkınma Amaçları ile Kurumsal Dönüşüm (p 162-185) Akademisyen Kitabevi, Ankara.

Yu, C., Xu, X., Lu, Y., (2015). Computer-integrated manufacturing, cyber-physical systems and cloud manufacturing–concepts and relationships. Manuf. Lett. 6, 5–9.

Zadeh, L. A. (1996). Fuzzy sets. In *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh* (pp. 394-432).

Zhang, D., Pan, S. L., Yu, J., & Liu, W. (2019). Orchestrating big data analytics capability for sustainability: A study of air pollution management in China. Information & Management, 103231.

Zhang, X., & Su, J. (2019). A combined fuzzy DEMATEL and TOPSIS approach for estimating participants in knowledge-intensive crowdsourcing. *Computers & Industrial Engineering*, *137*, 106085.

Zhang, Y., Ren, S., Liu, Y., Si, S., (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. J. Clean. Prod. 142, 626–641.

Zhang, Z., Li, X., Wang, X., & Cheng, H. (2017). Decentralized cyber-physical systems: A paradigm for cloud-based smart factory of Industry 4.0. In *Cybersecurity for Industry 4.0* (pp. 127-171). Springer, Cham.

Zhao, H., Zhao, Q. H., & Ślusarczyk, B. (2019). Sustainability and Digitalization of Corporate Management Based on Augmented/Virtual Reality Tools Usage: China and Other World IT Companies' Experience. *Sustainability*, *11*(17), 4717.

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of industry 4.0: a review. Engineering, 3(5), 616-630.

Zhou, K., Liu, T., & Zhou, L. (2015). Industry 4.0: Towards future industrial opportunities and challenges. In *2015 12th International conference on fuzzy systems and knowledge discovery (FSKD)* (pp. 2147-2152). IEEE.

Zhou, Q., Huang, W., & Zhang, Y. (2011). Identifying critical success factors in emergency management using a fuzzy DEMATEL method. *Safety science*, *49*(2), 243-252.

Zhu, Z., Branzoi, V., Wolverton, M., Murray, G., Vitovitch, N., Yarnall, L., ... & Kumar, R. (2014). AR-mentor: Augmented reality based mentoring system. In *2014 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (pp. 17-22). IEEE.

Zubizarreta, J., Aguinaga, I., & Amundarain, A. (2019). A framework for augmented reality guidance in industry. *The International Journal of Advanced Manufacturing Technology*, *102*(9-12), 4095-4108.

APPENDICES

Appendix 1. Questionnaire Form

SÜRDÜRÜLEBİLİRLİK BOYUTLARI DEĞERLENDİRME FORMU

Sayın Katılımcı,

İşletmenin kurumsal sürdürülebilirlik kapsamında süreçlerine dahil ettiği sosyal, çevresel ve ekonomik sürdürülebilirlik boyutlarında yer alan kriterlerin birbirleri üzerindeki etkilerini saptamak amacıyla yapılan bu ankete katılmanız, araştırmada doğru bilgiler elde etme bakımından son derece önemlidir. Elde edilecek bilgiler, GİZLİ tutulacak olup; sadece bilimsel amaçlarla kullanılacaktır. Talep etmeniz durumunda çalışmanın çıktıları sizlere de gönderilecektir. İşbirliğiniz ve katkılarınız için teşekkür eder, saygılar sunarız.

Doç.Dr. Aşkın Özdağoğlu

Araş. Gör. Elif Çirkin

Ölçek

Sayısal Değer	Sözel İfade
0	Etkisiz
1	Çok Az Etkili
2	Az Etkili
3	Orta Etkili
4	Fazla Etkili
5	Çok Fazla Etkili

Kriter ağırlıklarını belirlemek amacıyla kriterlerin birbirleri üzerindeki etkileri yukarıdaki tabloda verilen ölçek yardımı ile tespit edilmektedir. Yukarıda yer alan ölçek kullanılarak doldurulmuş olan örnek matris aşağıda gösterilmiştir.

Örnek Uygulama

	Kriter 1	Kriter 2	Kriter 3
Kriter 1	0	3	4
Kriter 2	2	0	2
Kriter 3	1	1	0

Örnek uygulamadaki değerleri açıklamak gerekirse, **kriter 1 satırı ile kriter 2 sütununun kesiştiği hücrede yer alan 3 değeri kriter 1'in kriter2 üzerinde orta düzeyde etkili olduğunu ifade etmektedir. Kriter 2 satırı ile kriter 1 sütununun kesişimindeki 2**

değeri ise kriter 2'nin kriter 1 üzerinde az etkisi olduğunu göstermektedir. Kriter 1 satırı ile kriter 3 sütununun kesiştiği hücrede yer alan 4 değeri kriter 1'in kriter 3 üzerinde çok fazla etkisi olduğunu ifade etmektedir.

Aşağıda yer alan kriterlerin önem derecelerini belirlemek üzere, yukarıdaki açıklamalı örneğe göre aşağıdaki matrisleri doldurmanızı rica ederiz.

A	**Sosyal Sürdürülebilirlik**
A1	İş Yeri Güvenliğinin Sağlanması
A2	Çalışma Standartlarının ve Koşullarının İyileştirilmesi (Çalışma saatleri vb. gibi)
A3	Yeni İş Tanımlarının Ortaya Çıkması (Robot mühendisliği, ağ geliştirme mühendisliği, büyük veri uzmanlığı, veri güvenliği analistliği vb. gibi)
A4	Nitelikli İş Gücü İhtiyacının Oluşması (Kas/emek yoğundan zihin yoğun işlere doğru yönelim)
A5	İşçi ve İşverenin Sosyal Refahının Artırılması

B	**Ekonomik Sürdürülebilirlik**
B1	Karlılık Oranının Artırılması
B2	Maliyetlerin Azaltılması (Operasyonel, işçilik, bakım maliyetleri vb. gibi)
B3	Üretimde Verimlilik Sağlanması
B4	Üretimde Esneklik Sağlanması
B5	Üretimde Kalite Kontrol ve Güvencenin Artırılması (Hata paylarının azaltılması, fire, atık vb. azaltılması gibi)
B6	Üretim, Sipariş ve Teslimat Sürelerinin Kısaltılması
B7	Rekabet Edilebilirliğin Artırılması
B8	Üretimde Şeffaflık ve İzlenebilirlik Sağlanması
B9	Süreç Optimizasyonu Sağlanması (Sürekli iyileştirme, yalın üretim, kaizen vb. gibi)
B10	Üretimde Standardizasyon Sağlanması

C	**Çevresel Sürdürülebilirlik**
C1	Yenilenebilir Enerji Kaynaklarının Kullanımının Artırılması
C2	Çevresel Kirlilik Önleme, Yönetim ve Kontrol (Hava, su, toprak, gürültü vb.)
C3	Geri Kazanım, Geri Dönüşüm ve Yeniden Kullanım Oranlarının Artırılması (Atık Yönetimi)
C4	Sera Gazı Salınımlarının Azaltılması (Karbon ayak izi azaltılması, Sera Gazları: C02, Metan vb. gibi atmosferde ısı tutma özelliğine sahip bileşiklerdir.)
C5	Kaynak ve Enerji Kullanımında Verimlilik Sağlanması
C6	Yeşil İnovatif Stratejilerin Geliştirilmesi

1. KRİTERLER ARASINDAKİ İLİŞKİNİN BELİRLENMESİNE DAİR MATRİSLER

ANA KRİTERLER	**Sosyal Sürdürülebilirlik**	**Ekonomik Sürdürülebilirlik**	**Çevresel Sürdürülebilirlik**
Sosyal Sürdürülebilirlik	0		
Ekonomik Sürdürülebilirlik		0	
Çevresel Sürdürülebilirlik			0

SOSYAL SÜRDÜRÜLEBİLİRLİK ALT KRİTERLERİ	İş Yeri Güvenliği Sağlanması	Çalışma Standartlarının ve Koşullarının İyileştirilmesi	Yeni İş Tanımlarının Ortaya Çıkması	Nitelikli İş Gücü İhtiyacının Oluşması	İşçi ve İşverenin Sosyal Refahının Artırılması
İş Yeri Güvenliği Sağlanması	0				
Çalışma Standartlarının ve Koşullarının İyileştirilmesi		0			
Yeni İş Tanımlarının Ortaya Çıkması			0		
Nitelikli İş Gücü İhtiyacının Oluşması				0	
İşçi ve İşverenin Sosyal Refahının Artırılması					0

EKONOMİK SÜRDÜRÜLEBİLİRLİK ALT KRİTERLERİ	**Karlılık Oranının Artırılması**	**Maliyetlerin Azaltılması**	**Üretimde Verimlilik Sağlanması**	**Üretimde Esneklik Sağlanması**	**Üretimde Kalite Kontrol ve Güvencenin Artırılması**	**Üretim, Sipariş ve Teslimat Sürelerinin Kısaltılması**	**Rekabet Edilebilirliğin Artırılması**	**Üretimde Şeffaflık ve İzlenebilirlik Sağlanması**	**Süreç Optimizasyonu Sağlanması**	**Üretimde Standardizasyon Sağlanması**
Karlılık Oranının Artırılması	0									
Maliyetlerin Azaltılması		0								
Üretimde Verimlilik Sağlanması			0							
Üretimde Esneklik Sağlanması				0						
Üretimde Kalite Kontrol ve Güvencenin Artırılması					0					
Üretim, Sipariş ve Teslimat Sürelerinin Kısaltılması						0				
Rekabet Edilebilirliğin Artırılması							0			
Üretimde Şeffaflık ve İzlenebilirlik Sağlanması								0		
Süreç Optimizasyonu Sağlanması									0	
Üretimde Standardizasyon Sağlanması										0

ÇEVRESEL SÜRDÜRÜLEBİLİRLİK ALT KRİTERLERİ	Yenilenebilir Enerji Kaynaklarının Kullanımının Artırılması	Çevresel Kirlilik Önleme, Yönetim ve Kontrol	Geri Kazanım, Geri Dönüşüm ve Yeniden Kullanım Oranlarının Artırılması	Sera Gazı Salınımlarının Azaltılması	Kaynak ve Enerji Kullanımında Verimlilik Sağlanması	Yeşil İnovatif Stratejilerin Geliştirilmesi
Yenilenebilir Enerji Kaynaklarının Kullanımının Artırılması	0					
Çevresel Kirlilik Önleme, Yönetim ve Kontrol		0				
Geri Kazanım, Geri Dönüşüm ve Yeniden Kullanım Oranlarının Artırılması			0			
Sera Gazı Salınımlarının Azaltılması				0		
Kaynak ve Enerji Kullanımında Verimlilik Sağlanması					0	
Yeşil İnovatif Stratejilerin Geliştirilmesi						0

ENDÜSTRİ 4.0 TEKNOLOJİLERİ ALTERNATİFLERİ DEĞERLENDİRME FORMU

Sayın Katılımcı,

İşletmenin kurumsal sürdürülebilirlik kapsamında süreçlerine dahil ettiği sosyal, çevresel ve ekonomik sürdürülebilirlik kriterlerini en iyi karşılayan Endüstri 4.0 teknoloji alternatiflerini saptamak amacıyla yapılan bu ankete katılmanız, araştırmada doğru bilgiler elde etme bakımından son derece önemlidir. Elde edilecek bilgiler, GİZLİ tutulacak olup; sadece bilimsel amaçlarla kullanılacaktır. Talep etmeniz durumunda hazırlanacak çalışmanın çıktıları sizlere de gönderilecektir. İşbirliğiniz ve katkılarınız için teşekkür eder, saygılar sunarız.

Doç. Dr. Aşkın Özdağoğlu

Araş. Gör. Elif Çirkin

Soruları cevaplamadan önce her bir gruptaki alternatifleri belirlenen kriterlere göre en önemliden en önemsize doğru sıralayınız. Ardından aşağıdaki örnekleri dikkate alarak soruları cevaplayınız.

Ölçek

Sözel ifade	Değer
Alternatif kritere göre çok kötü seviyede	1
Alternatif kritere göre kötü seviyede	2
Alternatif kritere göre kötü-orta arası seviyede	3
Alternatif kritere göre orta seviyede	4
Alternatif kritere göre iyi-orta arası seviyede	5
Alternatif kritere göre iyi seviyede	6
Alternatif kritere göre çok iyi seviyede	7

Bu tabloya göre örnek değerlendirme aşağıda verilmiştir.

Örnek Uygulama

Alternatif	Kriter 1
A1	4
A2	6
A3	7

Tabloyu açıklamak gerekirse, A1 kodlu Alternatif K1 kodlu kritere göre orta yeterlilik seviyesindedir. A2 kodlu Alternatif K1 kodlu kritere göre iyi seviyededir. A3 kodlu Alternatif K1 kodlu kritere göre çok iyi seviyededir.

Buna göre alternatifleri tüm kriterlere göre değerlendiriniz.

2. ALTERNATİFLER VE KRİTERLER ARASINDAKİ İLİŞKİLERİN BELİRLENMESİNE DAİR MATRİSLER

Endüstri 4.0 Teknoloji Alternatifleri	İş Yeri Güvenliği Sağlanması	Çalışma Standartlarının ve Koşullarının İyileştirilmesi	Yeni İş Tanımlarının Ortaya Çıkması	Nitelikli İş Gücü İhtiyacının Oluşması	İşçi ve İşverenin Sosyal Refahının Artırılması
Eklemeli Üretim					
Artırılmış Gerçeklik					
Otonom Robotlar					
Büyük Veri Analitiği					
Bulut Bilişim					
Siber Fiziksel Sistemler					
Nesnelerin İnterneti					
Sistem Entegrasyonu					
Simülasyon					
Akıllı Fabrikalar					

Endüstri 4.0 Teknoloji Alternatifleri	Karlılık Oranının Artırılması	Maliyetlerin Azaltılması	Üretimde Verimlilik Sağlanması	Üretimde Esneklik Sağlanması	Üretimde Kalite Kontrol ve Güvencenin Artırılması	Üretim, Sipariş ve Teslimat Sürelerinin Kısaltılması	Rekabet Edilebilirliğin Artırılması	Üretimde Şeffaflık ve İzlenebilirlik Sağlanması	Süreç Optimizasyonu Sağlanması	Üretimde Standardizasyon Sağlanması
Eklemeli Üretim										
Artırılmış Gerçeklik										
Otonom Robotlar										
Büyük Veri Analitiği										
Bulut Bilişim										
Siber Fiziksel Sistemler										
Nesnelerin İnterneti										
Sistem Entegrasyonu										
Simülasyon										
Akıllı Fabrikalar										

Endüstri 4.0 Teknoloji Alternatifleri	Yenilenebilir Enerji Kaynaklarının Kullanımının Artırılması	Çevresel Kirlilik Önleme, Yönetim ve Kontrol	Geri Kazanım, Geri Dönüşüm ve Yeniden Kullanım Oranlarının Artırılması	Sera Gazı Salınımlarının Azaltılması	Kaynak ve Enerji Kullanımında Verimlilik Sağlanması	Yeşil İnovatif Stratejilerin Geliştirilmesi
Eklemeli Üretim						
Artırılmış Gerçeklik						
Otonom Robotlar						
Büyük Veri Analitiği						
Bulut Bilişim						
Siber Fiziksel Sistemler						
Nesnelerin İnterneti						
Sistem Entegrasyonu						
Simülasyon						
Akıllı Fabrikalar						

3. KATILIMCIYA YÖNELİK SORULAR

1. İşletme büyüklüğü:
2. Çalışan sayısı:
3. İşletmedeki Göreviniz:
4. Kaç yıldır bu görevi yapmaktasınız?
5. Kaç yıldır şirketinizin bünyesinde sürdürülebilirlik kapsamında çalışmalar yapılmaktadır?
6. Kaç yıldır şirketinizin bünyesinde Endüstri 4.0 kapsamında çalışmalar yapılmaktadır?
7. Şirketinizde kurumsal sürdürülebilirliğe yönelik bir departman / birim / yönetici var mı?
8. Şirketinizde Endüstri 4.0 teknoloji ve uygulamalarına yönelik bir departman / birim / yönetici var mı?
9. Sürdürülebilirlik ile ilgili genel olarak düşünceleriniz ve öngörüleriniz nelerdir?
10. Endüstri 4.0 teknoloji ve uygulamaları ile ilgili genel olarak düşünceleriniz ve öngörüleriniz nelerdir?

Appendix 2. Mind Map