IMPACT OF DIGITALIZATION FOR INDUSTRY 4.0 ADAPTATION: THE MATURITY OF TURKISH AUTOMOTIVE SECTOR

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ABSTRACT

IMPACT OF DIGITALIZATION EFFORTS FOR INDUSTRY 4.0: THE ANALYSIS OF MATURITY LEVELS OF TURKISH AUTOMOTIVE SECTOR

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This thesis examines how Industry 4.0 technologies impact digitalization within the Turkish automotive sector. By reviewing existing literature and gathering expert inputs, the study pinpoints key criteria crucial for successful digitalization efforts within the industry. These criteria are then categorized into eight main factors, forming the basis for evaluating five digital transformation maturity levels defined in this thesis. Accordingly, the initial sub-criteria list was refined and grouped under main factors (criteria) using the survey results from Turkish Automotive Manufacturers (OTEP). The Best-Worst Method (BWM) was then employed to weigh the criteria classes and to compare digitalization (or namely digital transformation) performance across surveyed companies. On the following, this study introduces a novel approach to the Turkish automotive industry by employing bi-clustering method to quantify and analyse digitalization maturity levels. This analysis groups companies into distinct maturity levels based on pre-defined criteria, highlighting potential roadblocks hindering full Industry 4.0 integration. Finally, by analysing the key drivers and barriers to digitalization, this study identifies crucial criteria that require attention and improvement for each company surveyed. Overall, findings of this research provide valuable insights for decision-makers and industry professionals in the Turkish automotive sector to define maturity levels and strive for successful Industry 4.0 implementation.

Keywords: Digitalization, Industry 4.0, Maturity Level, Best-Worst Method (BWM), Bi-Clustering

ÖZ

ENDÜSTRİ 4.0 UYUMU İÇİN YÜRÜTÜLEN DİJİTALLEŞME ÇALIŞMALARININ ETKİSİ: TÜRK OTOMOTİV SEKTÖRÜNÜN OLGUNLUK DÜZEYİ ARAŞTIRMASI

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Bu tez, Endüstri 4.0 teknolojilerinin Türk otomotiv üretim sektöründeki dijitalleşme çalışmaları üzerindeki etkisini araştırmaktadır. İlk aşamada, literatür taraması ve uzman görüşleri yoluyla, sektörde başarılı Endüstri 4.0 uygulamaları kapsamında dijital dönüşüm çalışmalarının değerlendirilmesi için gerekli olan temel teknolojiler ve kriterler belirlenmiştir. Akabinde söz konusu temel kriterler arasından sekiz adet ana kriter sınıfı seçilerek belirlenen dijital dönüşüm olgunluk seviye sınıflarının değerlendirilmesinin temeli oluşturulmuştur. Bu temel kapsamında önce Otomotiv Teknoloji Platformu (OTEP) üyesi Türk otomotiv üreticilerinin ve yan sanayi firmalarının katılım sağladığı anket çalışmasının sonuçları değerlendirilerek, belirlenen alt kriterler ana kriter sınıfları altında gruplandırılmıştır. Çalışmanın devamında, ana ve alt kriterlerin ölçülmesi yolu ile, ankete katılan firmaların dijital dönüşüm performansını karşılaştırmak ve firmalar arasında tercihlerine göre sıralama yapmak için En iyi-En Kötü Yöntemi (BWM) kullanılmıştır. Son olarak, belirlenen dijital dönüşüm olgunluk seviyesi sınıflarında firmaları ilgili kriterlere göre gruplamayı mümkün kılan ve literatürde de yeni bir değerleme yaklaşımı olan ikili kümeleme (Bi-Clustering) yöntemi uygulanmıştır. Bu yöntem ile çalışmaya katılan firmaların ayrı ayrı dijitalleşme olgunluk seviyelerinin ölçülmesi amaçlanmıştır. Analiz sonucunda, tanımlanan kriterlere göre katılımcı firmaların farklı dijital dönüşüm olgunluk seviyelerini belirlenerek her bir firma özelinde Endüstri 4.0 uygulamalarının benimsenmesini etkileyen ana ve alt kriterler değerlendirilmiştir. Sonuç olarak, bu tezde dijital dönüşüm çalışmalarında dikkate alınması gerekli temel etmenler, itici güçler ve engeller vurgulanarak çalışmaya katılan firmalar ile sektör özelinde dijital dönüşüm olgunluğu ve dijitalleşme alanları değerlendirilmiştir. Çalışmanın bulguları, Endüstri 4.0 uygulamalarını Türk otomotiv sektöründe faaliyet gösteren firmalara başarılı bir şekilde entegre etmek isteyen karar vericiler ve uygulayıcılar için değerli öngörü bilgisi sunmaktadır.

Anahtar Kelimeler: Dijital Dönüşüm, Endüstri 4.0, Olgunluk Seviyesi, En iyi-En Kötü Yöntemi (BWM), İkili Kümeleme (Bi-Clustering)

This study is wholeheartedly dedicated to my beloved wife and family, who have been my source of inspiration and gave me strength when I thought of giving up, and who continually provided their moral and emotional support.

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Final words:

"In theory one is aware that the earth revolves, but in practice one does not perceive it, the ground upon which one treads seems not to move, and one can live undisturbed. So it is with Time in one's life."

Marcel Proust (1871 – 1922)

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CHAPTER 1

INTRODUCTION

The automotive sector is currently undergoing significant changes due to digitalization and the emergence of Industry 4.0 (Müller et al., 2018). This transformation has a profound impact on the industry, affecting various aspects such as production processes and supply chains. The digital transformation (sometimes called "Industry 4.0 transformation") of the automotive sector has revolutionized the way vehicles are designed, manufactured, and operated. With the integration of advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and big data analytics, automotive companies are redefining their production processes to enhance efficiency and quality. Additionally, digital transformation of automotive industry has also led to significant improvements in supply chain practices which resulted at minimizing delays and optimizing inventory management.

Moreover, by adopting Industry 4.0, automotive companies gain valuable insights into the effectiveness of their digital transformation initiatives. This deeper understanding enables them to make more informed decisions, tailoring their products and services to the evolving digital landscape. They can also pinpoint successful digitalization strategies, optimize processes, and ultimately deliver a more mature, digitally integrated, and responsive experience for their industrial development. As automotive companies increasingly embrace digital technologies, the potential for innovation and enhanced efficiency across the entire value chain remains substantial. This ongoing transformation will continue to shape the future of the automotive industry.

However, the digital transformation in the automotive sector is not only reshaping the industry but also driving new business models and partnerships (Calışkan et al., 2020). Digital transformation and/or digitalization is opening up avenues for collaborations between traditional automotive manufacturers and technology provider companies.

As the automotive sector continues to embrace digitalization within the framework of Industry 4.0, companies need to adapt to this paradigm shift by investing more in human resources, processes, and technologies that empower them to stay competitive in a rapidly evolving landscape.

Furthermore, while the automotive industry ventures further into the digital frontier of Industry 4.0, stakeholders must acknowledge the far-reaching effects of digitalization across the entire value chain. This necessitates prioritizing innovation, competitiveness, and sustainable growth as key drivers of transformation within the sector (Drath & Horch, 2014).

In conclusion, this thesis aims to examine the impact of digitalization in the automotive sector in Türkiye from an Industry 4.0 perspective. Through the utilization of a research model that incorporates Industry 4.0 principles, this research aims to provide a comprehensive understanding of how varying levels of digitalization, or maturity levels, are reshaping the automotive industry. The study identifies critical criteria and research areas that are most influential in the effective implementation of Industry 4.0 practices within the sector.

1.1. Problem Definition

The manufacturing industry is in a rapid and profound transformation. A confluence of factors, including globalization, rapid urbanization, increasing demand for personalized products, and shifting demographics, presents a complex landscape of challenges and opportunities that will reshape the future (Bartodziej, 2017).

While the Fourth Industrial Revolution, named as “Industry 4.0”, is driving rapid transformation, its practical integration into production processes remains uneven across various sectors. The adoption of Industry 4.0 technologies is occurring at different paces, often with limited scope and scale.

Within the limited scope and scale, the financial implications of adopting Industry 4.0 practices further complicate matters. The initial investment required can be substantial, with the risk of runaway costs if implementation is mismanaged.

Choosing the wrong Industry 4.0 technologies or approaches can lead to wasted resources, increased expenses, and ultimately, failed implementations (Winkelhake, 2021).

On the basis of aforementioned scope, scale and financial effects of Industry 4.0 transformation, a holistic approach, analysing the critical factors affecting the adoption of Industry 4.0 technologies and the maturity levels of Industry 4.0 practices, is crucial for unlocking the transformative power of digital transformation. Therefore, we assume that defining strategic criteria, including drivers and barriers influencing decision-making in the context of adoption and digitalization, is equally essential for accelerating the realization of the full potential of Industry 4.0.

In this perspective, we anticipate that advancements in digitalization on the basis of the “Smart Factory” concept will fundamentally reshape how value is created, work is structured, services are delivered, and businesses operate (Seidel et al., 2005). Despite Türkiye's strategic intent to capitalize on Industry 4.0, research specifically exploring this transformation within the Turkish automotive industry remains limited. While valuable studies like (Pamukçu & Sönmez, 2012) shed light on the sector's dynamics through the lens of technology transfer, a deeper understanding of Industry 4.0's impact is crucial.

The Turkish government's two-pronged approach, focused on enhancing domestic production efficiency and establishing the nation as a leading global automotive supplier through Industry 4.0 adoption, underscores the need for further investigation into the realization of these goals and their implications for the Turkish automotive sector. In light of this determination, our analysis focuses on a comprehensive statistical dataset extracted from a survey regarding the industrial development of the Turkish Automotive sector, provided by the Automotive Technology Platform (OTEP).

With regard to the survey results, our research problem is focused on the maturity levels of the integration by the company size and contractor class in the Turkish automotive industry and provides the first insights into the potential impacts of Industry 4.0 applications’ integration on Turkish companies.

1.2. Objectives

This thesis aims to develop a research framework to guide managers in identifying and focusing on key digitalization factors and their associated maturity levels. Given the absence of conclusive evidence on the most impactful criteria for digitalization for improving firm performance, this research aims to:

i. identify broad digitalization criteria that influence Industry 4.0 practices based on survey results and expert opinions.

ii. analyse survey data collected from industry experts within the Turkish automotive sector.

iii. define key digitalization criteria and sub-criteria to compare companies from both current/present and target/future perspectives.

iv. identify and rank companies based on influential criteria and sub-criteria within each defined maturity level using the Best-Worst Method (BWM).

v. categorize and analyse digitalization criteria and sub-criteria to demonstrate the maturity levels of companies.

vi. apply the Cheng and Church (CC) bi-clustering analysis to determine the maturity levels of companies within the established framework.

In general, this thesis investigates the potential impacts of Industry 4.0 and digitalization on the industry while analyzing critical factors that contribute to the success of this digital transformation. This thesis contends that Turkish automotive manufacturers, specifically, can derive significant benefits from examining the practicality of implementing Industry 4.0 and evaluating their organizational capacity for successful digital transformation. Complementarily, our research further aims to provide these companies recommendations for determining their digital maturity levels and understanding the key factors (criteria) that significantly influence the successful implementation of Industry 4.0. By identifying key criteria, opportunities and risks, we aim to provide practical solutions and a strategic roadmap for the effective integration of Industry 4.0 practices within the Turkish automotive manufacturing industry.

1.3. Research Titles

This thesis defines various research titles that center on analyzing the digital transformation of the Turkish automotive industry. The main titles of our research are listed below:

i. **Factor Analysis:** Clear steps and methodologies are defined to evaluate factors (criteria and sub-criteria) that directly or indirectly affect companies' digitalization efforts.

ii. **Ranking Methodology:** We developed a methodology to rank companies based on a set of defined factors (criteria and sub-criteria) to assess and showcase their digitalization performance based on the survey results.

iii. **Digitalization Maturity Model Assessment:** A dedicated maturity model is demonstrated to focus specifically on selected digitalization criteria and sub-criteria.

iv. **Targeted Advice:** Companies need specific advice and policy recommendations tailored to their digitalization efforts based on the findings of this research.

1.4. Research Questions

This thesis employs a multi-faceted approach to provide a comprehensive understanding of digital transformation within the Turkish automotive industry. As an initial step in the research approach outlined in Section 1.3, this thesis aims to pinpoint the crucial criteria driving digital transformation. This identification process will involve a factor analysis to establish a defined set of criteria. Second, a ranking study is conducted to assess the digitalization performance of companies using a specific *ranking methodology*. Subsequently, a well-defined digital maturity level framework is established through a *digitalization maturity model assessment*.

This framework, in turn, offers readers and decision-makers a structured method for evaluating a company's progress in its digital transformation journey, ultimately leading to the provision of *targeted advice*. In this respect, we seek to answer the following research questions:

i. **Question-1 (Q1):** How do companies work with partners to obtain digitalization capabilities?

ii. **Question-2 (Q2):** What are some strategies that companies can use to overcome barriers to digitalization?

iii. **Question-3 (Q3):** To what extent can companies employ drivers of digitalization?

iv. **Question-4 (Q4):** What is the maturity level of digitalization?

v. **Question-5 (Q5):** What influences the maturity level of digitalization within organizations?

1.5. Hypotheses

This thesis will examine the connection between a company's digitalization initiatives and their resulting digital maturity level.

This exploration will revolve around four key hypotheses listed below, each grounded in specific criteria and sub-criteria.

i. **Hypothesis-1 (H1):** Drivers lead to a more advanced level of digital maturity.

ii. **Hypothesis-2 (H2):** Reducing barriers leads to higher levels of digital maturity for a company.

iii. **Hypothesis-3 (H3):** Cultivating new capabilities helps to advance the digital transformation process.

iv. **Hypothesis-4 (H4):** Increased collaboration contributes to a higher level of digital maturity.

1.6. Thesis Outline

This thesis consists of six main chapters:

i. Chapter 1 provides an introduction to the thesis topic including research titles, research questions and hypotheses.

ii. Chapter 2 builds the foundational theoretical framework for the thesis. It begins by introducing the concept of Industry 4.0, reviewing previous industrial revolutions, and examining whether Industry 4.0 represents a revolution of comparable significance. The chapter then defines key aspects such as highlights, lean production, and value creation within the context of digital transformation. It proceeds to define digitalization terminology, encompassing its impact, challenges, barriers, drivers, and capability aspects. Furthermore, Chapter 2 delves into the impacts, challenges, drivers, barriers, and required capabilities associated with digitalization. Finally, it defines the main aspects of the maturity model based on existing literature.

iii. Chapter 3 outlines the specifics of the research conducted. It details the survey and data utilized to analyse the maturity model. The chapter then outlines the research framework, including the phases and processes involved, drawing upon relevant scientific literature and contributions. Finally, Chapter 3 acknowledges the limitations and restrictions encountered during the study.

iv. Chapter 4 outlines the methodological approach employed throughout the thesis. It defines digital maturity levels, identifies five distinct bi-clusters, and examines the digital maturity levels of companies within each group. The chapter also outlines the research framework based on insights from existing literature. Additionally, it describes the process of selecting criteria and sub-criteria for evaluating digital transformation. Finally, Chapter 4 presents the results of the BWM analysis, which ranks companies based on their digitalization performance, and showcases the findings of the bi-clustering analysis in relation to the defined digital maturity levels.

v. Chapter 5 presents the results of the analysis conducted in the study. It begins by providing descriptive statistics and examining correlations among the sub-criteria classes used in the survey. The chapter then determines the relative and global weights of the criteria using the BWM and ranks companies based on their current and future prospects. Finally, Chapter 5 evaluates potential digitalization maturity levels by employing a bi-clustering method to define relevant sub-criteria classes.

vi. Chapter 6 serves as the concluding chapter of the thesis, summarizing the key findings and offering recommendations based on the research. It outlines the study's results and proposes a strategic approach based on these findings. Additionally, the chapter interprets insights gathered from interviews, addressing the research questions posed at the outset. Finally, Chapter 6 acknowledges the limitations of the thesis and suggests potential areas for further research and exploration.

CHAPTER 2

THEORETICAL FRAMEWORK

2.1. Industry 4.0

The beginning of the 21st century has been marked by significant technological advancements, often referred to as Industry 4.0. These advancements, particularly in how information is created, used, and shared, are essential for enhancing global competitiveness, industrial output, and overall economic growth. The influence of technology on production, economic growth, and development has been extensively researched, resulting in accelerated industrial development. This progress significantly influences production dynamics, resulting in industrial development and increased manufacturing capacity.

In this respect, the term "Industry 4.0," synonymous with the fourth industrial revolution, is widely used in Germany as a German government initiative to advance their manufacturing sector's global competitiveness through technological innovation. While frequently discussed, Industry 4.0 lacks a universally agreed definition, but generally refers to the ongoing digital transformation of the manufacturing sector. This includes integrating digital technologies into products and systems, connecting the physical and virtual worlds, and increasing automation, flexibility, and customization in production processes.

In general, Industry 4.0 represents a shift from centrally controlled production (Industry 3.0) to a self-controlled and flexible system. This interconnected system, enables seamless information flow across the entire supply chain. Most of the time, Industry 4.0 encompasses digital technologies that can be integrated into manufacturing processes, holding the potential to significantly enhance the performance of manufacturing companies (Rizvi et al., 2023) As a result, the terminology Industry 4.0 describes the trend towards an ongoing digitalization of the manufacturing sector (Kaufmann, 2015). Furthermore, the Fourth Industrial Revolution signifies an integration of digital technologies into products and systems. This interconnectedness is a defining characteristic of Industry 4.0 with a focus on increased digitalization and flexibility (Wee et al., 2015)

2.1.1. Definition

In literature, the rise of Industry 4.0 is generally described as "evolution". Most of the researchers contend that this technological shift, while significant, represents a continuation and enhancement of existing technologies rather than a complete paradigm shift (Kagermann et al., 2013). Regardless of the terminology used, it is undeniable that global industry faces substantial "evolutionary" challenges driven by rapid technological advancements.

Table 1 summarises and describes characteristics and period of these evolutionary eras. However, comparing these different eras, the industrial pace has slightly changed by the determination of product innovation, variety, quality, and service (Rüttimann & Bruno, 2016).

However, to thrive in this changing environment, in the Fourth Industrial Revolution era, the *Industry 4.0 project of Germany*, defined a new research area. According to Walters and Rainbird (2007b), digital transformation, and digitalization necessitate integrated virtual and physical structures.

Like previous industrial revolutions, Industry 4.0 is marked by the emergence and adoption of new technological innovations. While the first two revolutions were driven by mechanization and electrification, the third, marked by increased automation and information technology, is a transition to Industry 4.0 (Valladares and Chanda, 2023). This new era integrates cyber-physical systems into manufacturing and logistics, leveraging the Internet of Things (IoT) and new services. (Athanasopoulou et al., 2019).

By leveraging advanced technologies, Industry 4.0 aims to create sustainable factories of the future (Ganzarain & Errasti, 2016; Kagermann, 2015).

Table 1 - An overview of the industrial revolutions

Era / Characteristics	Period / Approach
1st Industrial Revolution - Water- and steam powered mechanical manufacturing: ▪ Introduction of the power loom in 1784 ▪ Mechanization of production facilities with water and steam power to increase production capacity and productivity, versus manual craft work ▪ Focus on performing specific tasks faster and with less variation and in transportation and moving goods	**Period:** ▪ from 1784 to mid-19th century **Approach:** ▪ Emphasis on increasing production capacity, standardization, and low costs ▪ Directive management ▪ People as tools.
2nd Industrial Revolution - Industrialization: ▪ Introduction of the assembly line in slaughterhouses in 1870 ▪ Adaptation of electric power to industrial machines, replacing steam-powered systems by electric motors driving mass production and increasing automation across a variety of industries	**Period:** ▪ from late 19th century to1970s **Approach:** ▪ Electric-powered mass production based on the division of labour ▪ Emphasis on increasing production capacity, standardization, and lower costs ▪ Directive management ▪ People as resources.
3rd Industrial Revolution - Electronic automation: ▪ Development of the first programmable logic controller (PLC) in 1969 ▪ Increase the application of electronics and ICT (Information and Communication Technology) to automate production processes ▪ Introduction of computing power to the workplace replacing manual work by standalone robotic systems	**Period:** ▪ from the 1970s to 2014 **Approach:** ▪ Electronics and information technology drives new levels of automation of complex tasks ▪ People as value-added resources

Table 1 - An overview of the industrial revolutions (Continued)

Era / Characteristics	Period / Approach
4th Industrial Revolution - Smart Automation: ▪ Increased use of cyber-physical systems (CPS) ▪ Industry 4.0 German federal government project (started in January 2011) ▪ Governments, private companies, and industry associations have been focusing on Industry 4.0 and making investments since the 2010s ▪ Integrating the cyber-physical mechanisms to digitize, connect and automate end-to-end processes creating a smart factory of the future ▪ Machines learn to learn (artificial intelligence)	**Period:** ▪ from 2014 until now **Approach:** ▪ Sensor technology, interconnectivity and data analysis allow mass customization, integration of value chains and greater efficiency ▪ People as associates ▪ Emphasis on innovation and development ▪ Machines perform routine tasks

Source: Derived from Fonseca (2018)

In addition, advancements in computing power, particularly in internet-based technologies and services, are enhancing the growth and adoption of cloud computing and services. These technologies have the potential to revolutionize industrial systems by enabling service-based functionalities. However, for a successful digital transformation process, the development and implementation of these technologies require a skilled workforce, robust IT infrastructure, economic stability, and forward-thinking manufacturers (Ganzarain & Errasti, 2016; Karnouskos et al., 2014).

Key aspects of digital transformation are successfully summarized by Kagermann et al., (2013) as the rise of smart factories, cyber-physical systems, self-organizing operations, innovative distribution and procurement systems, advanced product and service development systems, a focus on adapting to human needs, and a growing emphasis on corporate social responsibility. Moreover, the defining characteristic of a smart (Industry 4.0) factory, as noted by Hermann et al., (2014), is its ability to anticipate future product demands and adapt to increasing variety and complexity while minimizing costs and environmental impact. In addition, the internet and its related technologies serve as a unifying infrastructure, connecting various elements of the manufacturing ecosystem, including physical objects, human workers, intelligent machines, production lines, and processes, both within and across organizational boundaries. This interconnectedness forms the foundation for intelligent, networked, digitalized, and agile production systems.

Respectively, as a developing economy, according to the World Bank’s 2023 rankings, Türkiye ranks 17th in global GDP. Despite facing global economic challenges, Türkiye exceeded growth expectations achieving a GDP growth rate of 4.5% in 2023. The industrial sector plays a significant role in Türkiye's economy, contributing more than 20% to the national GDP according to the Turkish Statistical Institute (TURKSTAT)’s national statistics. However, Small and Medium-Sized Enterprises (SMEs), defined as businesses with under 250 employees and less than 40 million Turkish Liras in assets or turnover, constitute a substantial 99.8% of all enterprises in Türkiye. Given their importance to the Turkish economy, understanding the current state of SMEs and their potential within the context of Industry 4.0 is also crucial.

In this respect, several studies to understand the current situation in Türkiye have been explored in the book edited by Şatoğlu et al., (2018) in order to systematize the interplay between manufacturing and Industry 4.0. For instance, Sanders et al. (2016) investigated the relationship between these two concepts, examining Industry 4.0's potential to facilitate lean implementation. The authors put forth a methodology that combines lean manufacturing principles with Industry 4.0 technologies, taking into account supplier, customer, process, human, and control factors. They suggest that research in Industry 4.0 can help identify solutions to address challenges encountered in implementing lean manufacturing practices.

Similarly, Rüttimann & Bruno, (2016) and Sibatrova, (2016) discussed the relevance of lean manufacturing within the context of Industry 4.0 trends, human resources, and time constraints. Besides, Doh et al., (2016a) conducted a comprehensive literature review of industrial revolutions, including Industry 4.0. The authors emphasized the importance of automation in production systems and supply chain management, with the goal of developing a framework for integrating information systems and technologies to improve efficiency.

In addition, Rauch et al. (2016) introduced an axiomatic design-oriented methodology to guide New Product Development (NPD) processes. This methodology, linked with Industry 4.0, demonstrates how to achieve smart product development using advanced technologies and instruments.

Similarly, Şatoğlu et al., (2018) denotes in various chapters of the book that the organizational capabilities and tools necessary for companies to successfully transform to Industry 4.0 using NPD methodologies. In addition, Biedermann et al., (2016) stated that maintenance needs to change to meet the requirements of Industry 4.0 and emphasized the necessity of knowledge and data management for improving predictive maintenance performance.

It will also be meaningful to mention a *little bit* about studies which addressed the interaction between digitalization and Industry 4.0. This thesis utilizes a conceptual framework for digitalization comprising interconnected areas, as grounded in the study "Digital Business Transformation" by Wade (2015). From his perspective, Industry 4.0 is not merely an upgrade to industrial processes; it represents a fundamental shift in value creation, human-machine interaction, and organizational structures. This transformation impacts business models, societal structures, and the environment (Acatech, 2013) Besides, Industry 4.0 provides the necessary technological foundation and infrastructure to enable these new, service-driven business models (Kagermann, 2015; Lasi et al., 2014).

On the basis of above commitment, while the initial definition of Industry 4.0 was broad, it emphasized a new level of organization and control across entire production value chains throughout a product's lifecycle. Bai et al., (2020) and Sirucek (2018) highlight the growing influence of Industry 4.0 characterized by automation and digitization, on the automotive manufacturing sector. This shift is depicted to be driven in part by government support and investment.

In addition, the integration of Industry 4.0 principles into Lean Production has led to the emergence of "Lean Automation," a concept focused on improving flexibility and information flow to meet changing market demands. Our study, echoing the findings of Bai et al., (2020), reveals that applying Industry 4.0 principles optimizes efficiency in line with lean production principles, as evidenced by survey data. Furthermore, our research demonstrates that Industry 4.0 technologies significantly enhance lean automation principles. These findings underscore the positive impact of Industry 4.0 on both supply chain effectiveness and the integration of automotive industry practices. Furthermore, our study provides evidence that adopting new strategies based on the implementation of Industry 4.0 directly correlates with higher maturity levels; and, new lean manufacturing practices positively affect operational performance and production performance.

2.1.2. Key characteristics

The fundamental concept of Industry 4.0 transformation (digitalization) revolves around the interconnection of production facilities, supply chain and service systems, with the emphasis on establishing interconnected networks that enhance value creation. In addition, this transformation hinges on the adoption of emerging technologies such as big data analytics, autonomous robots, cyber-physical infrastructure, simulation, horizontal and vertical integration / value chains, internet of things, cloud systems, additive manufacturing and augmented reality.

For instance, the use of the "Internet of Things" is fundamental to Industry 4.0. This interconnectedness enables seamless communication and data exchange between various distributed systems, including wireless sensor networks, cloud platforms, embedded systems, autonomous robots, and additive manufacturing technologies. Adaptive robots and cyber-physical systems are essential components, facilitating the creation of an integrated, computer-based environment. This environment leverages advancements in simulation, 3D visualization, and printing technologies.

Furthermore, robust data analytics and coordination tools are crucial for the effective functioning of the entire Industry 4.0 ecosystem. These tools empower real-time decision-making and autonomy in both manufacturing and service processes (Salkın et al., 2017). Wee et al. (2015) characterize Industry 4.0 as being driven by four key clusters of disruptive technologies; Data and Connectivity, Analytics and Intelligence, Human-Machine Interaction and Digital to Physical Conversion.

Industry 4.0 introduces the idea of "Smart Factories," where machines, raw materials, and products communicate and collaborate to streamline and improve production processes. For instance,

- raw materials (Davis 2015; Rüssmann et.al, 2015; Siemens, 2016),
- efficient mass customization (Davis 2015; Schlaepfer, 2015),
- increased production speed (Davis, 2015; Schlaepfer, 2015; Brettel et al., 2014; Rüssmann et al., 2015),
- enhanced productivity (Geissbauer et al., 2014)

may well be listed under this notion.

2.1.3. New Technologies

Industry 4.0 technologies are driving a paradigm shift towards a new and networked future, where the boundaries between the physical and digital realms dissolve. The process of digital transformation is strengthened by the convergence of new technologies, each playing a vital role. In Table 2, we have listed some of the key definitions and characteristics of Industry 4.0 applications (Kern and Wolff, 2019; OECD, 2017; Stentoft, 2019)

Table 2 –Industry 4.0 technology definitions

Technology	Description
Mobile Services	▪ Mobile connectivity forms the foundation for real-time data sharing and communication between devices, systems, and individuals, facilitating smooth interaction and collaboration. ▪ 5G communication technology represents a significant advancement in wireless cellular technology, offering significantly faster data speeds compared to 4G.
Advanced (Autonomous) Robotics	▪ Advanced cyber-physical systems, capable of being programmed, are designed to autonomously execute tasks and routines previously carried out by humans.

Table 2 –Industry 4.0 technology definitions (Continued)

Technology	Description
Additive (3D) Printing	▪ Additive manufacturing, also called 3D printing, is transforming production. It allows for the creation of complex products, and also speeds up production and allows for more innovative designs. It enables the creation of customized products on demand, reducing lead times while increasing design flexibility. ▪ Additive manufacturing, or 3D printing, uses Computer-Aided Design (CAD) models to build three-dimensional objects by adding materials layer by layer.
AI & Machine Learning	▪ Artificial Intelligence (AI) Artificial Intelligence focuses on developing machines that can emulate cognitive abilities usually attributed to human intelligence, such as reasoning, planning, learning, and perception. ▪ Often referred to as Cognitive Computing, AI encompasses various approaches, with Machine Learning being a prominent subset. Machine Learning focuses on training machines to develop and refine these cognitive functions through data-driven processes.
Automation	▪ Automation signifies a fundamental change in how work is performed. It uses technology to simplify and speed up tasks and processes, minimizing or even eliminating the need for manual human involvement.
Augmented Reality/Virtual Reality (AR/VR)	▪ Augmented Reality (AR) and Virtual Reality (VR) offer interactive experiences by merging computer-generated elements with real-world environments like consumer products etc. ▪ Augmented Reality (AR) alters a user's perception of their environment by imposing computer-generated information onto real-world objects. This enhancement can engage various senses, including sight, touch, hearing, and even smell, to modify how users experience their surroundings. ▪ Unlike AR, VR crafts a fully immersive experience by substituting the user's actual environment with a simulated one.
Robotics	▪ Advanced robotics, enhanced by AI and machine learning, are automating intricate tasks, leading to increased efficiency and productivity.
Smart Sensors and Sensor Fusion	▪ "Smart Sensors" are fundamental components of the Internet of Things. These devices can collect data from their environment, process that data to execute pre-programmed functions, and then generate intelligent outputs based on their analysis. ▪ "Sensor Fusion" is a new process that integrates data from multiple smart sensors. This process seeks to minimize uncertainty and produce more dependable information using data from individual sensors in isolation.

Table 2 –Industry 4.0 technology definitions (Continued)

Technology	Description
Big Data and Data Analytics	▪ Big data analytics tools and techniques reveal hidden patterns, trends, and correlations within large datasets, enabling well-informed decision-making and process optimization ▪ Big data, composed of hardware and software elements, is termed to store, analyse and systematically extract valuable insights and intelligence from collected datasets to support decision-making.
Cloud Computing	▪ Cloud computing delivers processing power and storage capacity required to manage the vast quantities of data produced by systems. This enables a scalable and adaptable infrastructure that supports Industry 4.0 applications.
Cybersecurity	▪ Cybersecurity provides a comprehensive framework of strategies, technologies, and best practices aimed at reducing the constantly changing threats and risks that interconnected devices and individuals encounter in the digital world. It represents a proactive and multifaceted approach to protecting sensitive information and ensuring operational continuity.
Human Machine Interface (HMI)	▪ Human-Machine Interfaces are comprised of the hardware and software components that enable communication and interaction between humans and devices
Block chain	▪ Block chain establishes a secure and transparent system for maintaining records. It generates a chain of digital records, known as blocks, which are linked together using cryptography.
Internet of Things (IoT)	▪ The Internet of Things (sometimes referred to as the Internet of Everything) connects a vast network of sensors, devices, and machines, allowing them to collect and exchange data. This enables real-time monitoring, control, and optimization of physical processes. ▪ IoT envisions a network connecting computing devices, and machines (both digital and mechanical) with respect to Industry 4.0
Quantum Computing	▪ Quantum computers have the distinctive ability to convert information between classical and quantum states. ▪ By harnessing quantum phenomena such as superposition and entanglement, quantum computers can perform computations in fundamentally different ways than classical computers. This unlocks significantly greater computational power and capacity.

Source: Derived from Adare S., (2020a); Stegmann (2014) and Fonseca (2018)

2.1.4. Basic Insights

In general, Industry 4.0 literature anticipates the following benefits:

i. savings in labour costs (evolution of HR management is utterly crucial)

ii. streamlined coordination across the supply chain, while maintaining or even enhancing product and process quality.

Supportively, the realization of Industry 4.0 is perceived as a *long-term* endeavour. Most of the literature estimates for company readiness (capability and capacity development) range from a minimum of 5 years to a decade. Besides, despite the recognized importance, the procurement function (supply and value chain principles) has been largely absent from Industry 4.0 discussions and implementation efforts.

In addition, this reluctance towards Industry 4.0 may stem from a *lack* of clear

understanding, with many executives perceiving it as a "marketing term." Even so, most of the literature has predicted that the term would change within 5 years at most. Nevertheless, most of the researchers acknowledge the significance of digitalization and collaboration for learning new skills for Industry 4.0, recognizing them as core elements of Industry 4.0.

This part highlights some of the basic insights gathered from a *generic* web review and related academic data sources like Science Direct, Scopus, etc. These insights summarized and paraphrased below on the basis of specific perspectives on Industry 4.0 and digitalization:

i. Technical Foundation and Automation:

    a. Industry 4.0 relies on the internet and network communication, shifting from manual to autonomous system coordination.

    b. It encompasses 100% digitalization, automation, and collaboration.

    c. Industry 4.0 leverages embedded systems, big data management, and cloud computing, impacting the entire supply chain.

d. Enhanced information processing, the Internet of Things, and data networks create interfaces beyond traditional computers.

ii. Vision, Implementation, and Scope:

a. Industry 4.0 is a vision for securing the Turkish automotive industry's competitiveness.

b. It represents an idea with promising approaches, but implementation lags behind the vision.

c. Industry 4.0 encompasses the digitalization of the entire economy, including innovative fields like learning, collaboration, autonomous systems, digital services, and 3D printing, all underpinned by high-performance computing.

iii. Impact and Benefits:

a. Data management and cybersecurity systems are consequences of Industry 4.0.

b. It signifies the digitalization of previously unconsidered industries, with government support potentially driving this integration.

c. Industry 4.0 envisions a fully digitized supply chain where managers support an automated system.

d. Increased collaboration in R&D, innovation, and value chain efforts grants access to new Industry 4.0 technologies.

e. Accurate, real-time data facilitates the optimization of production functions and schedules.

These perspectives highlight the multifaceted nature of Industry 4.0, encompassing technological advancements, strategic visions, implementation challenges, and potential benefits across various sectors. The existing research emphasizes that a strong understanding and effective implementation of digitalization is crucial for the success of Industry 4.0. This is especially true when considering the following key parameters and factors:

i. Change Management
ii. Collaboration
iii. Data Ownership
iv. Data security
v. Big data management
vi. Government supports
vii. High Investment costs
viii. HR training
ix. Industry Standards
x. Knowledge Management
xi. Lack of Best Practice Examples
xii. R&D and innovation

Finally, our review *partially* revealed that successful digitalization hinges less on overcoming technical integration barriers and more on addressing key management challenges as listed above. In this respect, we analysed and presented the criteria and sub-criteria identified by the interviewees as crucial for navigating these management challenges, based on the insights gathered from our survey.

2.1.5. Lean Production

Industry 4.0 is transforming the manufacturing landscape. Simultaneously, lean production, with its focus on continuous improvement, remains a cornerstone of operational efficiency. While initially perceived as distinct concepts, a growing body of research suggests that Industry 4.0 technologies can significantly enhance and complement lean production principles.

In general, lean production focuses on generating value by continuously minimizing the resources needed to create a product. This approach emerged as a departure from traditional mass production methodologies, as highlighted by Marodin et al. (2017).

He also argued that few organizations truly understand the underpinning principles and practices. Hence, rooted in the production theory, lean production emphasizes continuous improvement.

Each improvement serves a distinct purpose, offering solutions to specific challenges. Additionally, a consensus exists regarding the positive correlation between lean production and operational performance (Netland, 2015).

In this respect, Lewis (2000) cautioned that lean production is highly context-dependent on the basis of internal and external contextual dynamic factors. Consequently, the specific context of industries' adaptation for Industry 4.0 can also profoundly influence lean production and its outcomes. Over the past few decades, the understanding of lean production has evolved with the presence of Industry 4.0 transformation. The process has transitioned from a shop floor-centric approach to a digitalized value system. In addition, the process has enhanced conceptualization of

Industry 4.0 practices which have facilitated the adaptation and integration of lean production across diverse sectors, ranging from the automotive industry to parts manufacturing (Marodin et al., 2011).

Furthermore, Industry 4.0 facilitates real-time data collection and analysis, enabling manufacturers to identify bottlenecks, optimize processes, and minimize waste with unprecedented precision. For instance, sensors embedded in machines can monitor performance and predict maintenance needs, reducing downtime and improving overall equipment effectiveness, a key lean metric (Mrugalska & Beata, 2017). Technologies like "digital twins and simulation software" allow manufacturers to test and optimize production processes virtually before implementation. This minimizes waste associated with new approaches and facilitates rapid prototyping and continuous improvement cycles, aligning with the core principles of lean production. However, the integration of Industry 4.0 into lean production is not without its challenges.

Companies need to invest in infrastructure, develop new skills, and address cybersecurity concerns. Moreover, as another research dimension, a cultural shift is often required to embrace data-driven decision making and empower employees at all levels. In essence, Industry 4.0 provides a powerful set of tools to enhance and advance lean production principles. Manufacturers can achieve remarkable levels of efficiency, flexibility, and responsiveness by utilizing lean manufacturing principles as crucial driving factors. However, successful implementation of these principles requires meticulous planning, investment, and a dedication to continuous learning, adaptation, and value creation.

2.1.6. Value creation

Industry 4.0 is reshaping industries and redefining the notion of value creation. This section of this thesis delves into the relationship between Industry 4.0 and value creation, trying to explain how these technological advancements are transforming businesses and unlocking unprecedented opportunities for competitive advantage.
Fundamentally, Industry 4.0 leverages the capabilities of interconnected systems, data analytics, and intelligent automation to generate value through innovative and transformative approaches. As denoted in many different explanations, this paradigm shift is propelled by the convergence of several technological advancements, notably the Internet of Things, cloud computing, artificial intelligence, and cyber-physical systems (Cho & Hee-Jae, 2005; Landroguez et al., 2011; Walters, D., & Rainbird, 2007). These technologies consequently empower businesses to optimize processes, produce products / services and create entirely new value propositions.

One of the most profound impacts of Industry 4.0 on value creation lies in its ability to enhance productivity and efficiency (Brynjolfsson, 1993; Davis, 2015; Rüssmann et al., 2015). By harnessing the power of automation, robotics, and data-driven insights, businesses can optimize their operations, minimize waste, and allocate resources more effectively. This results in cost savings, shorter lead times, and enhanced overall productivity.

Furthermore, Industry 4.0 empowers businesses to create value through mass customization and personalization. By leveraging Industry 4.0 technologies like flexible manufacturing systems, 3D printing, and real-time customer data, companies can define new products and services that fit for extensive needs and preferences. For example, automotive manufacturers are increasingly using Industry 4.0 technologies to offer personalized car configurations, enabling customers to customize their vehicles to their exact specifications. In this respect, we may denote that Industry 4.0 technologies contribute to value creation as per below main settings:

- Enhanced Productivity and Efficiency: Value creation is expanded by automation, data analytics, and optimized processes streamline operations, reduce waste, and boost overall productivity

- Mass Customization and Personalization: Industry 4.0 enables businesses to

  cater to individual customer needs through flexible production lines and personalized product offerings.

- New Products and Services: Emerging technologies pave the way for innovative products and services, opening up new markets and revenue streams. Industry 4.0 fosters the emergence of entirely new products, services,

  and business models. The convergence of technologies like artificial intelligence (AI), internet of things (IoT), and augmented reality opens up possibilities for innovative product design that were previously impossible.

- Improved Customer Experience: Data-driven insights and interconnected systems allow for personalized interactions, better customer service, and enhanced customer satisfaction.

- New Business Models: Industry 4.0 is driving the creation of innovative business models, including new product, service offerings and platform-based business models.

Industry 4.0 is creating new ecosystems, value networks and connecting businesses with customers in unprecedented ways. However, there is a need to increase the understanding of horizontal and vertical integration due to the emergence of a new value network, as well as new business models (Sony, 2018; Subhash & Naik, 2019).

To further develop our hypotheses, our study investigated inter-organizational integration within the surveyed companies.

First, we aimed to understand which criteria and structures (horizontal or vertical) differ in their procurement processes, information exchange, planning, control mechanisms, and collaboration throughout the value creation process, ultimately impacting the production of goods and services (see Subhash & Michael (2020) for more explanations). According to Chukalov (2017), Industry 4.0 leverages horizontal integration to connect information technologies and production systems, facilitating data and information exchange between companies across geographically dispersed locations within the value chain. This interconnectedness, as highlighted by Lu (2017), is made possible by cyber-physical systems that enable networking across all stages of the value chain, manufacturing, marketing and sales, and outbound logistics.

Besides, Prinz et al. (2019) suggests, vertical integration in Industry 4.0 involves companies acquiring businesses that play a crucial role in their supply chain. This strategic move by companies aims to gain control over the entire production process by integrating different organizational levels (Schiele, 2010; Vanpoucke et al., 2014). In addition, OTEP's report published in 2019 indicated a potential link between the extent of digital transformation within a company's value chain and its overall digital maturity. Given the importance of the value chain in encompassing a company's entire operations, this study considered it also as a key indicator of overall digital transformation progress.

In conclusion, Industry 4.0 represents a paradigm shift in value creation, empowering businesses to enhance efficiency, use of new technologies and create entirely new value propositions. In this thesis, we targeted to elaborate maturity framework to measure and also to assess value creation in the context of their vertical and horizontal value drivers and their impact on business models and competitive advantage.

2.2. Digitalization and Transformation

2.2.1. Terminology

Industry 4.0 is transforming business operations by digitizing both horizontal and vertical value chains. However, it is important to note that the terms "digitization," "digitalization," and "digital transformation" are often used interchangeably, leading to confusion. Since there is a nuanced progression between them, companies typically evolve through *stages* built upon this terminology, though not always in a linear fashion. The terminology and stage definitions may be illustrated by an example over a manufacturing company and quick references are given in Table 3.

2.2.2. Definition

With respect to digital transformation phenomena, the rise of data-driven business models, empowered by cloud computing and big data infrastructure, is becoming increasingly common. The increase in data generation capacity is manifested in three dimensions: product innovation, process innovation, and business model innovation (Adare S., 2020). The ability to manage innovation in the value chain will also be crucial for enterprises to survive in the future because that the financial gains, innovations contribute significantly to enhancing value for many enterprises. (Birkel et.al., 2019; Giffi et al., 2020; Walters, D., & Rainbird, 2007)

However, digitalization, as defined in the report by Gartner, (2016), involves utilizing digital technologies to redefine business models and innovate for new products. In Section 2.1.3, we described these digital tools and technologies that enhance business practices as digital transformation in its core. On the other hand, as Wade (2015) implies, digital transformation guides digital business transformation, providing the technological foundation upon which businesses can become "digital." In essence, digital technologies are the building blocks for successful digital transformation and organizational change. Consequently, combining organizational change with digital transformation paves the way for enhanced production performance across multiple areas such as operational efficiency, technological engagement, and knowledge acquisition.

Moreover, the existing literature on the automotive industry's digital transformation explores various facets, particularly the resulting business model changes.

Piccinini et al., (2015) provide a comprehensive overview, categorizing these changes into four types: extension, revision, termination, and creation. Piccinini et al., (2015) and Riasanow et al., (2017) illustrate these types with examples like incorporating interactive customer elements (extension), adapting to self-driving cars (revision), the potential decline of traditional dealerships due to virtual showrooms (termination), and the emergence of novel driver and data services.

Further research delves into specific strategies for navigating digital transformation. Rothaermel & Hess, (2007) conducted a case study highlighting that digital transformation often begins *organically* with various organizational activities, even before top management establishes a formal strategy.

The significance of external knowledge acquisition is also emphasized by Remane et al. (2016), who found that digital technology-driven mergers and acquisitions positively impact digital transformation. This echoes Henfridsson (2014)'s assertion that Original Equipment Manufacturers (OEMs) must actively seek external knowledge to fully leverage digital innovations. Authors further emphasize that for OEMs embracing external collaboration within the evolving digital ecosystem is essential for the success of IT-enabled business models.

Drawing on the concept of organizational change, which highlights the importance of balancing the utilization of existing resources with the exploration of new digitalization capabilities, there are *valuable* research that investigated the evolving landscape of the automotive industry. However, as emphasized in Pamukçu & Sönmez, (2012), there is still a gap offering a comprehensive analysis of the ongoing digital transformation within the Turkish automotive industry.

In addition, the impact of digital innovations on business performance and user experience is supported by the theory of disruptive innovations. Given the importance of external knowledge, analysing the entire automotive ecosystem becomes paramount (Riasanow et al., 2017).

Piccinini et al., (2015) conducted a Delphi study identifying emerging challenges within this digital transformation, including competition from new and non-traditional players, the need for collaborative partnerships, bridging gaps between business units and ecosystem players, and enhancing information flow.

Table 3 – Terminology for Digitization, Digitalization and Digital Transformation

Terminology	**Definition**	**Explanation**	**Respected Formal Definition**	**Reference(s)**
Digitization	▪ *Foundational* stage involving converting analog information into a digital format.	Manufacturing company replacing paper-based work orders with a digital system	Digitization, is a material process of converting analogue streams of information into digital bits."	Papathomas & Konteos, (2023); Rooijen (2020); Wee et al. (2015)
Digitalization:	▪ This stage starts with using digital technologies to improve existing processes and create new opportunities ▪ It is about leveraging data to work smarter, not just faster	Manufacturing company uses sensors on machines to collect data on performance, predictive maintenance and reducing downtime	Digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities	Fabbe-Costes & Lechaptois (2022); Papathomas & Konteos, (2023); Syariah & Ilmu, (2016)
Digital Transformation	▪ *Complex* stage, representing a fundamental shift in how a company operates and delivers value to customers. ▪ It encompasses organizational culture, leadership, and customer experience.	Manufacturing company now leverages data and digital technologies to offer personalized products, optimize its supply chain and empower employees with data-driven insights	Digital transformation means the integration of digital technology into all areas of a business, deeply changing how organizations operate and deliver value to stakeholders	Geissbauer et al. (2014); Lundberg et al. (2018); Verhoef et al. (2021); World Economic Forum, (2016)

In conclusion, this thesis also addresses a gap in the existing research by classifying the driving forces behind digitalization and analysing the digital transformation of the automotive industry through a value chain lens. Finally, it is equally important to note that the terms "digital transformation" (referring to digitalization) and "Industry 4.0" are used synonymously throughout this thesis.

2.2.3. Drivers

As depicted in Section 2.2.1, one of the most important criteria for an effective policy-making at the industry level is to understand "drivers" in general. While the concept of "digitalization" defines a company's efforts to increase the capacity and capability

for the development of technologies, this thesis places the emphasis on the specific "drivers" that propel successful adoption of Industry 4.0 technologies, particularly in the nascent stages of implementation (Balasingham, 2016).

Drawing upon existing Industry 4.0 literature, we identify several key drivers crucial for successful Industry 4.0 adoption. These drivers include:

i. A strong justification for transforming existing processes: There is a clear understanding of why change is necessary and what benefits Industry 4.0 will bring (Kroll et al., 2016).

ii. Acceptance of the risks associated with new technologies: Embracing Industry 4.0 technologies requires acknowledging and mitigating risks (Moeuf et al., 2020).

iii. A solid understanding of the technologies themselves: Knowledge of how

   Industry 4.0 technologies work and their potential applications is essential (Zheng et al., 2011).

iv. A skilled and motivated workforce: first, employees need the right training and motivation to effectively utilize new technologies (Kumar et al., 2019).

v. Support from top management: financial support and a positive attitude for Industry 4.0 is essential (Walters, D., & Rainbird, 2007).

vi. Collaboration through partners: Industry 4.0 relies heavily on collaboration to function effectively (Han & Hui, 2022; Pamukçu & Sönmez, 2012).

This research identifies collaboration as a crucial element in driving Industry 4.0 adoption. However, it distinguishes between drivers that directly influence digital

transformation and those that have an indirect or independent impact. While collaboration is essential for achieving Industry 4.0 goals, it should be considered an independent means rather than a driver itself.

Respectively, this research also differentiates between the driving forces behind Industry 4.0 and the collaborative strategies needed to leverage them. It first defines the goals of Industry 4.0 adoption, represented by driver criteria, and then identifies specific collaborative approaches that directly support those criteria.

Finally, on the basis of the above-described motives, the significance of drivers for Industry 4.0 adoption is underscored by the failure of implementations, such as lean production systems, often attributed to a lack of organizational capability. Therefore, this thesis focuses on these critical drivers as key indicators of successful adoption and utilization of Industry 4.0 technologies.

2.2.4. Barriers

In literature, there has been a vast of research on the synthesis of barriers related to implementation of Industry 4.0 (Horváth Roland Zs., 2019; Kamble et al., 2018; Oesterreich Frank, 2016; Raj et al., 2020a; Wang Liwei; Yuan, Yong; Ni, Xiaochun; Han, Xuan; Wang, Fei-Yue, 2019)

Among the barriers, we should list as major ones as:

i. the lack of a skilled workforce (Kiel et al., 2017)

ii. shortage of resources (Geissbauer et al., 2014; Kiel et al., 2017)

iii. low degrees of standardization, poor infrastructure for the implementation of Industry 4.0. (Geissbauer et al., 2014)

iv. lack of knowledge and strategy for Industry 4.0 (Türkeș et al., 2019)

In addition, Alcácer & Cruz-Machado (2019) highlight that a company's level of digital transformation maturity directly affects how managers perceive barriers to Industry 4.0 adoption. Kamble et al., (2018) identified 12 barriers hindering the adoption of Industry 4.0, drawing upon a comprehensive literature review and the interviews with experts from both industry and academia. Notably, "legal and contractual uncertainty" emerged as the most significant barrier, directly or indirectly influencing all other identified obstacles.

Moreover, extensive research has explored the barriers hindering the adoption of Industry 4.0 technologies, particularly for companies in both developed and developing nations. Recent studies by Horváth & Szabó, (2019) and Türkeș et al., (2019) highlight key obstacles preventing companies from achieving digital readiness. The authors' analysis revealed a lack of knowledge about Industry 4.0, a primary focus on development costs, and a limited understanding of its strategic importance

2.2.5. Impacts

The increasing adoption of digital technologies by businesses is driving digitalization, which will inevitably impact the entire economy. The economic impact of digitalization and related technologies on the industry is significant and substantial. Digitalization is transforming internal business processes and reshaping how companies interact with their customers and suppliers (Oppitz & Tomsu, 2018).

In this respect, the EU has been actively advocating for Industry 4.0 and Europe Digital Transformation.

The report by EIT Digital (2021) emphasized the potential of digital transformation, highlighting its impact on business performance, job creation, and economic growth. According to the report, companies utilizing new digital technologies outperform competitors by a factor of ten, while a fully realized Digital Single Market could increase GDP by 6%, create 3.8 million jobs, and reduce administrative costs by 15-20%.

Moreover, the report inclines that the internet economy alone could generate 1.5 million new jobs. Big data technology, with a projected value of USD 16.5 billion and a 40% annual growth rate, can boost company productivity by 5-6%. Digitalization in European manufacturing could lead to a 15-20% increase by 2030. However, despite these opportunities, digital adoption remains a challenge, with only 14% of SMEs utilizing the internet for business in 2015, and 40% of EU companies yet to adopt advanced digital technologies.

While technological advancements could disrupt 54% of the EU workforce, evidence from German SMEs suggests a net positive impact on job creation, with 2.6 new jobs created for every job lost (EIT Digital, 2021). In a different research, global companies are termed to anticipate a significant surge in digitalization by 2021, with projections indicating an average increase of 38% in their digital level between 2016 and 2021 (Geissbauer et al., 2014)

From a complementary perspective, digitalization has also social impacts. Digital transformation and the shift towards Industry 4.0 are driving the creation of new business models, products, and services, leading to the emergence of new occupations. However, this transformation may be depicted to result in the displacement of numerous low- and middle-skilled jobs.

Moreover, the economic and social impacts of digitalization and the transition towards Industry 4.0 are also predicted to be substantial as depicted in the previous sections. Significant investments in digitalization will drive an increase in the digital level of individual companies (improves the maturity levels) and consequently, the entire economy.

We may also anticipate that digital transformation may require strong leadership and the adoption of collaboration stakeholder models and networks (Fonseca, 2018) Additionally, despite efforts to encourage the adoption of Industry 4.0 practices, the integration of advanced manufacturing technologies appears to be slow.
Existing research on the drivers and barriers to adoption often lacks a sector-specific perspective.

This study addresses this gap by focusing on the Turkish automotive industry to examine the impact of various Industry 4.0 technologies and identify key implementation challenges.

In summary, while many organizations recognize the impact of digitalization, most haven't established a clear implementation strategy. Therefore, this research opted for a comprehensive approach, identifying selected criteria to guide effective policy-making at the industry level.

2.2.6. Challenges

In addition to the literature review, on the basis of preliminary discussions conducted with surveyed industry leaders, several challenges (research statements), faced by Turkish automotive companies in adopting Industry 4.0 technologies and digitalization, may be listed as follows:

i. **Lack of Awareness and Resources:** Companies may lack awareness of Industry 4.0 or have incompatible resources, making adaptation difficult.

ii. **Digitalization Gap:** A common starting point is a disconnect from average levels of digitalization and smart automation capabilities.

iii. **Need for a company-specific Maturity Level definition:** A distinct ML-1 level for companies might be necessary to differentiate them from more advanced ones, recognizing that some lack the awareness and resources for Industry 4.0 adoption.

iv. **Adopting New Digital Technologies:** Companies listed in ML-1 stages need to be made aware of relevant digital technologies.

v. **Investment and Organization Change:** Companies at the ML-1 stage may require investments in technology, employee training and organizational change.

vi. **Strategic Misalignment and Strategy Planning:** Companies at the early stages (e.g., ML-1 or ML-2) may be strategically misaligned. In addition, a systematic methodology for Industry 4.0 adoption can motivate companies to develop their own Industry 4.0 vision.

vii. **Lack of Motivation:** Companies may need to construct a clear understanding for a basis of digitalization to sustain companies their own Industry 4.0 vision.

Luthra & Mangla (2018) conducted a comprehensive literature review, identifying 18 key challenges hindering the adoption of Industry 4.0. Their findings revealed that organizational challenges pose the most significant obstacle to achieving supply chain sustainability through Industry 4.0 within the Indian manufacturing sector.

In addition, despite benefits, we may note that German companies faced significant technical and economic hurdles in adopting Industry 4.0. Key challenges included limited financial resources, as depicted by Davis (2015), workforce skill gaps, resistance to data-driven business models, and legal concerns regarding liability and intellectual property.

2.3. Maturity Model for Digitalization

This thesis introduces a comprehensive maturity model on the basis of digitalization and/or digital transformation designed to assess surveyed companies. Existing maturity models in literature will shortly be discussed.

Our maturity model draws upon elements from other maturity models which may be referred to (Geissbauer et al., 2014; Leyh et al., 2016; Lichtblau et al., 2015). For instance, The Connected Enterprise Maturity Model (2018) proposes four crucial technology dimensions for achieving Industry 4.0: information infrastructure (hardware and software) data-driven controls and devices (sensors, actuators, etc.) networks facilitating information exchange, and robust security policies. In particular, other research suggests that a company's digital maturity level significantly influences managerial perceptions of Industry 4.0 barriers. Organizational resistance, particularly from employees and middle management, also poses a significant challenge to Industry 4.0 adoption. Several studies have also employed Multi-Attribute Decision-Making (MADM) techniques to analyse barriers.

For instance, Karadayi-Usta, (2020), Saatçioğlu et al., (2019) and Yun Gwan-Su, (2013) utilized the “Interpretive Structural Modeling” method, while Kamble et al., (2018) completed fuzzy MICMAC analysis focusing on the interrelationships between barriers within Indian manufacturing companies. On the other hand, Karadayi-Usta (2020) identified a "lack of education system" as a primary obstacle.

Similarly, Saatçioğlu et al. (2019) found that a "lack of vision" was the most influential barrier affecting other obstacles in Turkish companies. In this respect, (Raj et al., 2020) and Gunjan et al., (2020) demonstrate three different MADM techniques - Analytical Hierarchical Process (AHP), ISM and DEMATEL are applied to analyse and establish relationships between barriers. However, Karadayi-Usta (2020) and Kamble et al., (2018) applied an MADM approach to establish the contextual relationship between the identified barriers to Industry 4.0 adoption.

On the other hand, Gökalp et al. (2017) proposed a different Industry 4.0 maturity model that encompasses five key dimensions: asset management, data governance, application management, process transformation, and organizational alignment. They defined six maturity levels (0-5) ranging from "incomplete" to "optimizing" each characterized by specific practices and features within these dimensions.

Akdil et al. (2017) put forth an Industry 4.0 maturity model structured around four levels and three primary dimensions. These four levels of maturity have been defined as per their precious study covering different dimensions of adoption. These levels, representing the extent of Industry 4.0 adoption, are:

i. Level-1 Absence: Industry 4.0 requirements are entirely unmet.

ii. Level-2 Existence: Minimal utilization of key Industry 4.0 elements like integration, automation, data collection, digital technologies, and interoperability.

iii. Level-3 Survived: Moderate utilization of integration, data sharing, and interoperability.

iv. Level-4 Maturity: High-level utilization of integration, data sharing, and interoperability, indicating advanced Industry 4.0 adoption.

However, based on our in-depth analysis conducted in this research, the main aspects of a *more precise and simplified* five-level maturity model is presented below:

i. Level-1: Characterized by the use of basic digital tools, with limited integration and strategic planning.

ii. Level-2: Involves more systematic implementation of digital technologies in specific areas, with some degree of process automation and data analysis.

iii. Level-3: Represents a more strategic approach to digitalization, with defined processes, integrated systems, and a focus on data-driven decision-making.

iv. Level-4: Characterized by advanced digitalization across most functions, with a high level of automation, data analytics, and real-time insights.

v. Level-5: Represents full digital transformation, where digital technologies are seamlessly integrated into all aspects of the business, enabling agility, innovation, and a data-driven culture.

In this respect, we expect that each level described above may reflect increasing sophistication in digital transformation, adoption, data utilization, and the strategic integration of technology to drive business value.

Based on this expectation and assumption of ours, similar to Gökalp et al. (2017) and Akdil et al. (2017), defined practices, features and levels of maturity, our model comprises a five-levelled maturity model under 8 (eight) different dimensions evaluated with a detailed set of sub-criteria as described in Section 3.3.

CHAPTER 3

RESEARCH DEFINITION

Overall, this study identifies the main drivers, barriers, readiness (capabilities) and implications related to the adoption of Industry 4.0 practices by Turkish automotive industry. The study concludes to propose several policy recommendations aimed at promoting the adoption of Industry 4.0. Basically, our research aims:

i. to demonstrate the extent to which the surveyed companies are currently utilizing and investing in Industry 4.0 technologies to enhance their productivity, competitiveness, and growth

ii. to examine the diverse range of framework conditions and factors (criteria and sub-criteria) that can either motivate or hinder companies from investing in advanced manufacturing. These factors include financial considerations, legislation, human resources, skills development, government intervention, and the collaborative business environment

iii. to analyse the current maturity levels of companies as they strive to adapt to Industry 4.0 practices. We will also examine potential mid-to-long-term implications (both current and future expectations) such as organizational restructuring, training needs, cultural shifts, and the adoption of new business practices.

In alignment with aforementioned research framework, first, we conducted a comprehensive review of existing research to identify key factors (criteria and sub-criteria) influencing the adoption of Industry 4.0 technologies within the Turkish automotive industry, specifically focusing on criteria that either drive or hinder the integration of new technologies. These criteria and sub-criteria were then categorized into different maturity levels. Furthermore, literature-based conceptual work was conducted to develop a more detailed understanding of the various dimensions of these companies' maturity levels with regard to Industry 4.0 practices.

We aimed to present a comprehensive empirical analysis examining the factors driving and hindering the integration of Industry 4.0 applications within the Turkish automotive industry.

Therefore, we may state that our research specifically considered the industrial development context and key user-side factors among surveyed companies, exploring how these factors influence the adoption, maturity, and overall digitalization efforts related to Industry 4.0 technologies.

Through the use of interviews and a survey, a set of selective data were collected in a qualitative and quantitative manner.

Following the data collection through the survey, the subsequent chapters present an analysis to refine and interpret the research findings based on our research questions listed in Section 1.4. This refined analysis forms the basis for the concluding mathematical modelling and analysis presented later in the thesis.

In summary, this thesis introduces a new methodology to rank companies according to their current choices / future expectations and to define their Industry 4.0 maturity levels. The research also provides a comprehensive analysis of the strategic considerations, drivers, and barriers related to Industry 4.0 adoption and implementation within the Turkish automotive industry.

To achieve this aim, our research systematically examines relevant literature to develop a conceptual framework outlining key strategic criteria for adoption of Industry 4.0 and leverage between companies to consider when integrating Industry 4.0 technologies into their production operations.

3.1. Survey Details

This research sought to examine important management practices within the Turkish automotive industry. The study used survey results to understand common approaches and viewpoints within the industry.

3.1.1. Survey Information

"Digital Transformation Information Survey," commissioned by OTEP and supported by both the Automotive Suppliers Association of Türkiye (TAYSAD) and the Automotive Manufacturers Association (OSD), was finalized in 2018 and published in 2019. This survey revealed a significant growth potential for Industry 4.0 practices within the developing Turkish automotive industry. The report utilized a novel analytical approach to comprehensively assess the sector and evaluate the impact of Industry 4.0 technologies. The survey questions are listed in Appendix-A.

Established in 2008 with the support of TÜBİTAK, OTEP remains operational in Türkiye. This organization, directly related to the Automotive Suppliers Association of Türkiye (TAYSAD), focuses on developing capacities and R&D practices for its member companies. Their aim is to bolster members' competitiveness within the global automotive industry and foster a collaborative R&D strategy. Overall, OTEP's strategic objective is to identify and analyse the practices needed to achieve and maintain Türkiye's long-term competitiveness in the global automotive sector.

In 2018, OTEP conducted a survey focused on digital transformation among its member companies within the Turkish automotive manufacturing sector. This survey, structured across seven main themes and consisting of 53 questions, was distributed to over 200 member companies. Forty-seven companies participated, including six major automotive producers and 41 first-tier suppliers, resulting in a response rate of over 20%.

The main goal of the survey was to analyse a representative sample of the Turkish automotive industry. To achieve this, OTEP aimed to gather valuable data and receive a high response rate from key players in the industry. With responses from six major automotive producers and 41 first-tier suppliers, including an over 80% completion rate from 38 major first-tier suppliers, the survey successfully captured a significant cross-section of the Turkish automotive industry.

This high level of participation, especially from major automotive producers and key first-tier stakeholders, strengthens the study's ability to accurately reflect the prevailing viewpoints and practices within the sector. Moreover, most of the questions in the survey was additionally listed / prepared to collect information on the present and future prospects of companies. Hence, for those questions, as listed in Appendix A, “Current/Present (M)” and “Target/Future (G)” criteria were collected separately for each question. Survey questions were prepared to analyze both direct and indirect contributions of Industry 4.0 technologies to Turkish automotive manufacturers and suppliers.

The survey also aimed to quantify the impact of digitalization within the Turkish automotive industry and projected a *target year* selection criteria for achieving desired levels of digital transformation.

The initial report, published in 2019, showed a significant difference between suppliers and manufacturers in terms of their current digital transformation scores. The survey data indicated a strong commitment from companies to leverage digitalization for increased competitiveness.

The OTEP report findings suggested that, on average, main manufacturers aimed to achieve digital integration by 2020, while suppliers set their target for 2021. This difference highlights a shared ambition for swift digital transformation across the industry.

The 2019 report, while not highlighting a major overall difference, did reveal a distinct pattern of stage-based digitalization among first-tier supplier companies. It is also important to note that second and third-tier companies registered with OTEP were not included in the survey.

Moreover, the 2019 survey analysis, based on a 5-point Likert scale, revealed an average level of digitalization across companies. Main industry players, "producers," showed a slightly higher average level of digitalization (3.5) compared to supplier companies (3.2).

However, the report concluded that this difference was not statistically significant, especially among companies with strong IT infrastructure and robust organizational cultures. Therefore, this study will not differentiate between the digitalization performance of "producer" and "supplier" companies.

Finally, based on the theoretical framework described in Section 2, we may depict that survey targeted to draw upon the levels of maturity of digitalization for a sample of Turkish automotive manufacturers.

In this respect, parameters and scale of the survey have been evaluated / adapted from Stentoft et al. (2021) that structured its survey on seven different 5-point Likert scale questionnaire items.

Respectively, OTEP officials choose to modify the survey questions to expand the research with other criteria.

3.1.2. Survey Technique

This section details the preparation and execution of the survey designed by OTEP to provide actionable insights into the factors influencing digitalization maturity levels within the Turkish automotive industry. Generally, the survey employed a face-to-face questionnaire with ordinal scales to quantify qualitative characteristics, ensuring standardized responses and minimizing ambiguity. Open-ended questions were largely avoided in favour of direct questioning to reduce subjectivity and encourage concise answers.

Overall, the questionnaire comprised 53 questions (refer to Appendix A for a list of survey questions) with more than 600 sub-criteria (subsequent answers) defined linked to those questions. Most of the questions utilized an ordinal scale to compare the "Current/Present" state with the "Target/Future" state of participating companies. For these questions structured to compare current and target states, responses for each state were analysed separately.

Finally, our analysis aimed to rank companies based on their current digitalization efforts and their future aspirations in this respect.

3.1.3. Survey Data

The data used in this thesis is extracted from the OTEP's survey results conducted in 2018 and from the final report published by OTEP in 2019. The data has been extracted from the results of the report and survey itself.

With respect to the survey, rankings have been measured on an ordinal or continuous scale. Examples of ordinal variables include Likert scales (e.g., a 5-point scale from strongly agree through to strongly disagree), amongst other ways of ranking categories (e.g., a 5-point scale explaining how much a customer liked a product, ranging from "Not very much" to "Yes, a lot" and/or “Not at all important,” “Slightly Important,” “Important,” “Fairly Important,” and “Very Important,”).

Accordingly, Table 4 briefly describes the data characteristics of the survey data.

Table 4 - Data characteristics

Dimension	**Characteristics**
Data Source Availability	External-Closed (specific)
Data Source	Automotive manufacturers and suppliers
Data Aggregation	Survey Database
Data Ownership	One Legal Entity (OTEP)
Data Structure	Structured / Likert-scale
Data Format	Proprietary
Data Standardization	Syntax, Values
Data Completeness	High
Data Sharing	Proprietary / Limited

As denoted in Section 3.1.1, the data has been collected through the participation of the most important members of the platform with the intent of the examining the current situation of the automotive industry regarding digital transformation. Hence, the results of the survey can also be utilized in order to form the pool of information that will constitute the basis for defining the digitalization road map of OTEP member companies for the future.

3.2. Research Framework

This thesis explores the most impactful criteria influencing maturity levels (MLs) within the context of digitalization. The survey data as defined in Section 3.1 provided information for constructing a measure of the "maturity level of digitalization" while the data also included a comprehensive assessment of the automotive sector in Türkiye. By linking these aspects, this thesis generally targeted to investigate / forecast the long-term impact of digitalization.

Furthermore, we found out that Turkish automotive manufacturers recognize the need to cultivate specific capabilities to leverage Industry 4.0 practices and enhance their competitiveness. However, in general, *all* of the surveyed companies seem to struggle to prioritize which digitalization measures and Industry 4.0 practices to adopt. To address this challenge, this study establishes a research framework to guide managers in selecting and focusing on specific criteria linked to digitalization maturity levels. In this respect, to elaborate the research questions depicted in Section 1.4, we have identified and analysed sub-criteria in terms of their effects on maturity and on the following we have produced a conceptual framework.

As described above, given the lack of research identifying the key criteria that significantly enhance digitalization and Industry 4.0 performance in the surveyed companies, this study aims to:

i. identify the general criteria from existing literature

ii. conduct a questionnaire-based survey with industrial experts from Turkish automotive manufacturers to identify the list of *essential* criteria and sub-criteria & define a maturity model

iii. categorize the selected criteria and sub-criteria under different maturity levels in our model

iv. comprehend Multi-Attribute Decision Making (MADM)

v. apply the Best-Worst Method (BWM) in order to rank the companies on the basis of their digitalization performance with regard to selected criteria classes.

vi. identify influential criteria and sub-criteria within each maturity level category (1-5) by employing the CC bi-clustering method to determine the influence of the criteria defined within each level.

The solution methodology applied to the present study is defined under a mathematical analysis built over consistent results and associated criteria weights to define the weights of compared criteria for maturity levels. Figure 1 illustrates the fundamental research framework, connecting our research questions defined in Section 1.4 to the hypotheses defined in Section 1.5. Figure 1 also provides an overview of the chosen criteria classes linked to the research questions and hypotheses.

3.3. Research Phases

This research was designed using the mathematical models of the research paradigms described in Section 4.3. In addition, the bi-clustering method described in Section 4.4 was also consulted to conclude the research. This thesis adopts a *quantitative* research approach, which emphasizes understanding subjective experiences and interpretations.

The methodology utilized our research questions to assess and rank companies. In addition, the listed rankings are expected to reflect the collective preferences of the companies by analysing their maturity levels of digitalization performances, essentially measuring the influence and impact of respective criteria.

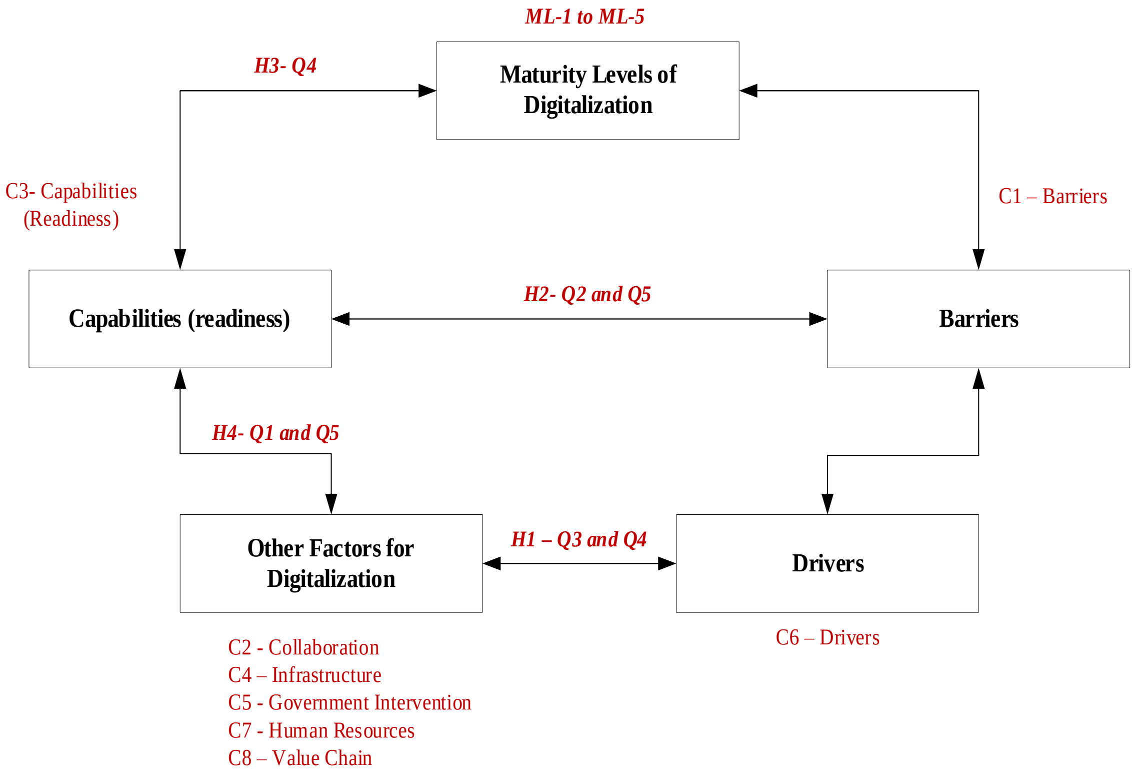

Figure 1 - Research Framework and Hypotheses

In this regard, first, expert-based answers relying on the subjective judgments of managers from selected companies were structured to help us to evaluate and categorize companies on perceived Industry 4.0 capabilities.

From the survey, experts provided their opinions on which main criteria and sub-criteria classes should be included in the ranking study and we assigned weights based on predefined criteria.

Sub-criteria, as the name suggests, are expected to combine elements of expert-based views and criteria derived from the literature. Bu using both, we integrated the "stated preferences" evident in Industry 4.0 adoption (digitalization) to create a more comprehensive ranking system.

This study aimed to determine the digitalization maturity levels and rankings of selected companies within the Turkish automotive industry. To achieve this aim, a five-phased approach was defined and implemented in the thesis:

- **Phase 0 – Determination of Maturity Levels:** Determination of maturity model and criteria.

- **Phase 1 – Classification of Criteria:** Determination and utilization of eight main sub-criteria extracted / supported from literature and from expert opinions

- **Phase 2 – Specification of Sub-Criteria:** Determination and utilization of a range of eighty-four sub-criteria.

- **Phase 3 – Firms Ranking with Best-Worst Method (BWM):** Ranking companies' Industry 4.0 performances on the basis of their "current / present" and "future / target" expectations.

- **Phase 4 – Maturity Level Analysis with Bi-clustering Method:** Bi-clustering of criteria and sub-criteria to evaluate and define the Maturity Levels of companies and digitalization capacity.

Figure 2 illustrates our five-phased approach used to analyse the research questions and hypotheses.

3.4. Research Process Definition

Following the research phases outlined in Section 3.3, criteria (categorized under eight main classes) and sub-criteria (grouped under various sub-classes) for successful digitalization within the Turkish automotive sector were identified through a literature review and expert input. In the subsequent stage, the relationships between these criteria were analysed using the BWM to rank participating companies.

This thesis leverages the strengths of quantitative approaches to provide a comprehensive and nuanced understanding of the research problems. Second, this research embraces a subjective approach by recognizing our role in interpreting and combining different perspectives found in the literature. In conclusion, by employing a mixed-methods approach through a systematic literature review and expert opinions, this thesis harnessed the strength of both BWM and bi-clustering methods to provide a robust and insightful exploration of Industry 4.0 implementation in Turkish automotive industry.

3.4.1. Research Process Visualization

In this thesis, we primarily targeted an exploratory approach to map the landscape of Industry 4.0 implementation in automotive industry in Türkiye. However, acknowledging the limitations of adhering to a single research paradigm, this thesis embraces a pragmatic approach by integrating quantitative methods, specifically the BWM and CC bi-clustering methodologies, within a systematic literature review framework.

Figure 3 provides a visual representation of this thesis's research design flow.

3.5. Restrictions

Yüksel (2020), in a review of digital transformation literature, highlights a survey conducted by UNIDO (2018) involving 5421 participants from Italian industry. This survey aimed to analyse how Industry 4.0 practices affect various aspects of businesses, including customer service, efficiency, productivity, costs, and the creation

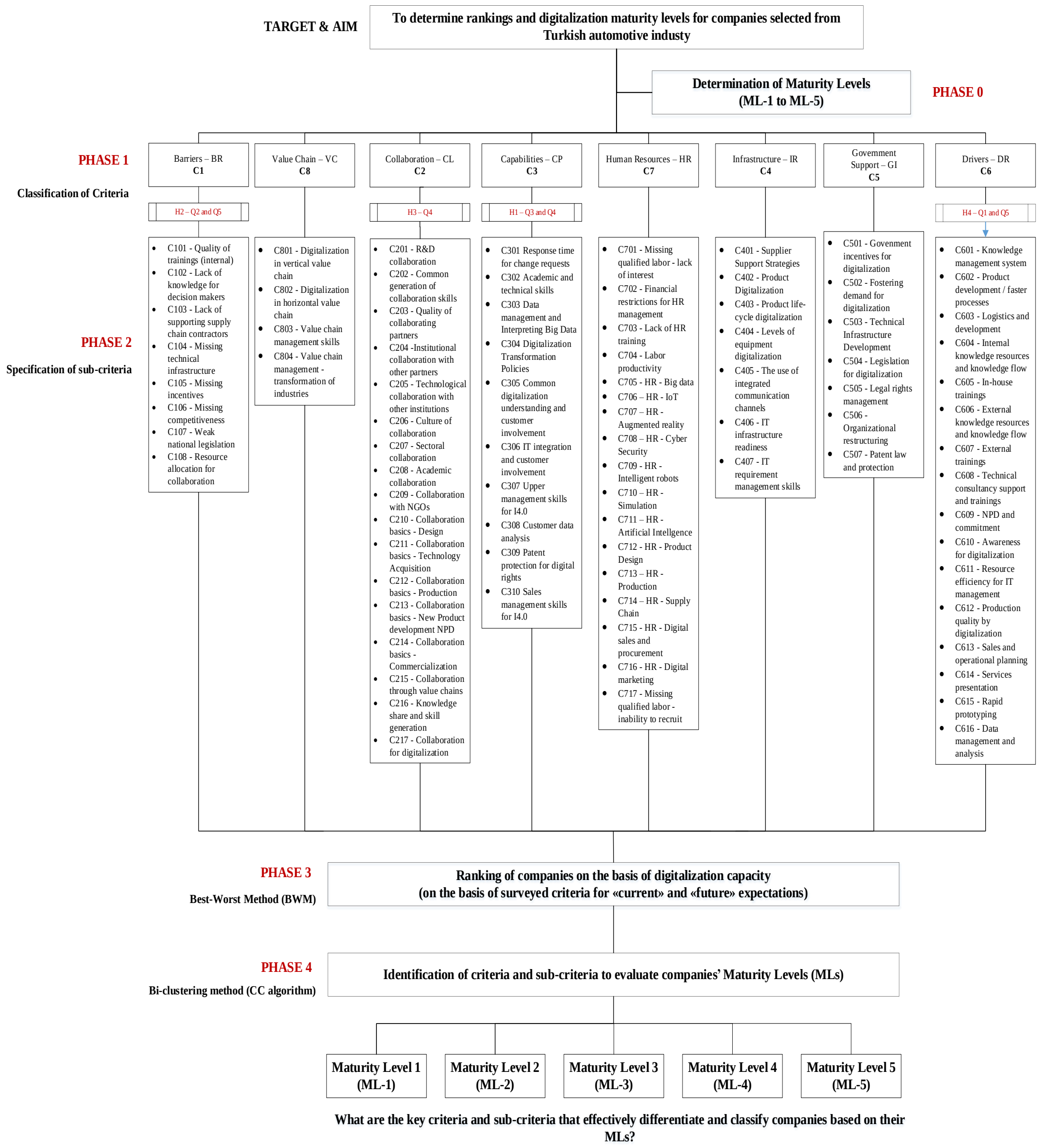

Figure 2 – Research Phases

of new markets. In another study, Geissbauer et al. (2014) discussed efficiency and customer orientation in over 200 companies surveyed on the basis of digitalizing factories. Accordingly, yet another comprehensive study conducted by the European Commission (2018) underlined the benefits of increased productivity, flexibility, new product / services development and lowered costs.

Comparably, in BDC (2017), the authors surveyed among 1000 companies in Canada and they have concluded / highlighted over the benefits of Industry 4.0 by productivity increase, cost decrease effects explain a roadmap for Canadian companies to adopt Industry 4.0 practices.

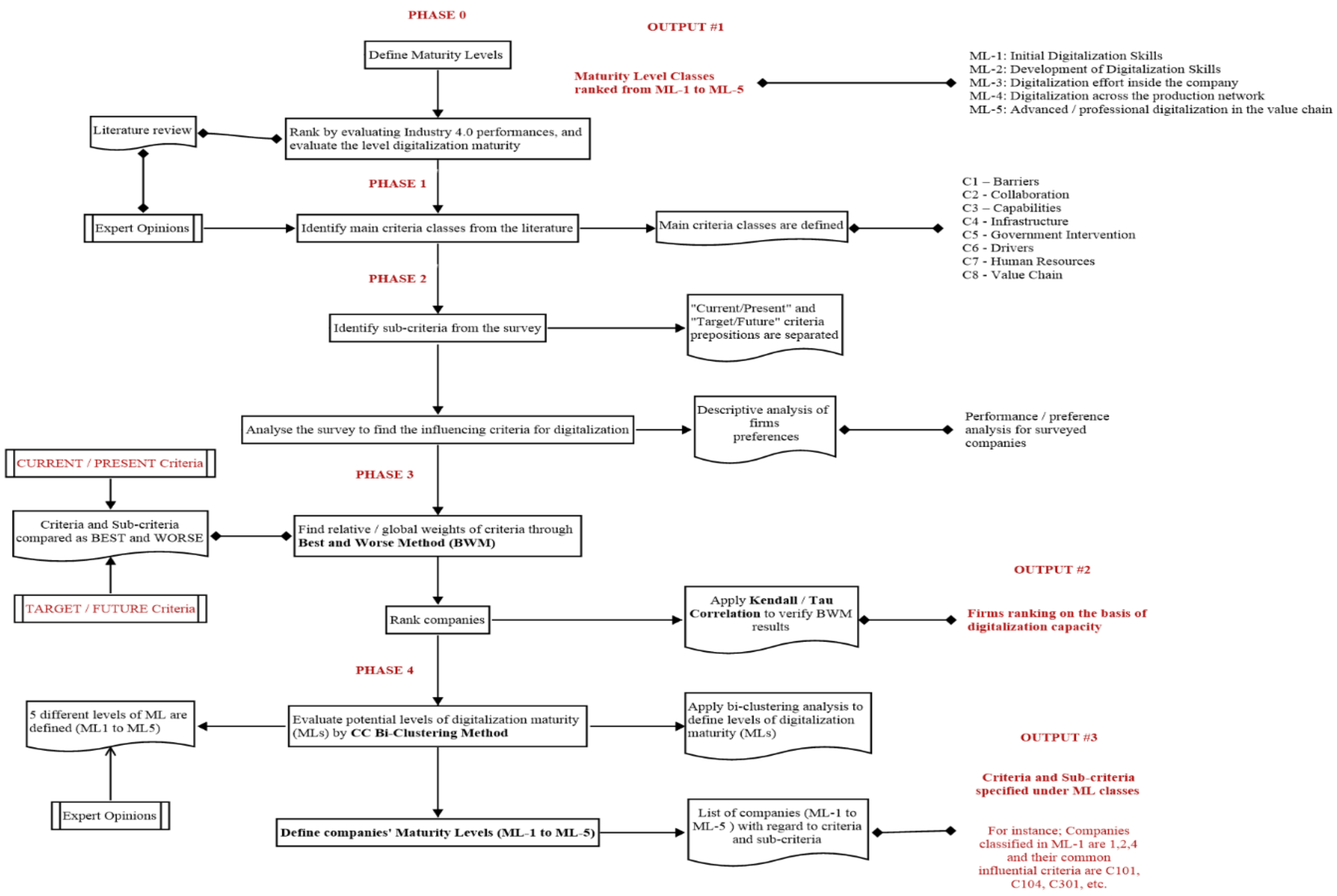

Figure 3 - Flow Chart of Research Process

Compared to the above listed studies conducted, with respect to other research entitled "Industry 4.0", the sample population is generally quite limited and concentrated on a few, larger firms. Despite the small sample size, our survey group exhibits a high degree of homogeneity, suggesting that generalization may be possible. This homogeneity is supported by a *Cronbach's alpha value* of 0.92, indicating strong internal consistency within the measurement instrument used. *(Items: 84, Sample units: 47)*.

In general, this research acknowledges two primary limitations. First, the developed maturity model, while informative, may not fully address the specific research questions and interview topics explored in this thesis. Second, the survey analysis was limited by the use of non-parametric criteria. Supportively, Gall et al. (2003) explain that while nonparametric statistical methods may have less statistical power and sensitivity compared to parametric methods, they are more suitable when working with data that violates the assumptions of normality or homogeneity of variances (as is the case with our clustered data).

In our analysis of survey responses from 47 prominent OTEP members, we assumed equal variances across the clustered data. Our initial goal was to rank Turkish automotive companies based on their digitalization efforts, utilizing the BWM, aligning with previous research focused on understanding the key advantages of Industry 4.0. Subsequently, we used Kendall-Tau statistics to analyse the strength of relationships between our chosen criteria.

CHAPTER 4

METHODOLOGY

This thesis analyses information on the factors influencing the adoption of advanced manufacturing within the Turkish automotive sector. The focus is on understanding how internal and external drivers and barriers have impacted decisions to implement Industry 4.0, and determining the specific criteria and sub-criteria affecting these decisions. The overall goal was first to rank companies based on their digitalization success using the BWM, with a focus on digital transformation. Initial findings revealed noticeable differences in digitalization efforts across companies, despite variations in their production networks.

To gain a more comprehensive understanding, the study also employed a bi-clustering methodology. This approach allowed for the analysis of a wider range of digitalization applications and facilitated a more effective assessment of maturity levels. The analysis took into account various Industry 4.0 criteria and technologies employed by the companies.

By combining both analysis results, bi-clustering results with company rankings derived from the Best-Worst Method (BWM), the study achieved a more accurate prediction of companies' digitalization maturity levels (MLs). This approach allowed for an evaluation of the companies' digitalization efforts. Furthermore, using the results of the bi-clustering analysis and aligning with lean production principles, the companies were categorized based on their digitalization levels across specific criteria.

While the initial ranking of surveyed companies based on their overall digitalization success, a closer look revealed subtle differences in their digitalization efforts within specific stages of their production chains.

To gain a more nuanced understanding, a MADM was conducted. Besides, this study goes beyond a simple ranking of companies' digitalization success by using a MADM analysis to provide a more detailed understanding of their progress. This approach evaluates companies based on various lean production principles, revealing nuanced differences in their digitalization efforts across different production stages.

Our analysis resulted to a strong correlation between MADM-derived clusters and companies' digitalization maturity rankings. Analysing 47 companies within this framework highlighted the practical applications of Industry 4.0 technologies and revealed distinct clusters (maturity classes each) with shared strengths and weaknesses.

In conclusion, our case study successfully demonstrated our framework's ability to predict the digitalization performance of the surveyed companies. The successful implementation of bi-clustering further highlights the framework's versatility and adaptability. Moreover, our study's findings underscore the significant potential of Industry 4.0 to revolutionize the Turkish automotive industry.

4.1. Phase 0 – Definition of Maturity Levels

As explained earlier in relevant chapters of this thesis, digitalization maturity models illustrate the stages a company goes through as it incorporates and utilizes digital technologies within its operational and business frameworks. These models typically range from initial experimentation with basic digital tools to a fully integrated, data-driven organization.

Companies at *lower maturity levels* may exhibit limited digital adoption, relying primarily on traditional processes. As they progress for *higher levels of maturity*, they embrace more sophisticated technologies, data analytics, and automation, ultimately leading to improved efficiency, innovation, and customer experience.

On the other hand, "IT readiness" refers to a company's capacity to effectively utilize and benefit from information technologies and to develop capabilities (Dyerson et al., 2016). While related, capability development (conceptualized as a sub-process of IT readiness in this thesis) and maturity are different concepts. Maturity is assessed during and after implementation. Accordingly, considering the models referred to in Section 2.3, the maturity levels defined in this thesis are ranged from *lower* levels / Maturity Level #1 (ML-1) (representing little to no digitalization) to *higher* levels / Maturity Level #5 (ML-5) (representing advanced, fully integrated digitalization). Our proposed model assesses a company's current digitalization progress and its adherence to Industry 4.0 principles. This assessment process of ours is based on grouping companies under five distinct maturity levels. In brief, the maturity levels listed below provide us a structured framework for evaluating a company's digitalization process and its alignment with the core principles of Industry 4.0:

i. Maturity Level-1 (ML-1): Initial Digitalization Skills

ii. Maturity Level-2 (ML-2): Development of Digitalization Skills

iii. Maturity Level-3 (ML-3): Digitalization effort inside the company

iv. Maturity Level-4 (ML-4): Digitalization across the production network

v. Maturity Level-5 (ML-5): Advanced / professional digitalization in the value chain

Table 5 provides detailed definitions of each maturity level. In addition, Table 6 outlines five distinct bi-clusters that correspond to our specified maturity levels. These bi-clusters are grounded in the assumptions detailed in Section 2.

4.2. Phase 1 – Classification of Criteria

Building upon the maturity model (maturity levels) established in the previous section, this section aimed to identify key criteria for evaluating the Turkish automotive sector's digital transformation progress. This involved first analysing expert opinions gathered from Turkish automotive manufacturing companies through the survey. Guided by the maturity model, the insights derived from this analysis (see Section 2.1.4) provided a framework for understanding the landscape of the Turkish automotive industry.

Table 5 - Definition of Maturity Levels

Main Criteria Class	Maturity Level-1: Initial Digitalization Skills	Maturity Level-2: Development of Digitalization Skills	Maturity Level-3: Digitalization effort inside the company	Maturity Level-4: Digitalization across the production network	Maturity Level-5: Advanced / professional digitalization in the value chain
Barriers (BR)	Limited knowledge; Lacking Supply Chain Management Skills; Weak Technical Infrastructure; Weak Digitalization Competiveness	Limited Knowledge and Skills; Developing Supply Chain Management Skills; Developing Infrastructure; Developing Digitalization Competiveness	Developing Knowledge Base and Skills; Organized Supply Chain; Transforming Infrastructure; Base Digitalization Competitiveness Skills	Knowledge of Digitalization; Advancing Supply Chain Skills; Developing new Infrastructure; Stronger Competitiveness	Strong knowledge and experience; Fully developed and Organized Supply and Value Chain; Advanced and Adapted Infrastructure; Globally Competitive
Drivers (DR)	Weak Knowledge System; Weak Internal and External Training; Weak operational Planning; Low Speed of Production and Development; Weak Logistics	Developing IT Knowledge System; Organized Internal and External Training; Focus on Operational Planning; Increased Speed of Production and Development; Developing Logistics Procedure	Advancing IT Knowledge System; Internal and External Trainings Planned; Advancing Operational Planning; Production Quality Development; Logistics Procedure	Professional IT Knowledge System; Complementary Internal and External Trainings; Professional Operational Planning; Quality Management System; Logistics Systems Development	IT Knowledge management; Training Management / Department; Operational Management; New Quality Procedures; Integrated Logistics Systems.

Table 5 - Definition of Maturity Levels (Continued)

Main Criteria Class	Maturity Level-1: Initial Digitalization Skills	Maturity Level-2: Development of Digitalization Skills	Maturity Level-3: Digitalization effort inside the company	Maturity Level-4: Digitalization across the production network	Maturity Level-5: Advanced / professional digitalization in the value chain
Collaboration (CL)	Weak collaboration; weak partnership	Developing collaboration; partnership development	Formal collaborations; business development with partnerships	Strategic mid-term collaboration; Strategic partnerships	Long-term collaborations; sectoral development through partnerships
Digitalization capabilities (DC)	Weak demand management; weak digital transformation;	Initial demand management; digital transformation planning	Formal Demand Management and Feasibility Skilled Development; Initial Digital transformation strategy	Supplier Network Management and Feasibility; formal Digital transformation strategy	Digital Supply Chain Management; Long-term Digital Transformation planning
Infrastructure (IR)	Weak IT systems and infrastructure; Weak product life cycle management; Weak communication systems	Developing IT systems and infrastructure; Initial product life cycle management; Developing communication systems	Developed IT systems and infrastructure; Product life cycle management and planning; Developed communication systems.	Advanced IT systems and infrastructure; Product life cycle procedures; Advanced Internal and External Communication Systems	Professional IT systems and infrastructure; Product life cycle strategy through IT systems; Qualified Communication Systems Management.

Table 5 - Definition of Maturity Levels (Continued)

Main Criteria Class	Maturity Level-1: Initial Digitalization Skills	Maturity Level-2: Development of Digitalization Skills	Maturity Level-3: Digitalization effort inside the company	Maturity Level-4: Digitalization across the production network	Maturity Level-5: Advanced / professional digitalization in the value chain
Government Intervention (GI)	Weak Incentives and R&D support; Weak knowledge on IT legislation; Weak organizational planning through procedures	Initial ventures for Incentives and R&D support; Knowledge development on IT legislation; Developing Organizational Planning	Intention to apply for Incentives and R&D support; IT legislation adaptation; Organizational Planning	Incentives and R&D support management; IT legislation applications; Advanced Organizational Planning	Incentives and R&D Management Department; IT legislation management; Professional Organizational Planning.
Human Resources (HR)	Weak human Resources; Weak training; unqualified workforce employment	Developing human Resources; HR training planning; Employment development	Initial Human Resources Management; Initial HR training procedures; Workforce employment practices development	Human Resources Management Department; HR training management; Qualified workforce employment	Professional HR Management; HR training department; Strategic Employment Planning (long-term)
Value Creation (VC)	Weak value chain digitalization; weak value chain management practice	Planning for value chain digitalization and Value chain management	Strategy development for value chain digitalization and management	Value chain digitalization and management practices application	Advanced Value chain digitalization and management

Table 6 – Bi-Cluster Definitions and Maturity Levels

Cluster	ML#	Definition
Bi-cluster #5	ML-5	▪ Cluster of companies at the professional level in which they focus on the management of value-chain, core business planning or advancing new Industry 4.0 applications and digitalization (Analysis on upper management- level)
Bi-cluster #4	ML-4	▪ Cluster of companies at the advancing level in which they focus on the whole value-chain, business models or evaluate the impact of Industry 4.0 from a holistic management perspective (Analysis on upper management-level)
Bi-cluster #3	ML-3	▪ Cluster of companies at the development level which focus on the whole value-chain, production network or develop new capabilities for Industry 4.0 from a holistic management perspective (Analysis on technology- and process-level)
Bi-cluster #2	ML-2	▪ Cluster of companies at the planning level in which focus on the strategy, development, business models for Industry 4.0 or evaluate the impact of Industry 4.0 (Analysis on technology- and process-level)
Bi-cluster #1	ML-1	▪ Cluster of companies at the beginning level in which they focus on how to implement Industry 4.0 technologies and concepts on the process-level

As the first step in our mixed-methods analysis, a comprehensive literature review was conducted. This review, supported by some basic insights defined, utilized scientific databases and data from various research projects and industry reports to extract relevant criteria, which allowed for the definition of relative criteria classes for the analysis. Second, following the initial identification of criteria, each research question underwent a thorough analysis to validate the classification of these criteria.

Finally, the defined criteria classes, which aim to assess the current digitalization maturity level and the factors driving its adoption, were reviewed and confirmed by a selection of the surveyed experts, ensuring the robustness and validity of the framework.

In this respect, Table 7 outlines the eight main criteria classes used to assess the maturity model described in Section 4.1.

4.3. Phase 2 – Specification of Sub-Criteria

In the context of this thesis, as described in the previous sections, the key objective was to define the major criteria classes that affect the adoption of Industry 4.0 technologies.

Hence, the defined criteria were to set the scene for a deeper analysis on the basis of the sub-criteria linked to them. In this context, first, we aimed to extract insights to define sub-criteria from the literature, to construct a comprehensive survey and to reveal first patterns to provide a basis for the definition of sub-criteria based on the main criteria.

First, our study revealed a broad-based update on the uptake of Industry 4.0 practices. Methodology and information sources were clearly linked to these practices.

On the following, as denoted earlier, through an in-depth analysis of literature and reports, we have gathered insights for the definition sub-criteria that should prevail the effects of digitalization.

This approach allowed:

i. to draw on a large and extensive dataset and to derive representative criteria and linked sub-criteria

ii. to define criteria to define main maturity levels

iii. to define sub-criteria that are stipulated to distinguish between various maturity levels of companies

iv. to gauge possible impacts of sub-criteria with respect to digitalization effort of companies.

Table 7 – Criteria Class Definitions

Criteria Class	Acronym	Criteria Class	Definition
Barriers	BR	C1	▪ This dimension of class assesses the extent to which digital technologies are integrated throughout the entire value chain, as highlighted by (Leyh et al., 2016) ▪ Barriers listed in this dimension encompasses the barriers of digital technologies starting from the initial product development stage, through the manufacturing process and product sale. ▪ In this thesis, we expect the companies to overcome most of the barriers in order to enhance digitalization efforts.
Collaboration	CL	C2	▪ This dimension of class measures the degree to which companies must collaborate on the basis of digital technologies to support their product development processes. ▪ To fully embrace Industry 4.0 standards, companies need a comprehensive and collaborative approach to product development. ▪ This involves digitally mapping every stage of collaboration, from initial partnerships to formal agreements. ▪ This digital representation facilitates a clear and direct business development strategy, fostering innovation and growth through new partnerships. (Leyh et al., 2016)

Table 7 – Criteria Class Definitions (Continued)

Criteria Class	Acronym	Criteria Class	Definition
Capabilities (Readiness)	CP	C3	▪ This dimension of class assesses the extent of digital technology feasibility and implementation within the production process. ▪ A fully capable company necessitates complete digitalization transformation strategy through digital technologies. ▪ On this basis, new digitalization strategies are crucial as per forming the basis for a flexible Industry 4.0 adapted manufacturing process.
Infrastructure	IR	C4	▪ This dimension of class evaluates the construction for a basis of digital technologies that speed up digitalization efforts. ▪ Targeting for an Industry 4.0 basis requires developed IT systems and infrastructure, a product life cycle (PLC) management and a developed communication infrastructure (Geissbauer et al., 2014)
Government Intervention	GI	C5	▪ This dimension of class focuses on the role of government policies and support in driving digital transformation. ▪ Companies need supportive policies, particularly regarding IT legislation and incentives for R&D, to successfully integrate digital technologies. ▪ Government initiatives can also encourage companies to prioritize digitalization in their service and maintenance operations. ▪ Essentially, a company fully embracing Industry 4.0 requires a supportive policy environment that promotes digital adoption and innovation

Table 7 – Criteria Class Definitions (Continued)

Criteria Class	**Acronym**	**Criteria Class**	▪ **Definition**
Drivers	DR	C6	▪ This dimension of class evaluates the level of digital technologies to be implemented across the production chain. ▪ A key aspect is the drivers that foster the seamless knowledge transfer across different departments within a company and beyond its boundaries (Lichtblau et. al., 2015) ▪ Ideally, we expect companies to strengthen the base for a knowledge system, plan for internal and external training. ▪ Achieving above levels of success (not limited to) for a complete digitalization necessitates also integration all criteria classes defined.
Human Resources	HR	C7	▪ This dimension of class examines the crucial role of human resources in successfully implementing Industry 4.0 technologies and achieving digital transformation. ▪ It emphasizes the importance of aligning HR practices with the demands of a digitalized workplace. ▪ This includes tailoring training programs to equip employees with the necessary digital skills and adapting recruitment strategies to attract talent proficient in utilizing Industry 4.0 technologies. ▪ Essentially, it highlights the need to optimize HR systems and the work environment to support the integration of human capabilities with digital systems, a critical factor in successful Industry 4.0 adoption.
Value Chain	VC	C8	▪ This dimension of class describes the value chain perspective that has to be integrated at the same level of digitalization which will eventually expected to lower the transaction cost. ▪ Value adding perspectives in the space of digitalization require companies to implement different business outlooks to integrate vertical and horizontal value chain digitalization and management practices.

In this respect, our conceptual work was conducted to develop a more detailed understanding of the various dimensions of digitalization with regard to the listed criteria and sub-criteria definitions listed in Table 9.

4.4. Phase 3 - Best-Worst Method (BWM)

4.4.1. Multi-Attribute Decision-Making (MADM)

MADM problems can be expressed by evaluating alternatives based on conflicting criteria (Malczewski, 1999). This main framework can be illustrated in Table 8.

Table 8 - Framework for a MADM Problem

	Criteria$_1$	**Criteria$_2$**	**...**	**Criteria$_n$**
Alternative$_1$	*Outcome$_{11}$*	*Outcome$_{12}$*	...	*Outcome$_{1n}$*
Alternative$_2$	*Outcome$_{21}$*	*Outcome$_{22}$*	...	*Outcome$_{2n}$*
...	...	...	...	...
Alternative$_m$	*Outcome$_{m1}$*	*Outcome$_{m2}$*	...	*Outcome$_{mn}$*
Importance	*Weight$_1$*	*Weight$_2$*	...	*Weight$_n$*

In Table 9, the determination of importance values, the sole unknown variable in the current step, can be achieved through three primary methods, which are outlined below.

Weighting Methods: This thesis provides an analysis of ranking, point allocation with decision-makers, and pairwise comparison methods.

Ranking Methods: This method entails ranking each criteria under consideration based on the decision-maker's preferences. For example, "the most important = 1", "second important = 2" etc.

Following this step, various ranking methods, such as Rank Sum, Rank Reciprocal, and Rank Exponent, can be employed. The way of obtaining importance values is shown in Eq. (1) - (3), respectively.

Table 9 – Criteria and Sub-criteria Definition

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
Barriers (BR)			**C1**			
BR-1	8	6	C101	Quality of trainings (internal)	Ability to train workers to tune digitalization capabilities	Argote & Ren, (2012); Bharadwaj et al., (2013); Bhatia & Kumar, (2022); Cui & Jiao, (2011); Lieberherr & Truffer, (2015); Wilden & Gudergan, (2015)
BR-2	11	1	C102	Lack of knowledge for decision makers	Inability to learn and exploit new opportunities or threats by implementing new/altered products, processes, or services,	Denford, (2013); Protogerou et al., (2012); Raj et al., (2020)
BR-3	11	2	C103	Missing supportive supply chain contractors	Ability to develop new skills from subcontractors to perform tasks more efficiently and effectively	di Stefano et al., (2010); Fischer et al., (2010); Gebauer, (2011); Helfat & Raubitschek, (2000); Vanpoucke et al., (2014)
BR-4	11	6	C104	Missing technical infrastructure	Inability to use own modern / updated infrastructure in order to develop ne capabilities to implement Industry 4.0 opportunities	Anand, (2009); Jantunen, (2012)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
BR-5	11	5	C105	Missing incentives	Inability to act to maintain the potential Industry 4.0 applications for continuous change by aligning and realigning tangible and intangible assets	Argote & Ren, (2012); Cui & Jiao, (2011); Lieberherr & Truffer, (2015); Wilden & Gudergan, (2015)
BR-6	11	7	C106	Missing competitiveness	Inability to react for strengthening the competitiveness on the basis of the companies' production capacity and technology absorption capability	di Stefano et al., (2010); Fischer et al., (2010); Helfat & Raubitschek, (2000); Vanpoucke et al., (2014)
BR-7	11	8	C107	Weak national legislation	Legal requirements/changed legislation on the basis of Industry 4.0 (e.g. CE labelling)	Jantunen, (2012)
BR-8	14		C108	Resource allocation for collaboration	Utilizing efforts for an efficient use of technology and human resources	di Stefano et al., (2010); Fischer et al., (2010); Helfat & Raubitschek, (2000); Vanpoucke et al., (2014)
Collaboration (CL)			**C2**			
CL-1	22	3	C201	R&D collaboration	Collaborating by R&D instead of competing regarding the necessary infrastructure development needed for Industry 4.0	Gebauer, (2011); Sawhney et al., (2005); Teece, (2007); Toorajipour et al., (2021)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CL-2	6		C202	Common collaboration skills	Skill generation with partners by common collaborating efforts during the era of digitalization	Han & Hui, (2022); Howard et al., (2006); Sawhney et al., (2005)
CL-3	21		C203	Quality of collaborative partners	Qualified partnership development in order to assure the excellence of digitalization	Chiou, (2011); Howard et al., (2006); Romero Arturo, (2011); Sawhney et al., (2005)
CL-4	46		C204	Institutional collaboration with other partners	Collaborating to inherit and to promote mutual understanding of Industry 4.0	Chiou, (2011); Howard et al., (2006); Romero Arturo, (2011); Sawhney et al., (2005)
CL-5	48	7	C205	Technological collaboration with other institutions	Collaboration with other partner / subcontractor companies to construct a solid Industry 4.0 basis	Korne, (2017); Pihkala et al., (2007); Symeonidis et al., (2007)
CL-6	12	1	C206	Culture of Supplier collaboration	Cultural alignment through suppliers' collaboration	Dahlgaard & Jens, (2006); Howard et al., (2006); Ke Kwok-Kee, (2008); Sawhney et al., (2005)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CL-7	12	5	C207	Sectoral collaboration	Collaboration among sector member companies	Han & Hui, (2022); Howard et al., (2006); Sawhney et al., (2005); Sonntag et al., (2021); Zhong et al., (2016)
CL-8	12	6	C208	Academic collaboration	Collaboration with institutions, universities and research centres	Han & Hui, (2022); Howard et al., (2006); Sawhney et al., (2005); Sonntag et al., (2021); Zhong et al., (2016)
CL-9	12	9	C209	NGO collaboration	Collaboration with supporting NGO on the basis of capability development	Han & Hui, (2022); Howard et al., (2006); Sawhney et al., (2005); Sonntag et al., (2021); Zhong et al., (2016)
CL-10	22	4	C210	Collaboration basis - Design	Collaboration for design	Han & Hui, (2022); Howard et al., (2006); Sawhney et al., (2005); Sonntag et al., (2021); Zhong et al., (2016)
CL-11	22	5	C211	Collaboration basis - Technology Acquisition	Collaboration for technology acquisition	Howard et al., (2006); D. Li et al., (2008); Sawhney et al., (2005); Sonntag et al., (2021); Zhong et al., (2016)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CL-12	22	6	C212	Collaboration basis - Production	Collaboration for production	Han & Hui, (2022); Netland, (2015); Rossini et al., (2019); Sawhney et al., (2005)
CL-13	22	7	C213	Collaboration basis - New Product development NPD	Collaboration for NPD	X. Lin & Germain, (2004); Nambisan, (2002; E. Rauch et al., (2016); Sawhney et al., (2005)
CL-14	22	8	C214	Collaboration basis - Commercialization	Collaboration for commercialization	Howard et al., (2006); Wu Tzyh-Lih, (2008)
CL-15	12	4	C215	Collaboration through value chains	Collaboration through supplier networks and value chains	Giffi et al., (2020); Howard et al., (2006); Walters, D., & Rainbird, (2007)
CL-16	22	1	C216	Share of knowledge and skills	Knowledge and skill generation through collaboration	Chiou, (2011); Denford, (2013); Romero Arturo, (2011); Secchi Arnaldo, (2016)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CL-17	22	2	C217	Collaboration for Digitalization	Collaboration for digitalization capacity development for Industry 4.0 integration	Chiou, (2011); Fabbe-Costes & Lechaptois, (2022); Parviainen et al., (2017); Romero Arturo, (2011)
Capabilities (CP)			**C3**			
CP-1	26		C301	Response Time for change requests	Latency reduction in response time for engineering change requests (ECR)	di Stefano et al., (2010); Helfat & Peteraf, (2009)
CP-2	12	7	C302	Academic and Technical Skills	Skills development through academic and technical studies	Augier David J., (2009); Vanpoucke Ann; Wetzels Martin, (2014)
CP-3	43		C303	Data management and Interpreting Big Data	Big data management and forecasting strengthened Industry 4.0 + digitalization skills	Rygh, (2018)
CP-4	37		C304	Digitalization Transformation Policies	Planning internal and external company policies / strategy for digital transformation	Lundberg et al., (2018); Verma, (2020)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CP-5	42		C305	Common digitalization understanding and customer involvement	Organization change and strengthening acceptance / perception for the digitalization of company	Brettel et al., (2014); Kagermann, (2015b)
CP-6	36		C306	IT integration and customer involvement	Developing capacities for IT integration and customer involvement	Chukalov, (2017); Justus et al., (2018); Schiele, (2010)
CP-7	45		C307	Upper management skills for Industry 4.0	Sustaining digitalization capabilities on the basis of developing capacities for upper management	Issa et al., (2018); Justus et al., (2018)
CP-8	20		C308	Customer data analysis	Digitalization perception development by gathering insights from customer behaviour, preferences and needs	Fabbe-Costes & Lechaptois, (2022); Parviainen et al., (2017)
CP-9	38		C309	Patent protection for digital rights	Strategy development for patent protection and digital rights	Verma, (2020)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
CP-10	18		C310	Sales management skills for Industry 4.0	Sales capability development by addressing digitalization capacities, requirements and needs for Industry 4.0	Fabbe-Costes & Lechaptois, (2022); Giffi et al., (2020)
Infrastructure (IR)			**C4**			
IR-1	13	2	C401	Supplier Support Strategies	Technical support procured for suppliers for the use and adaptation of Industry 4.0 technologies	Shubh, (2017); Verma, (2020)
IR-2	3		C402	Product Digitalization	Required infrastructure for digitalization efforts	Balasingham, (2016)
IR-3	4		C403	Product life-cycle digitalization	Digitalization efforts for product life-cycle	Issa et al., (2018); Justus et al., (2018)
IR-4	28		C404	Levels of equipment digitalization	The use of new / qualified equipment to ease of digitalization	Brettel et al., (2014); Kagermann, (2015b)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
IR-5	17		C405	The use of integrated communication channels	Strategic integration of communication technologies to ease use of Industry 4.0 technologies	Lundberg et al., (2018); Verma, (2020
IR-6	30		C406	IT infrastructure readiness	Increasing the readiness for Industry 4.0 approved technologies with respect to organizational change	Lundberg et al., (2018); Verma, (2020)
IR-7	31		C407	IT requirement management skills	Defining and setting technical skills for IT requirement management on the basis of Industry 4.0 adaptation	Osterrieder et al., (2020); Schiele, (2010)
Government Support (GI)			**C5**			
GI-1	1 3	1	C501	Government incentives for digitalization	Raising business incentives to invest more on Industry 4.0 technologies	European Commission, (2018); L. Y. Lin et al., (2008); Raj et al., (20(20a)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
GI-2	13	4	C502	Fostering demand for digitalization	Providing more resources and motivation that will foster the demand for use of Industry 4.0 technologies	(EIT Digital, 2021; L. Y. Lin et al., 2008; Raj et al., 2020)
GI-3	13	8	C503	Technical Infrastructure Development	Planning for the technical infrastructure development for Industry 4.0 technologies	(EIT Digital, 2021; L. Y. Lin et al., 2008; Raj et al., 2020)
GI-4	13	9	C504	Legislation for digitalization	Defining new rules and settings officially in order to restrain governmental legislation for digitalization efforts	Govindan & Cheng, (2015); Javaid et al., (2021); Ngai et al., (2008)
GI-5	13	10	C505	Legal rights management	Sustaining the basis for digital law transformation and legal rights to enhance accessibility and efficiency	Govindan & Cheng, (2015); Javaid et al., (2021); Ngai et al., (2008)
GI-6	13	11	C506	Organizational restructuring	Governmental support for organizational restructuring on the basis of digitalization by combining multiple efforts	L. Li, (2018); Malik & Kotabe, (2009)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
GI-7	13	6	C507	Patent law and protection	Defining the limits and borders for digitalization legislation and patent law	Lawson & Samson, (2001); Trappey et al., (2017)
Drivers (DR)			**C6**			
DR-1	7	1	C601	Knowledge management system	Defining new KMS strategy and methods by categorizing digital tools and analysing digitalization process	Kroll et al., (2016); Stentoft & Rajkumar, (2020)
DR-2	14	8	C602	Pace of product development / faster processes	The effect of digitalization on product development for faster processes	Kroll et al., (2016); E. Rauch et al., (2016); Synnes & Welo, (2016)
DR-3	14	9	C603	Logistic services and development	Digitalization of integrated Logistic Systems (ILS) used in companies	Barreto et al., (2017)
DR-4	48	1	C604	Internal knowledge resources and knowledge flow	Strengthening the basis for in-house department communication and knowledge flows by new technologies	Fakhar Manesh et al., (2021); Gonzalez & de Melo, (2018); Parent et al., (2007)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
DR-5	48	2	C605	In-house trainings	In-house trainings organized for Industry 4.0 adoption	Stek & Schiele, (2021); Verma, (2020)
DR-6	48	3	C606	External knowledge resources and knowledge flow	Strengthening the basis for product network communication and knowledge flows among subcontractors	Gonzalez & de Melo, (2018); Manesh et al., (2021); Parent et al., (2007)
DR-7	48	4	C607	External trainings	Out-sourced trainings organized for digitalization adoption	Promyoo et al., (2019); Verma, (2020)
DR-8	48	5	C608	Technical consultancy support and trainings	Gathering technical support and services for the integration of Industry 4.0 technologies from subcontractors	Promyoo et al., (2019); Verma, (2020)
DR-9	48	6	C609	New Product Development (NPD) and workers commitment	Supporting the process and strategy for NPD and the involvement of the workers in these processes	Hoyer et al., (2010); Rauch et al., (2016); Satoglu et al., (2006)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
DR-10	48	8	C610	Awareness for digitalization	Sustainable strategies to develop awareness for digitalization	Bharadwaj et al., (2013); Calabrese et al., (2020)
DR-11	14	2	C611	Resource efficiency for IT management	Management of resources for Industry 4.0 technology development and the adaptation of technologies	Dixon et al., (2014); Satoglu et al., (2006)
DR-12	14	5	C612	Production quality by digitalization	Increasing the product quality by adjusting new Industry 4.0 approved technologies	Rossini et al., (2019); Şatoğlu et al., (2018)
DR-13	14	6	C613	Sales and operational planning	Planning for sales and operational planning adjusted to Industry 4.0 requirements	Rossini et al., (2019); Şatoğlu et al., (2018)
DR-14	14	7	C614	Services presentation	Planning for new services for the development of Industry 4.0	Athanasopoulou et al., (2019); Liker & Morgan, (2006); Satoglu et al., (2006)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
DR-15	7	2	C615	Rapid prototyping	Advancing on additive manufacturing	Conner et al., (2014); Haleem & Javaid, (2019); Martinsuo & Luomaranta, (2018)
DR-16	5		C616	Data management and analysis	Big data management and analysis	Chen et al., (2012); Choi et al., (2018); Khan et al., (2014)
Human Resources (HR)			**C7**			
HR-1	8	2	C701	Missing qualified labor - lacking of interest	Lacking of labour and shortage of labour	Co et al., (1998); Jackson et al., (2014); Kumar et al., (2019); Santos, (2000); Wee et al., (2015)
HR-2	8	3	C702	Financial restrictions for HR management	Lacking for labour budget	Rossini et al., (2019); Şatoğlu et al., (2018)
HR-3	8	5	C703	Lacking HR training	Lacking planned and organized skills for HR training	Rossini et al., (2019); Şatoğlu et al., (2018)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
HR-4	14	1	C704	Labor productivity	Increase in the labour productivity by Industry 4.0 applications	Davis, (2015); Fantini et al., (20(20; Kumar et al., (2019)
HR-5	9		C705	HR requirement - Big data	Skilled labour requirement on the basis of big data	Autor et al., (2003); Chiarello et al., (2021); Co et al., 19)98
HR-6	9		C706	HR requirement - IoT	Skilled labour requirement on the basis of IoT	Co et al., (1998); Kumar et al., (2019); Rajput Surya Prakash, (2019)
HR-7	9		C707	HR requirement - Augmented reality	Skilled labour requirement on the basis of augment reality	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-8	9		C708	HR requirement - Cyber Security	Skilled labour requirement on the basis of cyber security	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
HR-9	9		C709	HR requirement - Intelligent robots	Skilled labour requirement on the basis of intelligent robots	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-10	9		C710	HR requirement - Simulation	Skilled labour requirement on the basis of simulation	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-11	9		C711	HR requirement - Artificial Intelligence	Skilled labour requirement on the basis of artificial intelligence	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-12	9		C712	HR requirement - Product Design	Skilled labour requirement on the basis of product design	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-13	9		C713	HR requirement - Production	Skilled labour requirement on the basis of production	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
HR-14	9		C714	HR requirement - Supply Chain	Skilled labour requirement on the basis of supply chain	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-15	9		C715	HR requirement - Digital sales and procurement	Skilled labour requirement on the basis of digital sales and procurement	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-16	9		C716	HR requirement - Digital marketing	Skilled labour requirement on the basis of digital marketing	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
HR-17	11	4	C717	Missing qualified labor - inability to recruit	Lacking skilled labour and expertise	Autor et al., (2003); Chiarello et al., (2021); Co et al., (1998)
Value Chain (VC)			**C8**			
VC-1	25		C801	Vertical value chain digitalization	Digitalization efforts in the value chain with regard to the vertical organization	Bordeleau et al., (2020); Giffi et al., (2020); Kagermann, (2015); Wagner et al., (2018); Walters, D., & Rainbird, (2007); Wang et al., (2016); Wenninger, (2012)

Table 9 – Criteria and Sub-criteria Definition (Continued)

Factor Class	Q#	QS#	C#	Sub-criteria Name	Definition	Resources
VC-2	29		C802	Horizontal value chain digitalization	Digitalization efforts in the value chain with regard to the horizontal organization (between other departments)	Bordeleau et al., (2020); Giffi et al., (2020); Kagermann, (2015); Wagner et al., (2018); Walters, D., & Rainbird, (2007); Wang et al., (2016); Wenninger, (2012)
VC-3	40		C803	Value chain management	Digitalization effects on the value chain management efforts	Bordeleau et al., (2020); Giffi et al., (2020); Kagermann, (2015); Wagner et al., (2018); Walters, D., & Rainbird, (2007); Wang et al., (2016); Wenninger, (2012)
VC-4	15		C804	Value chain management - transformation of industries	Value chain management efforts with regard to digital transformation	Bordeleau et al., (2020); Giffi et al., (2020); Kagermann, (2015); Wagner et al., (2018); Walters, D., & Rainbird, (2007); Wang et al., (2016); Wenninger, (2012)

Abbreviations:

Q# : Question number as listed in the survey
QS# : (if present) Question sub-clause number of the related question (for instance; for Question 9, “Big data” is listed as “1”)

$$w_j = \frac{n - r_j + 1}{\sum_{k=1}^{n} n - r_k + 1} \tag{1}$$

$$w_j = \frac{1/r_j}{\sum_{k=1}^{n} 1/r_k} \tag{2}$$

$$w_j = \frac{\left(n - r_j + 1\right)^p}{\sum_{k=1}^{n} (n - r_k + 1)^p} \tag{3}$$

In Eq. (1) - (3), w_j is the normalized weight for the jth criteria, n is the number of criteria (k $= 1, 2, \ldots,$ n), and r is the rank position of the criteria. There is an additional information required in Eq. (3) which is the weight p of the most important criteria on a $0 - 1$ scale. This weight is entered into the formula and solved for p by an interactive procedure. Once p is determined, weights for the remaining criteria can be calculated.

Point Allocation by Decision Maker: To illustrate this method, we would like to denote Malczewski's (Malczewski, 1999) simple example / case study. He considers a site suitability problem with three criteria: price, slope, and view. Determining the relative importance of these criteria can be achieved through pairwise comparison using a scale ranging from **1** (equal importance) to **9** (extreme importance). Table 10 presents a comparison matrix constructed for this specific application.

Table 10 - Comparison Matrix for BWM

Criteria	**Price**	**Slope**	**View**
Price	1	4	7
Slope	1/4	1	5
View	1/7	1/5	1

In this comparison matrix, price is moderate to strongly preferred over the slope with the value of 4, and other values can be interpreted like this. After obtaining the pairwise comparison matrix, computation of the criteria weights involves three steps:

(a) sum the values in each column; *(b)* divide each element in the matrix by its column total (the resulting matrix is called normalized pairwise comparison matrix) and *(c)* compute the average of the elements in each row of the normalized matrix. These average values provide the relative weights of the criteria being compared. After applying these steps, $w_{price} = 0.675$, $w_{slope} = 0.252$, and $w_{view} = 0.073$ values of weight are obtained (Malczewski, 1999). This method suffers from one major problem related to the number comparison executed: $n(n-1)/2$ total comparison. The following section explains a similar but improved version of this comparison logic used in the BWM (Jafar, 2015).

The primary objective in utilizing MADM is to rank the alternatives according to their overall scores. In this manner, many aggregation methods, like Simple Additive Weighting (SAW) methods, value / utility function approaches, Analytical Hierarchical Process (AHP), ideal points methods, concordance methods, and fuzzy aggregation operations, can be used to obtain the overall scores for each alternative. For a further explanation of these methods, reader can refer to (Malczewski, 1999). In this thesis, SAW function is used to obtain the overall score V_i for alternative i as shown in Eq. (4):

$$V_i = \sum_{i=1}^{n} w_j o_{ij} \tag{4}$$

BWM is employed to determine the importance values (w_j), is elucidated in greater detail below. In Eq. (4), BWM which is explained in a greater detail in the subsequent section is employed to determine the importance values w_j.

4.4.2. BWM Approach

The approach used in BWM eliminates the main disadvantage of the pairwise comparison method. In this approach, the comparison is performed in 2 (two) main steps (Jafar, 2015):

(a) determine the best (most desirable, most important) and the worst (least desirable, least important) criteria

(b) compare the best criteria with others and other criteria with the worst criteria.

For example, consider a mobile phone case with the criteria price, processor, camera, and storage. Decision maker identified the least important criteria as storage and the most important as processor. After defining the best and the worst criteria, the best (processor) is compared with price, camera, and storage. In the second step, price and camera are compared with the worst criteria (storage). After applying these two steps, two preference matrices are obtained and other steps are applied, as explained below. Instead of $n(n - 1)/2$ comparisons, $2n - 3$ comparisons are executed in total with this logic.

4.4.3. Steps of BWM

BWM comprises 5 (five) consequent steps, with are outlined below. Implementing these steps yields the optimal values for w_j and ζ.

1. Determine decision criteria.
2. Determine the best and the worst criteria.
3. Determine the preferences of the best over all the others using a value between 1 and 9. The resulting best-to-others vector would be:
$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$
where a_{Bj} indicates the preference of the best criteria over the criteria j.
4. Determine the preferences of all the criteria over the worst criteria using a value between 1 and 9. The resulting others-to-worst vector would be:
$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})$$
where a_{jW} indicates the preference of criteria j over the worst.
5. The optimal weight for the criteria is the one where, for each pair of w_B/w_j and w_j/w_W, $w_B/w_j = a_{Bj}$ and $w_j/w_W = a_{jW}$ conditions are satisfied. The maximum absolute differences $\left|\frac{w_B}{w_j} - a_{Bj}\right|$ and $\left|\frac{w_j}{w_W} - a_{jW}\right|$ should be minimized to satisfy these conditions. This problem can be expressed as the following mathematical model:

$$\min_{j} \max \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}$$

$$subject\ to$$

$$\sum_j w_j = 1;\ w_j \geq 0 \quad \text{for all } j \tag{5}$$

This model can be transferred to the following problem:

$$min\ \zeta$$

$$subject\ to$$

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \zeta \quad \text{for all } j$$

$$\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \zeta \quad \text{for all } j$$

$$\sum_j w_j = 1;\ w_j \geq 0 \quad \text{for all } j \tag{6}$$

Solving the mathematical model in Eq. (6), the optimal $(w_1^*, w_2^*, \dots, w_n^*)$ and ζ^* are obtained. In the next section, the consistency ratio is mentioned using ζ^*.

4.4.4. Consistency Ratio

A comparison is fully consistent if

$$a_{Bj} \times a_{jW} = a_{BW} \text{ for all } j,$$

which may not be possible for some j. Hence, the consistency ratio is evaluated with Eq. (7).

$$ConsistencyRatio = \frac{\zeta^*}{Consistency\ Index} \tag{7}$$

where the consistency index can be found in Table 11.

Table 11 - Consistency Index (CI) Table

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index	0	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

It can be seen from Eq. (7) that the bigger the ζ^*, the higher the consistency ratio, and the less reliable the comparisons become. For a full understanding of consistency ratio calculation, the reader can refer to Jafar, (2015).

Figure 4 explains the brief steps definition for BWM:

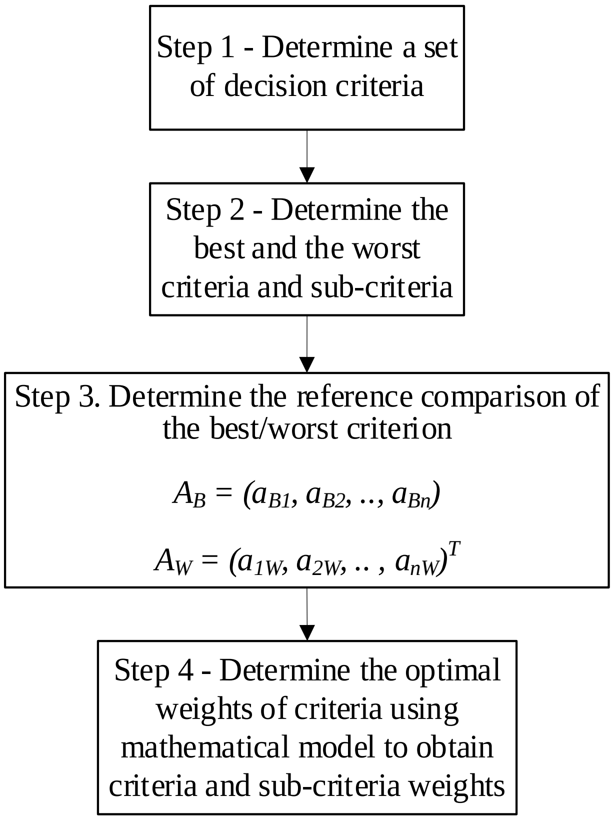

Figure 4 - BWM Process

Source: Moazzeni et al. (2023)

4.4.5. Applications of BWM

Complex MADM problems arise in various fields, demanding significant effort due to their potential size and complexity. Based on the potential challenges, it is important

to use more efficient methods. BWM requires less computational effort and can be extended using methods such as fuzzy sets and other MADM methods. Considering its advantages, it is evident that BWM can be applied in various areas within the literature. These areas are summarized in Table 12:

Table 12 - Example References for BWM Application Areas

Application Area	References
Group MACDM	Gholamreza et al., (2021); Seyyed et al., (2022); Soroush et al., (2018)
Medicine	Jangre et al., (2023); Yazdani et al., (2020)
Manufacturing	Sharfuddin et al., n.d.
Computer Science	X. Li et al., (2020); Sheikh et al., (2022)
Economy	Anchal & Rajesh, (2021
Automotive	Arian et al., (2020); Geerten et al., (2017); Gunjan et al., (2020); Kumar et al., (2018), (2019); Wankhede & Vinodh, (2021)

4.4.6. Kendall's tau-b Statistics

To verify the BWM results, Kendall's tau-b (τ) statistic was used by calculating the correlation coefficient. Kendall’s tau-b is a statistical method used to quantify the strength and direction of association between ordinally scaled variables (meaning the data can be ranked). It serves as a nonparametric test and is particularly useful when the data violates one or more of its assumptions.

In brief, Kendall's tau is a useful statistical tool when researchers work with ordinal data or exploring relationships that demonstrate a consistent trend without being strictly linear. This makes it particularly well-suited for factor analysis, where it can provide valuable information about the stability of the identified factor structure and

the overall reliability of the measurement instrument. By assessing the *monotonic* relationship between variables, Kendall's tau helps researchers determine if the factors and their corresponding items consistently *move* in the same direction, thus strengthening the validity of the analysis (Kendall, 1938).

Kendall’s tau-b can be considered a suitable test when dealing with our sample containing numerous tied rankings. To further validate our findings and ensure “present / current” and “target / future” choices were not due to random chance, we employed Kendall's tau-b analysis.

This method allowed us to compare our ranking results derived from two different settings (present / current vs. target / future), specifically examining the concordance or discordance between them. This approach helped us to confirm a relationship between the rankings, indicating that our results are not simply random occurrences.

The statistics is as follows:

- Kendall's tau-b is a statistical test used to assess the strength of dependence between two choices (relationship between rankings). For instance, Kendall's correlation (τ) can be computed by first counting the number of concordant pairs (*C*) and the number of discordant pairs (*D*). A pair is said to be concordant if they appear in the same order in their ranking lists. Simply:

  If M = (*C* - *D*) then τ_B = M / (*C* + *D*)

  In detail:

$$\tau_B = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

$$n_0 = \frac{n(n-1)}{2}, \text{ where n is data size}$$

$$n_c(C) = \text{number of concordant (x, y) pairs}$$

$$n_d(D) = \text{discordant pairs}$$

$$n_1 = \sum_j \frac{t_j(t_j-1)}{2} \left(t_j = \text{number } x \text{ values tied at } j \text{ th value }\right)$$

$$n_2 = \sum_k \frac{u_k(u_k-1)}{2} (u_k = \text{number y values tied at kth value })$$

To simplify the interpretation of Kendall's Tau, we refer to the work of Joshi, (2021). In his study, the author utilized Kendall's Tau to compare different seasons of Netflix series, aiming to determine if the rankings demonstrated agreement or disagreement in audience preferences.

Similarly, we used this approach to assess the level of agreement between two ranking results of BWM analysis.

4.5. Phase 4 - Bi-Clustering Method

BWM method is chosen to rank the companies. However, since BWM primarily focuses on pairwise comparisons to establish preferences and derive weights for ranking, BWM also does not have the capability to list / compare the companies listed by their choices. BWM, in general, does not inherently group similar objects based on distance or similarity measures, which is fundamental to clustering. Besides, BWM operates on preference information elicited from decision-makers rather than directly on the data itself. While BWM lacks the mechanisms to fully represent and handle the complexities of the data compared to the matrices, bi-clustering can effectively define criteria under different data classes defined like maturity levels. Therefore, to confirm the validity of the BWM results and provide a more in-depth analysis, bi-clustering was employed. This method allowed for the analysis of the underlying mechanisms and factors (criteria) driving the different maturity levels observed among companies, ultimately providing a robust validation of the initial findings.

4.5.1. Traditional Clustering Methods and Challenges

Clustering is a fundamental technique in data analysis, enabling the identification of meaningful patterns and structures within datasets. However, traditional clustering approaches often fall short when it comes to capturing the inherent complexities of data that exhibit relationships in both rows and columns. This limitation arises because traditional clustering methods typically focus on identifying clusters based on the similarities or dissimilarities, without considering the interplay between the two dimensions. Traditional clustering methods may miss crucial insights into the underlying structure of data (Pontes et al., 2015; Steinbach et al., 2004). Bi-clustering addresses this limitation by simultaneously clustering both rows and columns. This powerful approach helps uncover hidden relationships that would otherwise remain undetected.

In this respect, bi-clustering is a data mining technique that allows us to simultaneously cluster rows and columns of a data matrix.

Unlike traditional clustering methods that group similar objects based on all features, bi-clustering identifies subgroups of objects that exhibit similar behaviour across a subset of features (Fraiman & Li, 2020; Zhao et al., 2012). Bi-clustering considers the relationships between the two dimensions concurrently (Fraiman & Li, 2020; Sebastian, 2011; Zhao et al., 2012). The application of this approach is particularly valuable as it allows them to identify groups that exhibit coordinated expression patterns across a subset of samples (Bhattacharya & De, 2009). The difference between traditional clustering and bi-clustering can be seen in Figures 5 and 6.

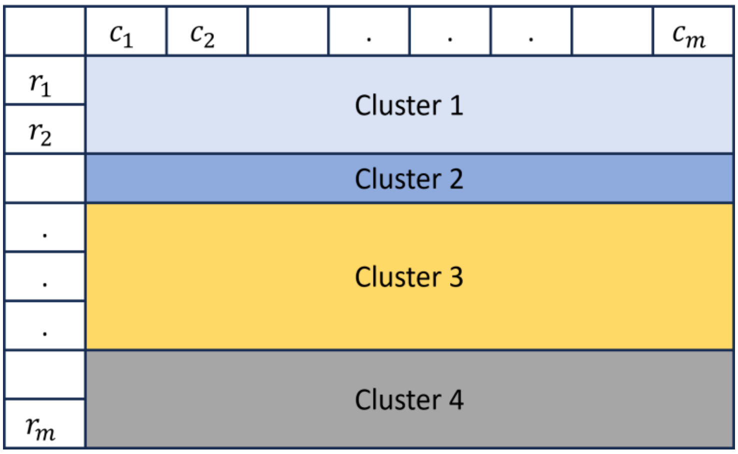

Figure 5 - Traditional Clustering Demonstration

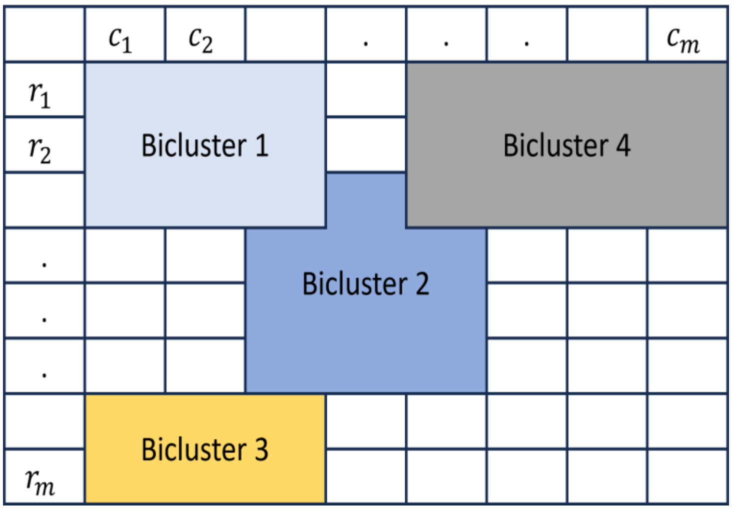

Figure 6 - Bi-Clustering Demonstration

Moreover, bi-clusters can be categorized based on the relationship between the selected rows and columns and the values within the bi-cluster. Some common types are listed and described below (Fraiman & Li, 2020; Sebastian, 2011; Zhao et al., 2012):

i. **One Bi-cluster:** This general term refers to any submatrix within the data that exhibits a distinct pattern. The pattern could be constant values, constant rows, constant columns, or any other coherent structure (see Figure 7).

ii. **Exclusive row and column bi-cluster:** In this type, both the selected rows and columns are exclusive to the bi-cluster.

    This means that the rows (objects) in the bi-cluster are not found in any other bi-cluster, and the same applies to the columns (features) (see Figure 8).

iii. **Checkerboard structure:** This type refers to bi-clusters that exhibit alternating patterns of high and low values, resembling a checkerboard. This pattern suggests an interaction effect between specific rows and columns (see Figure 9).

iv. **Exclusive rows:** Here, the bi-cluster contains a unique set of rows not found in other bi-clusters, but the columns can be shared with other bi-clusters. This indicates that the specific objects exhibit a distinct pattern across a subset of features (see Figure 10).

v. **Exclusive columns:** This type is the opposite of exclusive rows, where the bi-cluster has a unique set of columns, but the rows can be shared.

    This suggests that a specific subset of features exhibits a unique pattern across some objects (see Figure 11).

vi. **Non-overlapping bi-clusters:** In this scenario, the bi-clusters within the data matrix do not share any rows or columns. Each bi-cluster represents a completely distinct subgroup of objects and features (see Figure 12).

Understanding the different types of bi-clusters is crucial for selecting the appropriate algorithm and interpreting the results in the context of the data. Each type provides unique insights into the relationships and patterns hidden within complex datasets.

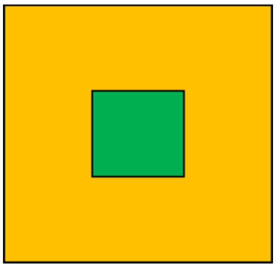

Figure 7 - One Bi-Cluster

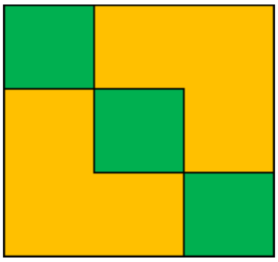

Figure 8 - Exclusive Row and Column Bi-Clusters

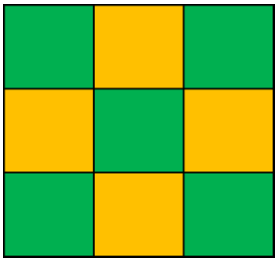

Figure 9 - Checkerboard Structure Bi-Clusters

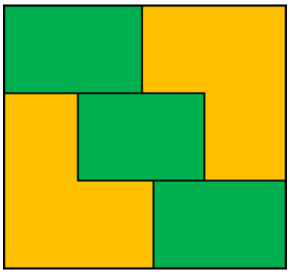

Figure 10 - Exclusive Rows Bi-Clusters

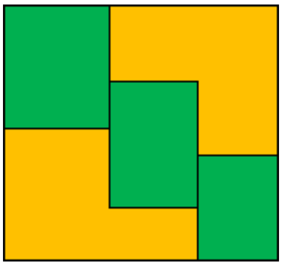

Figure 11 - Exclusive Columns Bi-Clusters

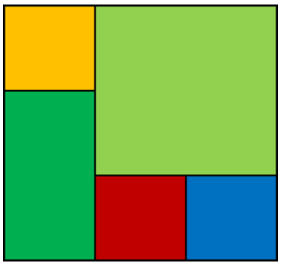

Figure 12 - Non-Overlapping Bi-Clusters with Tree Structure

In detail, originally based on above models, the concept of bi-clustering was first introduced in Hartigan, (1972) but became widespread after first described by Cheng & Church, (2000). Following the work introduced by Cheng and Church, numerous bi-clustering algorithms to refine bi-clusters have emerged, including *Bimax, Plaid, Quest, xMotif, and Spectral*. These algorithms utilize various techniques to identify bi-clusters, such as minimizing the mean squared residue, discovering bi-clusters with large variance or high correlation coefficients, or employing matrix factorization approaches. Each algorithm has its own strengths and weaknesses, making them suitable for different types of data and research questions.

The development of these diverse bi-clustering algorithms has greatly advanced the field, enabling researchers to explore the complex relationships within two-dimensional data more effectively.

4.5.2. Bi-Clustering Types and Structures

Bi-clustering presents challenges in finding optimal solutions through exhaustive search, especially within large datasets.

This is a practical approach by navigating different solution spaces and iteratively refining candidate solutions based on a defined quality measure. While they do not guarantee finding the absolute best solution, meta-heuristics provide a powerful means of achieving near-optimal results. This section reviews key contributions to solving the bi-clustering problem using various meta-heuristic techniques, highlighting their strengths and limitations.

In an aim to assess the quality of bi-clusters, this section reviewed different bi-cluster models based on their ability to evaluate different patterns. We present a comprehensive review of prominent bi-clustering approaches that rely on evaluation measures, categorizing them based on their defining characteristics. It is important to note that these categories are not mutually exclusive, as some algorithms may exhibit traits belonging to multiple groups. While we have categorized them based on their most distinctive features, some algorithms could be classified under multiple groups.

Furthermore, complex MADM problems require substantial effort to address due to their potential scale and intricacy.

Given these challenges, employing more efficient methods becomes crucial. Bi-clustering, with its reduced computational demands, offers a compelling alternative. Its versatility is further enhanced by its compatibility with techniques like fuzzy sets and other MADM methods. Most bi-cluster models target to reach to a local optimum at each step targeting to find a global optimum. Hence, its adaptability and potential for solving complex problems toward global optima make it a highly promising approach for various fields.

In our case, the Turkish automotive industry is marked by complex interdependencies, with manufacturers and suppliers operating within networks. Bi-clustering, a data mining technique, is used to find means of uncovering hidden relationships with respect to Industry 4.0 criteria to guide strategic decision-making.

By simultaneously bi-clustering of companies (e.g., main industry and suppliers) and relevant attributes (e.g., criteria and sub-criteria) revealed groups of companies with similar strengths and weaknesses across different maturity levels as defined in Section 3.1. This insight enabled us to identify the global optima for each company based on criteria and sub-criteria.

Bi-cluster method is used in many different sectors. Basically, to be used to find a optimal point, a bi-cluster structure can be represented as follows:

$$\begin{bmatrix} a_{11} & b_{12} & . & . & . & a_{1|J|} \\ a_{21} & a_{22} & . & . & . & a_{2|J|} \\ . & . & . & & & . \\ . & . & & . & & . \\ . & . & & & . & . \\ a_{|I|1} & b_{|I|2} & . & . & . & a_{|I||J|} \end{bmatrix} \tag{8}$$

In this representation, $\boldsymbol{a_{ij}}$ shows the element in $\boldsymbol{i}^{\text{th}}$ row and $\boldsymbol{j}^{\text{th}}$ column. Some formulas used in the bi-clustering algorithms are shown below:

$$a_{Ij} = \frac{1}{|I|}\sum_{i=1}^{|I|} a_{ij} \tag{9}$$

$$a_{iJ} = \frac{1}{|J|}\sum_{j=1}^{|J|} a_{ij} \tag{10}$$

$$a_{IJ} = \frac{1}{|I||J|}\sum_{i=1}^{|I|}\sum_{j=1}^{|J|} a_{ij} \tag{11}$$

In these formulations, a_{Ij} is the mean of j^{th} column, a_{iJ} is the mean of i^{th} row and a_{IJ} is the general mean.

In this respect, some of the most used bi-cluster algorithm forms that are used to find global optimal are summarized in Table 13. These forms include constant values in rows, columns or both, non-constant values with additive values, multiplicative values or both. In an aim to compare the forms of constant or non-constant values, case specific structures are also shown in Figures 13 and 14, respectively.

In Figure 13, (a) is totally constant bi-cluster, (b) is column constant bi-cluster and (c) is row constant bi- cluster.

Figure 14 (a) is additive bi-cluster, (b) is multiplicative bi-cluster and (c) is both additive and multiplicative bi-cluster.

Table 13 – Main Bi-Clustering Applications

Algorithm	Acronym	Brief Definition	Reference(s)
Direct Clustering	DC	This algorithm employs a divide-and-conquer approach to bi-clustering. It recursively partitions the input matrix into smaller sub-matrices until it obtains k such matrices, where k is a user-defined parameter specifying the desired number of bi-clusters.	Hartigan (1972)
Cheng and Church Algorithm	CC	This algorithm utilizes a sequential covering approach to identify and extract a set of n bi-clusters from an expression data matrix. The quality of each bi-cluster is evaluated using the Mean Squared Residue (MSR) metric.	Cheng & Church (2000)
Maximum Similarity Bicluster algorithm	MSB	MSB does not rely on data discretization however it excels at identifying both overlapping bi-clusters and those exhibiting additive coherence patterns.	Liu & Wang, (2007)
Hierarchical approach with Automatic Relevant dimension selection for Projected clustering algorithm	HARP	This algorithm introduces a novel evaluation metric called the Relevance Index (RI) to assess bi-cluster quality. The RI is calculated by summing the relevance indices of all columns within a given bi-cluster.	Yip et al., (2004)

Source: Revised from Pontes et al. (2015)

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

(a)

1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

(b)

1	1	1	1	1
2	2	2	2	2
3	3	3	3	3
4	4	4	4	4
5	5	5	5	5

(c)

Figure 13 - Constant Structure Bi-Cluster Types

1	2	0	3	2
2	3	1	4	3
3	4	2	5	4
4	5	3	6	5
5	6	4	7	6

(a)

1	2	6	3	9
2	4	12	6	18
3	6	18	9	27
4	8	24	12	36
5	10	30	15	45

(b)

1	3	7	5.3	15
2	5	13	7.3	21
3	7	19	9.3	27
4	9	35	11	32
5	11	31	13	28

(c)

Figure 14 - Non-Constant Structure Bi-Cluster Types

4.5.3. Cheng and Church (CC) Algorithm

The selection of bi-clustering methods in the literature is often contingent upon the structure and nature of the data, as well as the overarching objective of the analysis. We have described some of the main approaches of bi-clustering algorithm in the previous section.

This thesis employs CC algorithm to identify sub matrices (bi-clusters) within the data. Defined first in the Cheng & Church (2000), authors constructed this theory to assess the coherence within a bi-cluster by considering the average gene expression levels and the average condition values present within that bi-cluster. This similar approach was suitable to our case since we targeted to demonstrate companies' maturity levels within different bi-clusters defined by ML-1 to ML-5 and the average sub-criteria values within that bi-cluster.

The CC algorithm has garnered significant attention and is widely regarded as one of the most popular algorithms in the field. Authors defined bi-clusters as sub matrices within a dataset, exhibiting a high degree of similarity. The algorithm's underlying principle dictates that these selected subsets should yield a low mean squared residue (MSR) value, indicating a strong coherence within the bi-cluster. Lastly, the CC algorithm accommodates overlapping bi-clusters, thereby enhancing its capacity to discern a wider array of biological patterns within the data.

Definition: Let X be the set of companies (both main industry and suppliers are listed in the same manner), Y the set of sub-criteria, a_{ij} be the element of the expression matrix A representing the logarithm of the relative abundance of a company of the ith company under the jth sub-criteria, and $I \subset X$ and $J \subset Y$ be subsets of companies and sub-criteria respectively. The pair (I, J) specifies a sub matrix A_{IJ} with the following mean squared residue score:

$$H(I,J) = \frac{1}{|I||J|} \sum_{i \in I, j \in J} \left(a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}\right)^2 \tag{12}$$

where

$$a_{iJ} = \frac{1}{|J|} \sum_{j \in J} a_{ij}, \quad a_{Ij} = \frac{1}{|I|} \sum_{i \in I} a_{ij} \tag{13}$$

and

$$a_{IJ} = \frac{1}{|I||J|} \sum_{i \in I, j \in J} a_{ij} = \frac{1}{|I|} \sum_{i \in I} a_{iJ} = \frac{1}{|J|} \sum_{j \in J} a_{Ij} \tag{14}$$

are the row and column means and the mean in the sub matrix (I, J). A sub matrix A_{IJ} is called a δ – bi-cluster if $H(I, J) \leq \delta$ for some $\delta \geq 0$.

As depicted by Cheng & Church, (2000) attaining the lowest possible score of 0 for the $H(I, J)$ value may signify a synchronous fluctuation in companies maturity level expression levels within the corresponding maturity class (bi-cluster). While a score of 0 for $H(I, J)$ indicates synchronous fluctuation, it could also signify the presence of trivial or constant maturity class (ML-1 to ML-5) (bi-cluster) characterized by an absence of fluctuation. Although these bi-clusters may hold limited interest, their identification and subsequent masking are crucial for uncovering more meaningful patterns on the basis of demonstrative sub-criteria. Consequently, CC algorithm proposes employing row variance as a metric to effectively filter out such trivial bi-clusters.

$$V(I,J) = \frac{1}{|J|}\sum_{j\in J}\left(a_{ij} - a_{Ij}\right)^2 \qquad (15)$$

The CC algorithm is conceptualized as a three-step procedure, encompassing single node deletion, multiple node deletion, and node addition algorithms.

They demonstrated that the task of identifying the largest square-shaped ($|I| = |J|$) bi-cluster belongs to the NP-hard complexity class. The algorithm's time complexity is characterized as $O((n+m)nm)$, where n represents the number of rows and m denotes the number of columns in the dataset.

Algorithms 1, 2, and 3 represent single node deletion, multiple node deletion, and node addition, respectively. These algorithms enable the discovery of one bi-cluster at a time.

However, Cheng & Church, (2000) proposed a consolidated algorithm, Algorithm-4. This integrated algorithm combines the functionalities of the previous three, allowing for the identification of multiple bi-clusters. Their method progressively uncovers potential bi-clusters by iteratively applying Algorithm-4 to the data matrix. Algorithm-4 validates each iteration to signify a step towards a higher level of maturity in identifying significant bi-clusters within the data. Hence, we have defined our maturity levels (ML-1 through ML-5) by leveraging Algorithm-4 to identify bi-clusters within our data. These bi-clusters, representing distinct groupings of sub-criteria, effectively delineate the characteristics of each maturity level, with higher numbered levels signifying greater maturity.

To prevent rediscovery of the same bi-cluster, the sub matrix corresponding to a previously identified bi-cluster is replaced with random values in subsequent iterations. On the basis of our approach, theoretical definitions of Algorithms 1 through 4 are provided below:

Algorithm-1 (Single Node Deletion)

1: **Input:** A, a matrix of real numbers, and $\delta \geq 0$, the maximum acceptable mean squared residue score.

2: **Output:** A_{IJ}, a δ - bi-cluster that is a sub matrix of A with row set I and column set J, with a score no larger than δ.

3: **Initialization**: I and J are initialized to the companies and criteria sets in the data and $A_{IJ} = A$.

4: **Iteration:** Compute a_{iJ} for all $i \in I$, a_{Ij} for all $j \in J$, a_{IJ}, and $H(I,J)$. If $H(I,J) \leq \delta$, return A_{IJ}.

5: Find the row $i \in I$ with the largest

$$d(i) = \frac{1}{|J|} \sum_{j \in J} \left(a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}\right)^2$$

and the column $j \in J$ with the largest

$$d(j) = \frac{1}{|I|} \sum_{i \in I} \left(a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}\right)^2$$

remove the row or column whichever with the larger d value by updating either I or J.

Algorithm 2 (Multiple Node Deletion)

1: Input: A, a matrix of real numbers, and $\delta \geq 0$, the maximum acceptable mean squared residue score, and $\alpha > 1$, a threshold for multiple node deletion.

2: Output: A_{IJ}, a δ - bi-cluster that is a sub matrix of A with row set I and column set J, with a score no larger than δ.

3: Initialization: I and J are initialized to the gene and condition sets in the data and $A_{IJ} = A$.

4: Iteration: Compute a_{iJ} for all $i \in I$, a_{Ij} for all $j \in J$, a_{IJ}, and $H(I,J)$. If $H(I,J) \leq \delta$, return A_{IJ}.

5: Find the rows $i \in I$ with

$$\frac{1}{|J|} \sum_{j \in J} \left(a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}\right)^2 > \alpha H(I,J)$$

6: Find the rows a_{Ij}, a_{IJ}, and $H(I,J)$.

7: Find the columns $j \in J$ with

$$\frac{1}{|I|}\sum_{i\in I}\left(a_{ij}-a_{iJ}-a_{Ij}+a_{IJ}\right)^2 > \alpha H(I,J)$$

8: If nothing has been removed in the iterate, switch to Algorithm 1.

Algorithm 3 (Node Addition)

1: Input: A, a matrix of real numbers, I and J signifying a δ – bi-cluster.
2: Output: I' and J' such that $I \subset I'$ and $J \subset J'$ with the property that $H(I',J') \leq H(I,J)$.
3: Iteration: Compute a_{iJ} for all $i \in I$, a_{Ij} for all $j \in J$, a_{IJ} and
$H(I,J)$.
4: Add the columns $j \notin J$ with

$$\frac{1}{|I|}\sum_{i\in I}\left(a_{ij}-a_{iJ}-a_{Ij}+a_{IJ}\right)^2 \leq H(I,J)$$

5: Recompute a_{Ij}, a_{IJ}, and $H(I,J)$.
6: Add the rows $i \notin I$ with

$$\frac{1}{|J|}\sum_{j\in J}\left(a_{ij}-a_{iJ}-a_{Ij}+a_{IJ}\right)^2 \leq H(I,J)$$

7: For each row i still not in I, add its inverse if
8: Find the columns $j \in J$ with

$$\frac{1}{|J|}\sum_{j\in J}\left(-a_{ij}+a_{iJ}+a_{Ij}+a_{IJ}\right)^2 \leq H(I,J)$$

9: If nothing is added in the iterate, return the final I and J as I' and J'.

Algorithm 4 (Finding a Given Number of Bi-Clusters)

1: Input: A, a matrix of real numbers with possible missing elements, $\alpha \geq 1$, a parameter for multiple node deletion, $\delta \geq 0$, the maximum acceptable mean squared residue (MSR), and n, the number of δ – bi-clusters to be found.
2: Output: n δ – bi-clusters in A.
3: Initialization: Missing elements in A are replaced with random numbers from a range covering the range of non-null values. A' is a copy of A.
4: Iterate for n times:
5: Apply Algorithm 2 on A', δ, and α. If the row (column) size is small (less than 100), do not perform multiple node deletion on rows (columns). The matrix after multiple node deletion is B.

6: (Step 8 of Algorithm 2) Apply Algorithm 1 on B and δ and the matrix after single node deletion is C.
7: Apply Algorithm 3 on A and C and the result is the bi-cluster D.
8: Report D, and replace the elements in A' that are also in D
with random numbers.

This thesis utilizes Algorithm-4, which is based on the work of Cheng & Church, (2000), to conduct its analysis. This algorithm is deterministic, meaning *it will consistently identify the same bi-clusters if the data remains unchanged.* This is equally important to analyse the companies' positions with respect to different bi-clusters.

To ensure the discovery of multiple, distinct bi-clusters within the same dataset of companies, a masking technique was employed by using the "current" company data available in the OTEP dataset. We excluded any data related to "future" projections of the surveyed companies.

In this respect, to avoid repeatedly identifying the same bi-clusters, a technique similar to handling missing data was employed. Once a bi-cluster was found, the values within its submatrix were replaced with random numbers. This prevented the algorithm from getting stuck on already discovered patterns, enabling it to uncover a broader spectrum of bi-clusters in the data.

4.5.4. Implementation and Visualization

The BWM and bi-clustering algorithms were implemented in the R programming language and effectively processed the datasets on a standard computer, successfully identifying five bi-clusters. The programming code sample was presented in Appendix-B. Moreover, visualizations (heat maps) were generated for each bi-cluster, illustrating the expression levels of the associated genes under the specific conditions defining the bi-cluster. Figures 18 to 22 illustrate a selection of bi-clusters identified through the analysis of OTEP automotive industry data.

CHAPTER 5

ANALYSIS RESULTS

The goal of data analysis is to reveal hidden patterns and gain meaningful insights from complex datasets. Two distinct yet powerful methodologies, the *joint* use of BWM and CC bi-clustering, offer a unique approach to demonstrate patterns and discover insights. It provides a comprehensive examination of the strengths, limitations, and suitable applications of each method, emphasizing the benefits of their combined use. While BWM excels in prioritizing and ranking criteria based on expert judgments and effectively simplifies MADM, to validate the results, bi-clustering exemplifies uncovering patterns and relationships within data matrices, revealing subgroups (bi-clusters) and their defining characteristics (characteristics of maturity classes / levels). Our analysis begins with descriptive statistics, followed by a thorough examination of both bi-clustering and BWM methods. We aim to demonstrate how these approaches, working in tandem, can provide a comprehensive understanding of our data. This includes revealing insights into the digital transformation performance levels of companies and identifying key criteria that characterize different maturity levels.

5.1. Descriptive Statistics

The survey yielded a rich dataset encompassing numerous criteria across a multitude of Turkish automotive companies. To facilitate analysis, this section presents a concise summary of the data, employing both correlation coefficient heat maps and frequency distributions of survey responses.

First, in order to ease the whole analysis (inc. BWM and bi-clustering) we used abbreviations in the coding. The names of criteria and the abbreviations of them are presented in Table 14.

Table 14 - Criteria Names and Abbreviations

Criteria #	Abbreviation	Definition	Sub-Criteria Abbreviation
C1	BR	Barriers	C1XX
C2	CL	Collaboration	C2XX
C3	CP	Capabilities	C3XX
C4	IR	Infrastructure	C4XX
C5	GI	Government Intervention	C5XX
C6	DR	Drivers	C6XX
C7	HR	Human Resources	C7XX
C8	VC	Value Chain	C8XX

As a first step in the analysis, as a crucial aspect of data analysis we analysed correlation coefficients to provide a fundamental measure for understanding relationships between criteria.

Illustrated in Figure 15, the heat map reveals a *high degree of independence* between variables within the dataset, indicating a low degree of correlation in the collected responses.

This correlation analysis leverages the survey results to establish a foundation for determining organizational maturity levels. Subsequently, our correlation heat map provides a visual representation of the relationships between sub-criteria. Each cell in the heat map corresponds to the correlation between two specific variables, with the colour intensity reflecting the strength and direction of the relationship.

Here, bright colours, such as red, indicate a *strong positive* correlation, meaning the variables tend to increase or decrease together. Conversely, darker colours, like blue, represent a *strong negative* correlation, where one variable tends to increase as the other decreases.

The diagonal line of the heat map, representing the correlation of each variable with itself, always displays the highest intensity, as a variable is always perfectly correlated.

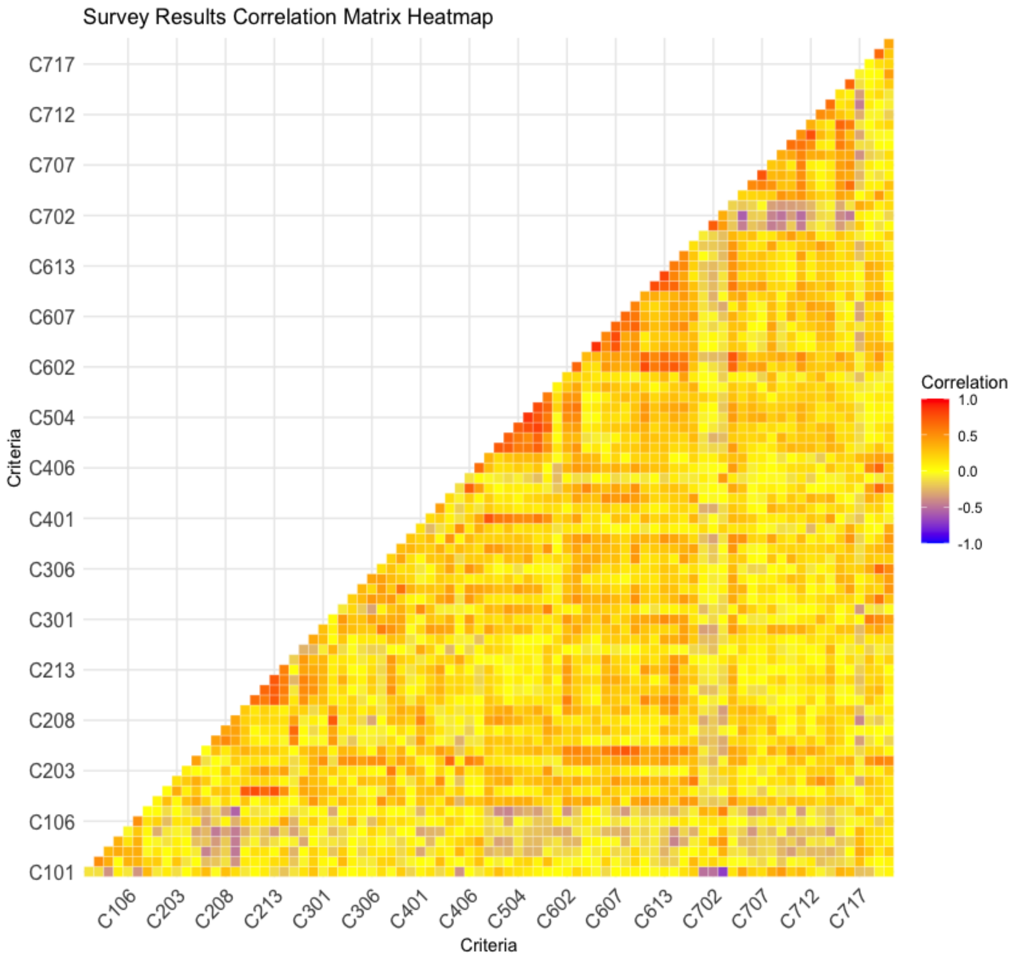

Figure 15 - Correlation Coefficient Heat map of Survey Data

Positive correlation coefficients range from 0 to 1, where 0 indicates no correlation, and 1 indicates a perfect positive correlation. However, negative correlation coefficients range from 0 to -1, where 0 indicates no correlation, and -1 indicates a perfect negative correlation. As a reminder, the strength of the correlation can be inferred from the magnitude of the correlation coefficient. The closer the coefficient is to 1 or -1, the stronger the correlation.

Consequently, our visual representation allows us for quick identification of strong correlations, both positive and negative. In this respect, Figure 9 illustrates the distribution of survey responses using a plot that shows the normalized frequency of each response category.

Plot aggregates responses by criteria groups.

Specifically, the responses for all sub-criteria within some given primary criteria (for instance; C101, C102, etc. belonging to main class C1) are averaged to represent the overall score for those primary criteria.

The plot clearly shows that scores for the criteria class C5 are mostly concentrated within a specific range, while criteria class C1 criteria scores are primarily grouped within the worst range. This summarized visualization offers helpful insights that will guide the upcoming evaluation of maturity levels for each company involved.

In addition, we have tabulated the answers with the Likert Scale (1 to 5) offering an effective method for the analysis of our bivariate data. As a reminder, we used Likert scales amongst other ways of ranking categories (for instance; a 5-point scale explaining how much a surveyor liked a product, ranging from "Not very much" to "Yes, a lot"). Hence, we have illustrated the frequency of all criteria by combinations of two or more nominal or categorical variables. The frequency of sub-criteria appearing together in answer combinations is visually represented as a joint distribution. This representation helps to understand the co-occurrence patterns of different sub-criteria in the responses.

In this analysis, we defined / grouped under 3 (three) combined classes (answer groups) for the Likert Scale explaining our assumptions:

- Class-A (Likert Scale 1-2): We have considered a scenario with data on the joint distribution of variables (patterns) whether answers 1 (one) equals to “strongly disagree” and 2 (two) equals to “disagree” may be categorized as the “worst answers” in similar or different across interviewers.

- Class-B (Likert Scale 3 Class): We have considered a scenario whether the answers with 3 (three) may be categorized as the “neutral” for answers for answers that has no *direct* effect (given no clue on the choice of interviewer) on the analysis through the survey

- Class-C (Likert Scale 4-5 Class): We have considered a scenario with data on the joint distribution of variables (patterns) whether answers 4 (four) equals to “weak positive” and 5 (five) equals to “highly positive” may be categorized as the “best answers” in similar or different across interviewers.

As we initially assumed, a frequency table revealed patterns in the joint distribution of multiple variables. In our research, for instance, Table 15 demonstrated whether the distribution of sub-criteria (linked to main criteria categories) is consistent across the surveyed companies or if variations exist. This analysis helped us to understand if certain sub-criteria are more frequently observed together in specific companies, indicating potential trends or relationships. Representing this analysis, Figure 16 and Table 15 demonstrates the correlation of company’s responses to the level of implementation of Industry 4.0 technologies. Results show us an uneven distribution of Class-A (GREEN coloured), favouring barriers (BR) and human resources (HR). Conversely, Class-C (GREY coloured) showed a *biasedness* towards each criteria class except infrastructure (IR) and the distribution of Class-B (RED coloured) appears more balanced, with criteria C1 (Barriers -BR), C6 (Drivers-DR) and C2 (Collaboration - CL)

Finally, the marginal totals in Table 15, located in the last row and column of the table, provide a summary by summing frequencies across each category. The summarized view presented in the Table also provides insights that may help to demonstrate the subsequent assessment of maturity levels for each participating company. Invariably, as part of our survey, we collected information regarding the maturity level for Industry 4.0 adoption. In detail, we did not explore / omitted the effects of company sizes, HR data or finance data at the choice of implementation of Industry 4.0 technologies. Rather, we seek for:

- ways to verify our hypothesis if there is a significant difference on the level of implementation of industry 4.0 technologies according to choices (e.g. sub-criteria to define the level of maturity using bi-cluster method).
- evidence to demonstrate significant difference on the level of implementation of industry 4.0 technologies (maturity level differentiation) according the main criteria defined

- results to rank companies by their choices of interest and strategy for Industry 4.0 implementation (e.g. ranking of surveyed companies by their current choices vs. future expectations using BWM)

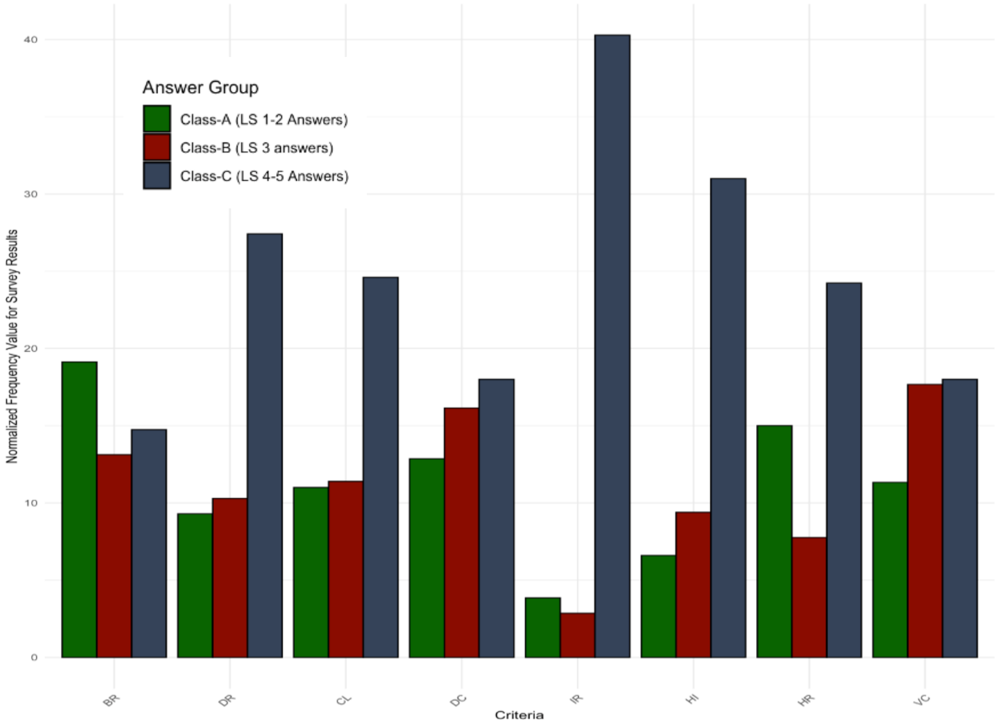

Figure 16 - Frequency distribution for Classes A to C

Table 15 - Frequency distribution for Classes A to C

Criteria Name	Criteria #	Abbreviation	Class-A	Class-B	Class-C
Barriers	C1	BR	19.13	13.13	14.75
Collaboration	C2	CL	9.29	10.29	27.41
Capabilities	C3	CP	11	11.40	24.60
Infrastructure	C4	IR	12.86	16.14	18
Government Intervention	C5	GI	3.86	2.86	40.29
Drivers	C6	DR	6.60	9.40	31
Human Resources	C7	HR	15	7.76	24.24
Value Chain	C8	VC	11.33	17.67	18
		Min	*3.86*	*2.86*	*14.75*
		Max	*15.00*	*17.67*	*40.29*

5.2. BWM Ranking Results

This thesis conducted a four-level analysis. At the third level, BWM is employed to analyse survey data collected from company representatives. This analysis established a ranking of the participating companies based on their digital maturity.

The analysis results served as a foundation for applying the bi-clustering method. This approach acted as a form of validation, strengthening the reliability of the findings. Additionally, it is important to note that both the BWM results and hypotheses were statistically tested using a 95% confidence interval. To commence, the weighting system employed to derive the ranking results will be elucidated, followed by a presentation of the firm rankings.

First, we defined the best (e.g. most desirable, most important) and the worst (e.g. least desirable, least important) criteria for our analysis. The best and the worst is chosen as C3 (capabilities) and C8 (value chain) respectively. Pairwise comparison for the best and the worst criteria and sub-criteria presented in Tables 16 and 17.

In addition, Table 18 also demonstrates the weight of the criteria (parameters)

Table 16 - Pairwise Comparison for the Best Criteria

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
Capabilities: C3 Best Criteria	5	3	1	7	8	4	4	8

Table 17 - Pairwise Comparison for the Worst Criteria

Criteria	C1	C2	C3	C4	C5	C6	C7	C8
Value Chain: C8 Worst Criteria	4	3	2	5	6	3	4	1

To summarize, Table 19 presents a ranked list of the BWM analysis results, showcasing the digitalization performance of the surveyed companies based on their current and target states.

Table 18 – Pairwise Comparison for the Best-Worst Sub-criteria

Criteria Name	**C#**	**Weight**	**Best**	**Worst**
Barriers	C1	0.11300	C104	C105
Collaboration	C2	0.17125	C202	C206
Capabilities	C3	*0.30930*	C303	C308
Infrastructure	C4	0.08316	C403	C404
Government Intervention	C5	0.03396	C501	C503
Drivers	C6	0.15523	C609	C614
Human Resources	C7	0.11254	C703	C706
Value Chain	C8	*0.02156*	C801	C804

Table 19 – BWM Ranking List of Companies

Firm #	**Rank # (for Current / Present)**	**Rank # (for Target / Future)**	**Firm #**	**Rank # (for Current / Present)**	**Rank # (for Target / Future)**
40	1	11	**23**	25	29
3	2	43	**46**	26	16
6	3	9	**13**	27	39
15	4	5	**24**	28	44
19	5	1	**38**	29	35
11	6	10	**29**	30	30
16	7	12	**47**	31	17
37	8	13	**17**	32	34
35	9	18	**43**	33	41
42	10	21	**4**	34	27
44	11	8	**18**	35	36
41	12	7	**26**	36	33
12	13	32	**10**	37	45
2	14	4	**20**	38	25
31	15	20	**36**	39	40
1	16	12	**21**	40	38
45	17	19	**25**	41	2
9	18	15	**28**	42	6
7	19	26	**14**	43	37
33	20	14	**22**	44	42
34	21	24	**27**	45	46
39	22	31	**30**	46	47
32	23	23	**8**	47	22
5	24	3			

Finally, since our analysis employed the BWM to determine the relative importance of different criteria, as a key indicator of the reliability of BWM results, we calculated the *Consistency Ratio (CR)* separately which measures the consistency of pairwise comparisons made during the process. CR of 0 represents perfect consistency; on the contrary, CR > 0.10 represents strong inconsistency.

In our case, the calculated CR is *0.00209175*, indicating a *very high level of consistency* in the judgments since CR ≤ 0.10 and lending strong support to the reliability and robustness of the derived weights for the criteria.

5.2.1. Kendall Tau Statistics

In order to validate the ranking's correlation in our listing as per the results of Section 5.2, additionally, we used Kendall's tau to assess and *additionally* validate the consistency between factor loadings (rankings) comparing the "current/present" and "future/target" rankings. In this respect, we targeted to examine the relationship between two different ranking list based on two choices. Since this statistic method ease to extract underlying factors, we tested our results whether they can lead to a slightly different factor pattern. Hence, we calculated Kendall's tau for each pair of corresponding ranking for each item in the ranking table given in Table 19 (Kendall, 1938).

In conclusion, our analysis resulted Kendall's tau statistics as *0.474560* and p-value ($p<0.001$ condition) as *0.0000025456*.In social science research, a Kendall's tau score of 0.47 is considered statistically significant, demonstrating a strong positive relationship between the rankings obtained. This finding, exceeding the threshold of 0.45, suggests a high level of agreement between the rankings produced by the BWM and the established factor structure, indicating the stability and reliability of the BWM results. On the other hand, if tau stats were between 0.27 and 0.45, it might represent moderate positive agreement between the ranks and if tau was between 0.09 and 0,27 or smaller than it might raise concerns about the consistency of the factor structure across methods. Comparing our rankings, our results showed us a consistent rank order. However, Kendall tau values can be subjective and can relatively be interpreted differently based on the field of study.

5.3. Bi-Cluster Analysis of Maturity Levels

The fourth phase of our analysis in this thesis employs a bi-clustering method applied to a selection of key sub-criteria. In our analysis, we treated the rows of our dataset as "companies" and the columns as "sub-criteria" on the basis of this algorithm.

This approach allowed us to define sub-matrices within our dataset, similar to the model used in Cheng & Church, (2000). Moreover, we have successfully identified five distinct bi-clusters, each representing a unique grouping of companies with shared characteristics in their digital transformation journeys. Each cluster represents a different stage of maturity. Similarly, Figure 17 utilizes a heat map to present the results of our bi-cluster analysis.

This visualization highlights the sub-criteria with the *strongest* presence and interconnections within each identified cluster, offering valuable insights into the defining characteristics of each group.

In a common bi-clustering heat map, each cell's colour represents the frequency of occurrences sub-criteria. Brighter colours (e.g., yellow) indicate a *lower occurrence*, while darker colours (e.g., red) indicate a *higher occurrence*.

By examining a bi-cluster heat map, we tend to identify sub-criteria that are *strongly* or *weakly* explains the clusters. In respect, the analysis targets to define *proximity and similarity* among sub-criteria to explain similar values (higher or lower occurrence) suggesting that patterns are influenced by sub-criteria within specific main criteria classes.

CC algorithm is applied through the survey data and the bi-clusters are presented in the Figure 17. Consequently, Table 20 provides further details and explanations to enhance the understanding and interpretation of the patterns visualized in this heat map.

In this respect, Figure 17 is a *primary* heat map that offers a comprehensive overview of the analysis results.

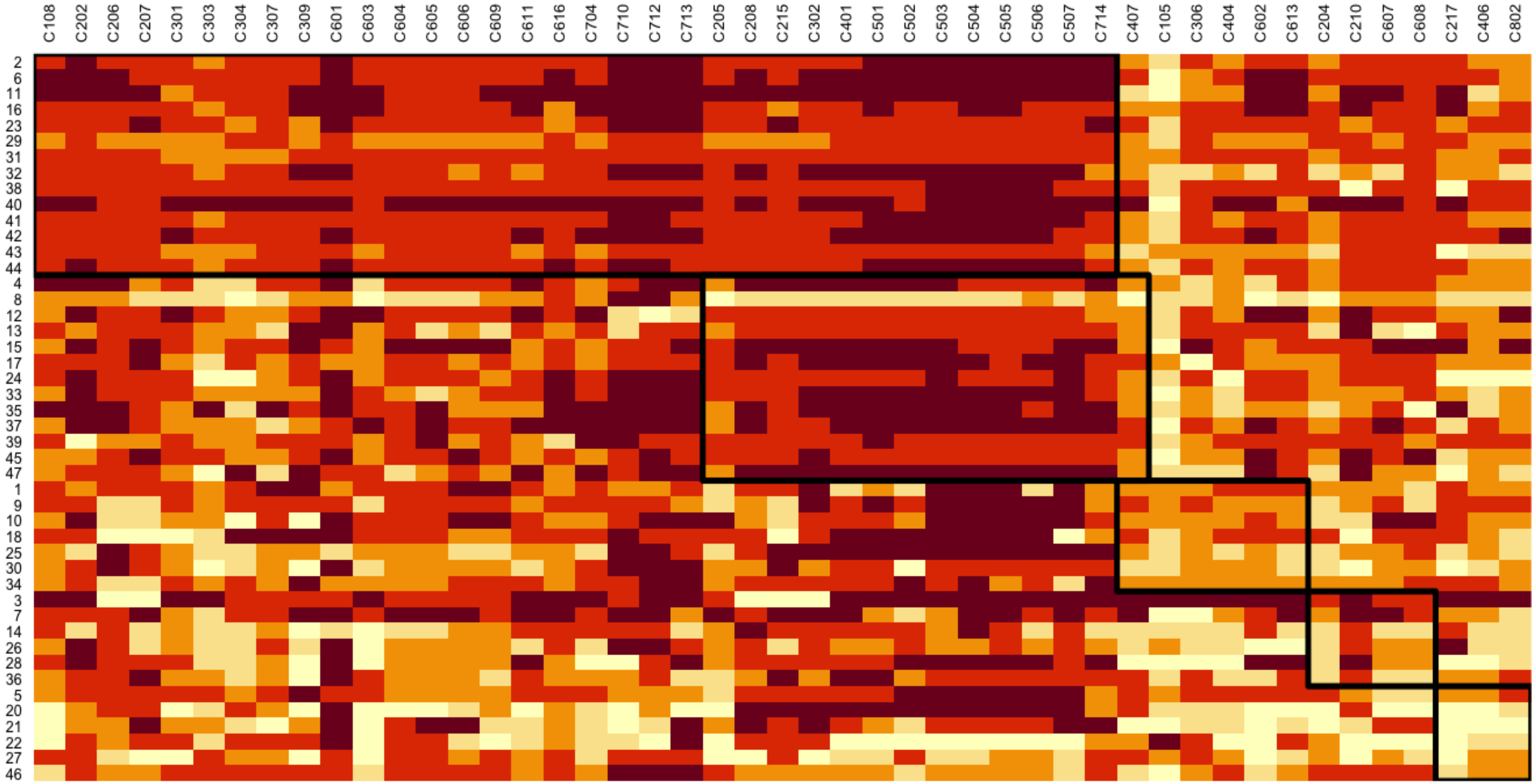

Figure 17 - Bi-Cluster #5 (ML-5) Heat map

Furthermore, the analysis generated five more additional plots (Figures 18 to 22), each focusing on a specific bi-cluster to offer a more detailed perspective on the characteristics and composition of each group (maturity level).

In conclusion, we provided the key insights from the review of the maturity level of companies involved resulting from the bi-clustering analysis as outlined in Section 5.1.5. Content analysis of the sub-criteria forming the 5 (five) bi-clusters and 84 sub-criteria are linked to the 46 of the companies surveyed; and results were reviewed.

The focus was targeted to capture our main criteria so as to understand the effects of drivers and barriers in the adoption and implementation of Industry 4.0 while the others may be screened out.

5.3.1. Bi-Cluster #5 Analysis (ML-5)

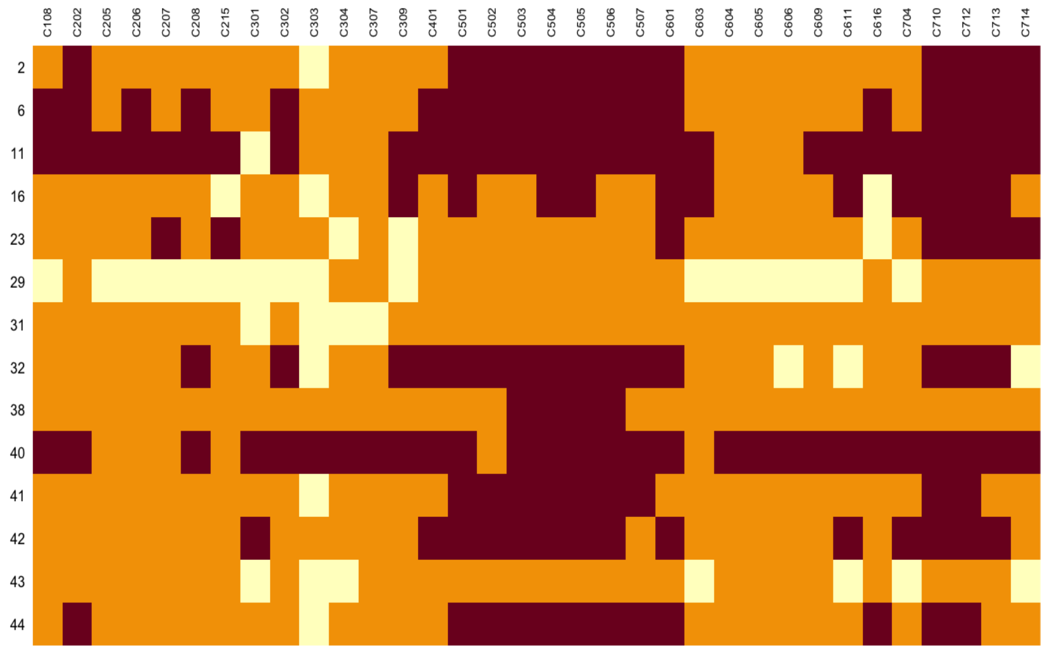

Figure 18 - Bi-Cluster Heat map for ML-1 to ML-5

This bi-cluster representing 30,43% of the data and encompasses 31 sub-criteria under 7 (seven) main classes throughout the survey, reveals a consistent pattern of companies' preliminary steps for digitalization.

Table 20 – Bi-cluster (ML classes) identification table

Bi-Cluster	**Reference Figure Number** ***(Figure-X)***	**Maturity Level Definition (*)** **(*ML-X*)**	**Companies listed in Bi-Clusters (*Maturity Levels*)**	**Main Criteria Classes Listed in Bi-Cluster (**)**	**Sub-Criteria Listed in Bi-Cluster**
Bi-cluster #5	Figure 12	ML-5	2, 6, 11, 16, 23, 29, 31, 32, 38, 40, 41, 42, 43, 44 (%30,43)	C1, C2, C3, C4, C5, C6, C7	C108, C202, C205, C206, C207, C208, C215, C301, C302, C303, C304, C309, C401, C501, C502, C504, C505, C506 C507, C601, C603, C604, C605, C606, C609, C616, C707 C710, C712, C713, C714
Bi-cluster #4	Figure 13	ML-4	4, 8, 12, 13, 15, 17, 24, 33, 35, 37, 39, 45, 47 (%28,26)	C2, C3, C4, C5, C7	C205, C208, C215, C302, C401, C407, C501, C502, C503, C504, C505, C506, C507, C714
Bi-cluster #3	Figure 14	ML-3	1, 9, 10, 18, 25, 30, 34 (%15,21)	C1, C3, C4, C5, C6	C105, C108, C306, C307, C404, C407, C503, C504, C602, C604, C605, C613, C616

Table 20 – Bi-cluster (ML classes) identification table (Continued)

Bi-Cluster	**Reference Figure Number** ***(Figure-X)***	**Maturity Level Definition (*)** **(*ML-X*)**	**Companies listed in Bi-Clusters (*Maturity Levels*)**	**Main Criteria Classes Listed in Bi-Cluster (**)**	**Sub-Criteria Listed in Bi-Cluster**
Bi-cluster #2	Figure 15	ML-2	3, 7, 14, 26, 28, 36 (%13,04)	C2, C3, C5, C6, C7	C204, C205, C210, C304, C307, C505, C507, C605, C606, C607, C608, C609, C616, C712
Bi-cluster #1	Figure 16	ML-1	5, 20, 21, 22, 27, 46 (%13,04)	C2, C4, C6, C7, C8	C202, C217, C406, C611, C616, C704, C802

(*) Reader can refer to Table 5 for maturity level definitions.
(***) Acronyms: C1-Barriers, C2-Collaboration, C3-Capabilities, C4-Infrastructure, C5-Government Support, C6-Drivers, C7-Human Resources, C8-Value Chain

Figure 18 illustrates that companies achieving Maturity Level 5 exhibit a balanced profile in sub-criteria related to collaboration and developing new capabilities. This suggests that reaching this highest level of digital maturity involves a well-rounded approach, with equal emphasis on fostering collaborative practices and nurturing a culture of continuous learning and skill development. In this bi-cluster, *lowest* occurrences may be listed as collaboration (C2) and capabilities (C3) described with collaboration sub-criteria C202, C205, C206, C207, C208, C215 and capabilities sub-criteria of C301, C302, C303, C304, C309.

In addition, companies grouped within this bi-cluster appear to be in the *latest* stages of developing the necessary skills and partnerships for digital transformation. These companies are *strongly* related with:

- Building Collaboration (C2): Companies listed in this bi-cluster are strengthening their collaborative practices, expanding their networks to include more partners (especially institutions), and fostering a culture that embraces collaboration.

- Developing Digital Skills (C3): There is still a recognized need to cultivate both academic and technical skills related to data management and the broader digitalization process.

Furthermore, two criteria stand out as particularly important (having the highest occurrence) for companies in this bi-cluster:

- Government Incentives (C5): Government support and incentives for digitalization appear crucial, likely viewed as catalysts for driving demand and accelerating the adoption of digital technologies.

- Human Resources (C7): Developing a skilled workforce is paramount, with a particular focus on addressing initial skill gaps in areas like simulation, product design, production, and supply chain management.

In essence, ML-5 companies may be commented on laying the groundwork for digital transformation by prioritizing collaboration, skill development, and leveraging government support.

Comparing the listed companies with their rankings in BWM results as described in Section 5.2, we may comment that these companies recognize the importance of a skilled workforce and are actively seeking opportunities to enhance their capabilities in key areas. Above findings also indicates that companies within ML-5 class remains relatively consistent throughout affected main criteria C2, C3, C5 and C7. In conclusion, this information may verify *H3: Cultivating new capabilities helps to advance the digital transformation process* and *H4: Increased collaboration contributes to a higher level of digital maturity* in such a way that sub-criteria distribution in this class identifies potential bottlenecks in collaboration to gather new skills for digitalization and tailoring strategies to meet the specific human resource requirements.

5.3.2. Bi-Cluster #4 Analysis (ML-4)

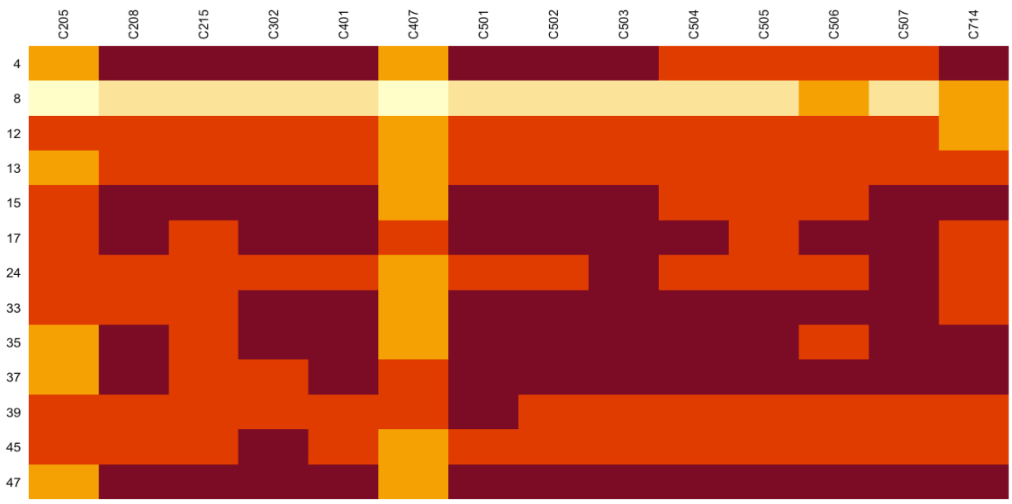

Figure 19 - Bi-Cluster #4 (ML-4) Heat map

This bi-cluster represents 28.26% of the total sample and encompasses 14 (fourteen) sub-criteria under 6 (six) main classes. Similar to companies listed at ML-5, these firms demonstrate advanced development, particularly in two key criteria: Collaboration (C2) and Government Support (C5).

Looking at Figure 19, we can see that companies at Maturity Level 4 show a *homogeneous* pattern when it comes to collaboration and government support. This pattern of distribution in specific sub-criteria suggests these factors play a significant and comparable role in reaching this advanced stage of digitalization. In this bi-cluster, *highest* occurrences may be listed as collaboration (C2) and capabilities (C3) demonstrated with sub-criteria C205, C208, C215, C501, C502, C503, C504, C505, C506, C507, respectively.

Above statement highlights that government support (C5) and collaborative efforts (C2) are essential for companies to achieve advanced levels of digital transformation (digital maturity). While some companies might not be at the peak level of digital maturity yet, their focus on these criteria indicates they are on a promising path to reach it soon.

In brief, below definitions may be emphasized by combining the qualitative results:

- Government Support (C5): This support may involve funding requirements for research and development of new technologies, tax incentives for companies adopting digital solutions and the creation of a regulatory environment that encourages innovation.

- Collaboration (C2): This initiative may involve constructing partnerships between companies to share knowledge and resources, Industry-academia collaborations to develop a skilled workforce and open-source platforms that foster innovation.

For companies listed in this bi-cluster, we may also comment despite not being at the top level currently, the companies' focus on government support and collaboration indicates they are on the right track and expected to reach peak digital maturity soon. In addition, for ML-5 and ML-4 government support and a collaborative ecosystem are vital for companies to thrive survivability in the digital age.

5.3.3. Bi-Cluster #3 Analysis (ML-3)

This Bi-cluster represents 15.21% of the total sample and encompasses 12 (twelve) sub-criteria under 5 (five) main classes.

Figure 20 reveals a *trend* among companies grouped within the Maturity Level 3 bi-cluster: their sub-criteria distribution leans towards a relatively balanced profile. This near-neutral distribution suggests that these companies demonstrate a comparable level of performance across the assessed criteria, without significant outliers or areas of extreme strength or weakness. In this bi-cluster, *lowest* occurrences may be listed as barriers (C1) and drivers (C6) described with collaboration sub-criteria C105, C108 and sub-criteria of C602, C604, C605, C613, respectively.

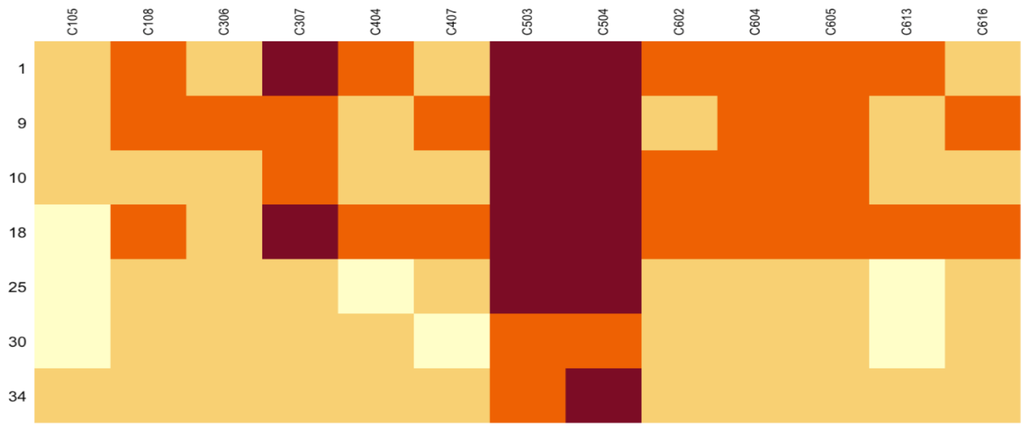

Figure 20 - Bi-Cluster #3 (ML-3) Heat map

We may argue that companies grouped in ML-3 cluster face barriers (C1). While their performance in other areas is *blurry*, they still lag behind ML-4 companies due to this bottleneck.

In addition, these companies place high importance on various drivers (C6), including:

- Product Development and Process Efficiency: Companies recognize the need for faster processes, particularly in logistics and product development.
- Knowledge Management: Both internal and external knowledge resources, along with knowledge sharing practices, are deemed crucial.
- Training and Development: Investing in training, both in-house and externally sourced, is seen as vital for skill development.

- Technical Expertise: Access to technical consultancy and specialized training is highly valued.

- Innovation and Commitment: New Product Development and worker commitment are considered as key drivers.

- Digital Awareness and Resource Optimization: Understanding digitalization and ensuring efficient IT management are prioritized.

- Production Quality and Operational Excellence: Leveraging digitalization to enhance production quality and optimize sales and operations planning is a focus.

This emphasis on drivers, despite the barriers (C1), presents a roadmap for advancement. By strategically addressing the identified barriers, particularly those hindering the effectiveness of these drivers (C6), companies in ML-3 can pave the way towards achieving ML-4.

Crucially, a significant disparity exists in C2 (collaboration), where these firms lag behind their ML-4 counterparts. This gap represents also as a *barrier* to advancement, as collaboration is widely recognized as a cornerstone of successful digital transformation.

In conclusion, companies in this bi-cluster share a reliance on government support (C5) as a key driver of their digitalization efforts. However, they face inconsistencies in other areas crucial for digital maturity, leading to a lower overall ranking compared to companies in ML-4. One critical area also where these companies fall short is collaboration (C2).

This may demonstrate that they have not developed the same level of collaborative practices as their more advanced counterparts listed in ML-4 and ML-5, hindering their progress. Under these findings, our additional observations from the qualitative

(interview) results provide evidence to support *H1: Drivers leads to a more advanced level of digital maturity* and *H2: Reducing barriers leads to higher levels of digital maturity for a company.*

The analysis of ML-3 might reveal specific barriers and drivers hindering these companies' progress, particularly in collaboration and capability development.

Addressing these barriers, such as by fostering a more collaborative environment and providing targeted training to enhance digital skills, could pave the way for these companies to achieve higher levels of digital maturity.

5.3.4. Bi-Cluster #2 Analysis (ML-2)

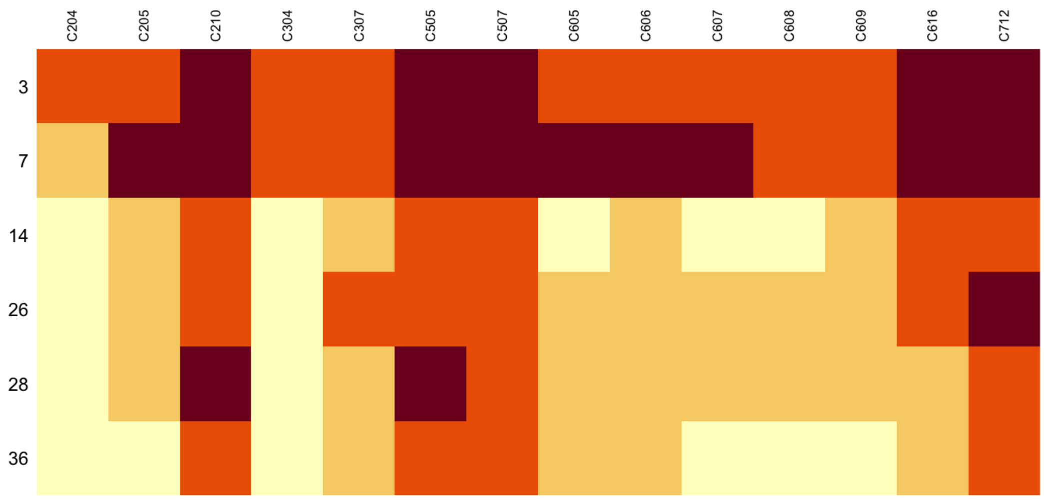

Figure 21 - Bi-Cluster #2 (ML-2) Heat map

This bi-cluster represents 13.04% of the total sample and encompasses 14 (fourteen) sub-criteria under 5 (five) main classes.

Figure 21 visually illustrates that companies categorized in ML-2 exhibit a *consistent* and *similar* pattern across various sub-criteria.

This homogeneity suggests a shared set of characteristics and challenges within this group. In this bi-cluster, *highest* occurrences may be listed as collaboration (C2), capabilities (C3) and drivers (C6) described with sub-criteria C204, C205, C210, C304, C307, C605, C606, C607, C608, C609, respectively.

Rather, companies listed in ML-2 face significant challenges in two key areas:

- Collaboration (C2): Companies might struggle to establish effective collaborative practices, hindering their ability to leverage shared knowledge and resources.

- Capability Development (C3): Building the necessary skills and expertise for digital transformation might prove difficult for these companies.

These weaknesses in collaboration and capability development put them at a disadvantage compared to companies in ML-3 and higher.

Furthermore, these companies appear to acknowledge the significance of several key drivers (C6) in propelling their digital transformation journeys, particularly:

- Investing in Training: They may prioritize both in-house training programs and seeking external training opportunities to enhance their workforce's skills.

- Leveraging External Knowledge: Accessing and integrating external knowledge resources and expertise may be crucial.

- Seeking Technical Guidance: Companies may value technical consultancy and specialized training to support their digitalization efforts.

- Fostering Innovation and Commitment: New Product Development (NPD) and a committed workforce may be considered as essential drivers.

While companies in this bi-cluster face challenges, their focus on key drivers (C6) provides a clear path forward. To advance their digital maturity, we may comment that they should prioritize initiatives that directly address their weaknesses in capability development (C3).

Specifically, two areas demand extra attention:

- Digitalization Transformation Policies: Establishing clear and comprehensive policies may provide a framework for successful digital transformation.

- Upper Management Skills for Industry 4.0: Equipping leadership with the necessary skills and knowledge related to Industry 4.0 may be crucial for effective decision-making and driving change.

By concentrating on these specific capability gaps, companies in Bi-cluster #2 can unlock their potential and progress towards higher levels of digital maturity.

The findings regarding ML-2 offer compelling support for *H3: Cultivating new capabilities helps to advance the digital transformation process*. The analysis reveals that despite facing challenges, companies in this group recognize the significance of various capabilities for digital transformation. However, their progress is hindered by specific capability gaps, highlighting a direct link between addressing these gaps and achieving higher maturity levels.

By focusing on developing crucial capabilities, particularly those related to C304 "Digitalization Transformation Policies" and C307 "Upper Management Skills for Industry 4.0," these companies can effectively leverage the identified drivers and unlock their potential for advancement in digital maturity.

5.3.5. Bi-Cluster #1 Analysis (ML-1)

This bi-cluster represents 13.04% of the total sample and encompasses 7 (seven) sub-criteria under 5 (five) main classes.

Figure 22 highlights that companies at ML-1 display an unclear pattern across various sub-criteria, indicating a lack of focus in their digitalization efforts. This suggests common challenges within this group, particularly in three key areas:

- Collaboration (C2): Specifically, difficulties in "Sharing a common digitalization strategy" (C202) and "Sharing knowledge about digitalization technologies" (C217) might hinder their progress.

- Infrastructure for digitalization (C4): Limitations in "Availability of secure data storage solutions" (C406) might pose a significant obstacle.

- Value chain perspective (C8): Struggles in "Digitalization in horizontal value chain" (C802) might limit their ability to leverage digitalization across different operational areas.

These weaknesses in collaboration, infrastructure, and value chain integration put them at a disadvantage compared to companies in ML-2 and higher.

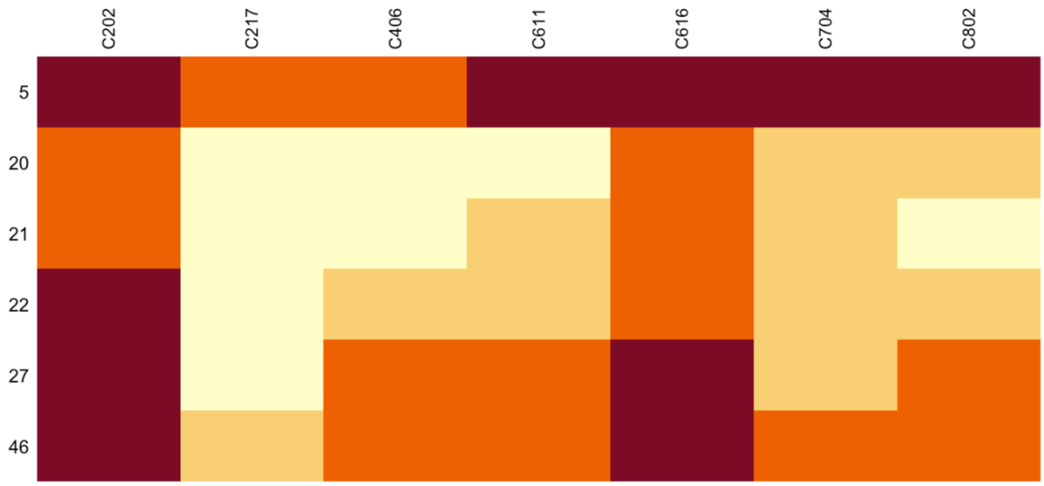

Figure 22 - Bi-Cluster #1 (ML-1) Heat map

In focus, a company's different departments and functions – like procurement, production, marketing, and sales – as links in a horizontal chain. The horizontal value chain represents how these different parts connect and work together across the organization. In detail, ML-1 companies may lack of:

- Data strategy: They might not have a clear plan for collecting, storing, and using data effectively.
- Digital skills: Their workforce might lack the necessary skills to implement and manage Industry 4.0 technologies.
- Chained operations: Without proper digitalization, departments may operate in isolation, leading to inefficiencies, miscommunication, and missed steps / opportunities of Industry 4.0.
- Visibility and awareness: This lack of transparency makes it difficult to monitor progress and make informed, data-driven decisions that optimize the entire value chain.
- Innovation Infrastructure: Companies may struggle to develop and implement

new digital solutions (data storage, etc.) hindering their ability to innovate and stay competitive.

Hence, it is important to note that "Digitalization in the horizontal value chain (C802)" especially prevents companies from harnessing the full potential of digital transformation. In conclusion, addressing all these criteria is crucial for companies to advance their digital maturity to the next level.

5.4. Results Validation (BWM with Bi-clustering)

As shown in Table 21 and 22, to assess the consistency between the BWM and bi-clustering results, we compared the company rankings generated by the BWM analysis with their performance in the bi-clustering analysis. It is important to acknowledge that some data points might be missing. We can assume a "Missing at Random" pattern for our company data, meaning that the incomplete company responses on certain sub-criteria are likely unrelated to other data points.

However, this suggests that hidden factors, such as other sub-criteria, might be influencing why these data points are missing. For instance, the way other sub-criteria are evaluated could be connected to the missing responses. Therefore, we have excluded company numbered *19* from our analysis due to its some missing values. The presence of numerous missing values across important variables made it an outlier, disrupting the bi-clustering algorithm's ability to identify meaningful patterns and group companies effectively.

A clear and logical pattern emerges when we compare the average rankings of companies based on their current choices against their assigned maturity levels from the bi-clustering analysis.

These findings are summarized in Table 21.

Accordingly, since each bi-cluster represents a distinct group of companies with shared core digitalization capabilities, the average rankings within each maturity class support and strengthen the validity of our analysis and its findings.

Table 21 – Comparison of ML Classes with BWM rankings

Bi-cluster ML Class	# of Companies per ML Class (%)		# of Sub-Criteria per ML Class (%)		Average of Rankings per BWM results
ML-5	14	30.43%	34	41.46%	15.64
ML-4	13	28.26%	14	17.07%	22.46
ML-3	7	15.22%	13	15.85%	30.57
ML-2	6	13.04%	14	17.07%	30.16
ML-1	6	13.04%	7	8.54%	36.16
AGG TOTAL	46 ([4])	100%	47	100%	

While the average rankings within each maturity class demonstrate a unique relationship between each class and its associated sub-criteria, a broader pattern emerges when we examine the results more closely. The analysis found that maturity classes ML-3, ML-2, and ML-1 are very similar, with ranking scores so close that they are statistically indistinguishable. This suggests that despite differences in their sub-criteria, their overall digital maturity levels might not be significantly different.

Specifically, the CC algorithm prevents overlapping bi-clusters by substituting random values for the original data points within a newly identified bi-cluster. This substitution process makes it unlikely that those same data points will be incorporated into any future bi-clusters (Pontes et al., 2015).

Furthermore, the CC algorithm's element *masking* and *dataset-specific threshold* can potentially introduce biasedness into the results. To mitigate this, we implemented a threshold requiring bi-clusters to include at least 50% of the sub-criteria based on the survey data. Additionally, data sparsity posed a challenge, leading to the exclusion of some sub-criteria with a high number of missing values. Due to data limitations, our analysis concentrated on a consolidated group of 47 sub-criteria that have highest occurrence in the analysis.

Table 22 – ML Classes of Companies with BWM rankings

Firm #	BWM Current / Present Ranking	BWM Target / Future Ranking	Bi-cluster ML Class	Deterministic Criteria	Deterministic Sub-criteria
40	1	11	ML-5	C3, C6, C7	C302, C605, etc.
3	2	43	ML-2	C2, C5	C210, C505, etc.
6	3	9	ML-5	C5, C7	C501, C710, etc.
15	4	5	ML-4	C2, C5	C215, C501, etc.
19	5	1	N/A	N/A	N/A
11	6	10	ML-5	C1, C5, C7	C108, C202, etc.
16	7	12	ML-5	C7	C712, etc.
37	8	13	ML-4	C3, C5	C502, C503, etc.
35	9	18	ML-4	C3, C5	C502, C503, etc.
42	10	21	ML-5	C5	C504, C505, etc.
44	11	8	ML-5	C5	C504, C505, etc.
41	12	7	ML-5	C2, C5	C207, C501, etc.
12	13	32	ML-4	C2, C7, C3	C208, C714, etc.
2	14	4	ML-5	C5, C7	C505, C710, etc.
31	15	20	ML-5	C2, C5, C6	C206, C606, etc.
1	16	12	ML-3	C3, C5	C506, C307, etc.
45	17	19	ML-4	C2, C4, C5	C504, C505, etc.
9	18	15	ML-3	C1, C5, C6	C504, C604, etc.
7	19	26	ML-2	C2, C6, C5	C205, C605, etc.
33	20	14	ML-4	C4, C5	C401, C502, etc.
34	21	24	ML-3	C5	C504, C503, etc.
39	22	31	ML-4	C2, C3, C5	C215, C504, etc.
32	23	23	ML-5	C5	C505, C506, etc.
5	24	3	ML-1	C2, C6	C202, C616, etc.
23	25	29	ML-5	C2, C7	C207, C710, etc.
46	26	16	ML-1	C2, C8	C202, C802, etc.

Table 22 – ML Classes of Companies with BWM rankings (Continued)

Firm #	BWM Current / Present Ranking	BWM Target / Future Ranking	Bi-cluster ML Class	Deterministic Criteria	Deterministic Sub-criteria
13	27	39	ML-4	C2, C3, C4	C208, C302, etc.
24	28	44	ML-4	C2, C3, C4	C215, C401, etc.
38	29	35	ML-5	C5, C7	C505, C704, etc.
29	30	30	ML-5	C5, C6, C7	C503, C712, etc.
47	31	17	ML-4	C2, C3, C4	C215, C302, etc.
17	32	34	ML-4	C2, C3, C7	C208, C714, etc.
43	33	41	ML-5	C3, C5, C6	C207, C505, etc.
4	34	27	ML-4	C2, C3, C4	C302, C401, etc.
18	35	36	ML-3	C3, C5	C307, C504, etc.
26	36	33	ML-2	C3, C6	C307, C607, etc.
10	37	45	ML-3	C3, C6	C307, C604, etc.
20	38	25	ML-1	C2, C6	C202, C616, etc.
36	39	40	ML-2	C2, C6, C7	C210, C712, etc.
21	40	38	ML-1	C2, C6	C202, C616, etc.
25	41	2	ML-3	C1, C5	C105, C503, etc.
28	42	6	ML-2	C2, C7	C210, C505, etc.
14	43	37	ML-2	C2, C6, C7	C616, C712, etc.
22	44	42	ML-1	C2, C6	C202, C616, etc.
27	45	46	ML-1	C2, C6	C202, C616, etc.
30	46	47	ML-3	C5	C503, C504, etc.
8	47	22	ML-4	C5, C7	C506, C714, etc.

In brief, as observed in Table 21 and 22:

- **Top Performers:** The top 10 companies (specifically, companies numbered 40, 3, 6, 15, 19, 11, 16, 37, 35, and 42), identified by their high scores in "current" digitalization choices, also demonstrate significantly better performance in their "future" rankings compared to other companies. It is important to note that 80% of these top performers are categorized within the highest maturity levels, ML-5 (companies 11, 40, 6, 16, and 42) and ML-4 (companies 15, 37, and 35). This alignment strongly suggests a link between current success and future potential in digitalization.

- **Bottom Performers:** Conversely, the bottom 10 companies (companies 20, 36, 21, 25, 28, 14, 22, 27, 30, and 8), those with the lowest scores in "current" choices, also exhibit the weakest performance in their "future" rankings. Reinforcing this pattern, 70% of these companies fall into the lower maturity classes: ML-1 (companies 38, 40, 44, and 45) and ML-2 (companies 28, 14, and 36).

We also observed some interesting contradictions when we looked at companies numbered 3 and 8 from the Table 22. Company 3, despite being ranked 3rd overall, falls into the mid-level maturity class ML-2. On the other hand, company 8, ranked 47th, belongs to the high-maturity class ML-4. These inconsistencies suggest that the BWM ranking and the bi-clustering results are not always perfectly aligned. This discrepancy may highlight a crucial point that *both analyses should be considered independently and holistically rather than assuming a direct one-to-one correspondence*. Furthermore, these variations might indicate an imbalance between different aspects of digital maturity. A company might excel in certain areas, leading to a higher BWM ranking, while lagging in others, resulting in a lower maturity class placement.

In conclusion, these findings provide substantial evidence that the results from the BWM are consistent and significant when compared with the results from the CC bi-clustering analysis. This convergence strengthens the validity of both methods and highlights the robustness of our overall analysis.

CHAPTER 6

CONCLUSION AND DISCUSSION

This thesis provides a comprehensive examination of digitalization and the transition towards Industry 4.0, with a particular emphasis on the Turkish automotive industry. Furthermore, this thesis delves into the core concepts of Industry 4.0 and digitalization by exploring a 5-levelled maturity analysis in which each maturity level is defined as a bi-cluster relevant criteria. The enhancement of digitalization efforts is presented in detail covering different aspects on the basis of our maturity analysis.

In addition, this thesis investigates the current state of Industry 4.0 adoption within the automotive sector and its potential to revolutionize the industry, building upon a foundation of lean manufacturing principles and incorporating insights from both existing literature and expert opinions. The analysis delved into the crucial role of identified criteria and sub-criteria, exploring their impact on digital transformation efforts. We also examined the broader consequences of digitalization within the automotive landscape on the basis of our maturity analysis.

To address our research questions, our thesis draws upon insights gained from interviews conducted with representatives from the manufacturing and supplier companies. These interviews, informed by the theoretical framework, explored the companies' digital maturity levels using a specifically developed maturity model. This model, along with the interview findings, provided answers to the research questions and related hypothesis offering a *valuable* assessment model and some insights into the digital transformation landscape within the Turkish automotive industry. Evidence collected from the survey shows us that Industry 4.0 presents both opportunities and challenges for companies, influencing their level of digitalization maturity.

While large manufacturing companies are primarily driven by strategic opportunities, most supplier companies focus on operational benefits. However, regardless of size of companies, we may depict that challenges hinder Industry 4.0 implementation.

Our survey results revealed that the lack of technical skills (capabilities) and expertise is a major barrier. This is often followed by limited financial resources and knowledge. Similar challenges, such as high investment costs, unclear returns on investment, and inadequate technological infrastructure, are reported in other studies in Türkiye.

In general, the thesis highlights a range of challenges hindering Industry 4.0 adoption. These include:

- Digital skills gap: Lack of digital culture and education, lack of training, difficulties finding skilled workers, and training existing employees.

- Knowledge and information barriers: Lack of understanding regarding the complexity of Industry 4.0, insufficient information about its benefits and implementation, and unclear starting points and priorities.

- Financial and technological constraints: Limited financial resources, lack of big data management skills, high investment and operational costs and insufficient technological infrastructure.

- Other challenges: Resistance to transformation, lack of government supports, data management concerns, etc.

As outlined in Section 1.4, we aimed to analyse 5 (five) central research questions concerning digitalization within the automotive manufacturing sector:

- Question 1 - Collaboration with Partners: The research revealed a significant variation in how automotive manufacturers collaborate with external partners to acquire digital technology capabilities. While some companies engage in extensive collaborations, others rely primarily on purchasing digital software solutions.

- Question 2 - Overcoming Barriers to Digitalization: The study suggests that integrating digitalization and lean production principles can lead to substantial benefits for automotive manufacturers, particularly in optimizing manufacturing processes and supply chain management. This, in turn, can lead to lower costs, and increased innovation activity / productivity.

- Question 3 - Utilizing Drivers for Digitalization: The analysis revealed that the most common factors driving the adoption of digital technologies among the interviewed companies were productivity gains, cost reductions, market demand, and the desire to keep pace with technological advancements.

- Question 4 - Level of Digitalization Maturity: The study utilized a specifically designed maturity model to evaluate the digital advancement levels of the participating companies. In general, the findings indicate that a majority of these manufacturing and supplier companies fall under ML-5 and ML-4 classes. This finding of ours suggests that these companies have already successfully navigated and overcome a significant portion of the challenges / barriers associated with digitalization. ML5- and ML-4 companies' positions imply a higher likelihood of gaining the benefits of digital transformation, such as increased efficiency, enhanced productivity, and greater agility in responding to market demands. However, it is important to note that even companies at these higher maturity levels may face ongoing challenges in fully leveraging emerging technologies and adapting to the ever-evolving digital landscape.

- Question 5 – Influence of Maturity Levels: Similar to the previous question, the research highlighted that the most frequently cited determinants influencing the integration and adoption of digital technologies were response time, academic and technical skills, data management and Interpreting Big Data, digitalization policies, customer involvement and IT integration.

  This underscores the crucial role of developing robust digitalization capabilities within these companies. In addition, by investing in human resources, skills, infrastructure, and organizational structures that support digital transformation,

these companies are better positioned to harness the power of these technologies to drive efficiency, reduce expenses, meet evolving customer needs, and stay ahead in a rapidly changing marketplace.

Consequently, our analysis revealed that the interviewed manufacturing and supplier companies that are in the early to middle stages of their digital transformation journeys toward Industry 4.0 (ML-1 to ML-3 class) acknowledge the potential impact of digital technologies and digitalization, and are still in the process of developing their digital maturity. According to the evidence presented, *none* of the companies seem to have *fully* integrated digital technologies across all aspects of their operations, indicating significant room for further development and implementation of Industry 4.0 principles. However, despite being in the early stages of their digitalization journeys, the companies demonstrated a strong commitment to digital transformation, viewing it as a critical *long-term strategy* rather than a passing trend. They have plans to intensify their focus on digitalization and Industry 4.0, recognizing their importance for future success.

The study also suggests that companies prioritizing skills development and workforce expansion in areas like big data, product design, production, supply chain management, digital sales, and procurement tend to have a competitive edge in establishing robust digitalization capabilities. This proactive approach to human capital development in key digital areas appears to be a significant factor in successfully increasing the competitiveness in the global market.

In conclusion, this thesis provides a comprehensive overview and an *assessment model* that examines the potential benefits and challenges confronting manufacturing companies at various maturity levels, drawing upon the findings and criteria discussed throughout the research. The findings highlight that the Turkish automotive industry is on the verge of a significant digital revolution, driven by the adoption of transformative technologies. However, this technological shift also presents a challenge, as new competitors from China, etc. leveraging digital tools could rapidly disrupt the market, similar to what has occurred in other industries. Therefore, Turkish automotive manufacturers and suppliers may embrace flexibility and proactively pursue digitalization to avoid being outmaneuvered by agile, digitally adept competitors. Failure to adapt could lead to obsolescence in an increasingly competitive marketplace.

6.1. Policy Recommendations

The findings of this thesis are further aligned with the findings in the OTEP (2019) report. Our analysis had revealed a *strong* correlation between digitalization / maturity level of a company and a company's ability to adopt Industry 4.0 practices. This accomplishment of adoption in this context appears to originate from a well-defined technology environment based on Industry 4.0 preferences and a strategic approach to leveraging the drivers and mitigating the barriers identified within this thesis. While these impacts were not directly measurable, our study found that *over 60%* of companies reported high levels of agreement (4 or 5 on a 5-point Likert scale) regarding the perceived benefits of digitalization across various aspects of Industry 4.0. Our approach, drawing upon the maturity level analysis, has pinpointed seven key research areas and policy measures crucial for driving successful digital transformation within the Turkish automotive industry. These key areas, accompanied by concise policy recommendations, are outlined in Table 24.

In general, to ensure the continued competitiveness of Turkish automotive manufacturers, we may underline the fact that the policymakers and institutions should prioritize the development of effective short-term and long-term strategies as made in other respective developing countries. Based on existing research, and on relative analysis results gathered for the Turkish automotive manufacturers, achieving this goal likely requires a phased, multi-step approach as follows:

1. Assessment: Researchers are expected determine the maturity levels (generally, structured by current level of industrialization, adoption and awareness of new technologies).

2. Collaboration and Planning: Companies are expected to facilitate more collaborations with their subcontractors, other technology supplier companies, academics, policymakers, institutions, and NGOs to share findings from the assessment stage.

3. Governance: The Turkish government is expected to implement appropriate incentives, funding mechanisms, and awareness campaigns to encourage the adoption of new technologies and trends.

4. Implementation: Companies are expected to develop and adopt efficient lean production methods, technologies, and systems that align with Industry 4.0 principles and higher maturity requirements based on selected criteria (capabilities).

This thesis explored various strategies that can help Turkish manufacturers succeed in the rapidly changing landscape of Industry 4.0. Ultimately, this research provides valuable insights for companies looking to utilize Industry 4.0 technologies to achieve sustainable production processes.

In summary, this research proposes a unique "two-stepped" assessment model (utilizing BWM and bi-clustering) to determine a company's maturity level regarding Industry 4.0 adoption. *Our versatile assessment method, using BWM and bi-clustering together, may evaluate first a group of companies' progress in implementing digital transformation strategies, then, may offer valuable insights for each company into their current digital maturity level and pinpointing areas with potential for further development.*

6.2. Limitations

This thesis acknowledges several limitations. First, given the rapidly evolving nature of the Industry 4.0 practices, the reliance on older data in the survey results (e.g., survey is completed 2018 and the data published is published in 2019) may impact the transferability of findings to the current Industry 4.0 development scheme for Turkish automotive sector. Second, *comparably*, the limited number of interviews restricts the generalizability of the results.

A larger and more diverse sample size could yield different outcomes. Moreover, setting overly strict similarity thresholds when analyzing company sub-criteria data can lead to fragmented clusters that are too small to reveal meaningful patterns or support statistically sound conclusions, especially given the typically sparse nature of this type of data where companies choose to answers questions within *only* a limited number of criteria.

Third, it is important to note that this research primarily focuses on the automotive sector. This means the findings might not directly apply to other industries, as they often have unique characteristics and face different challenges in their digitalization journeys. Additionally, our analysis heavily relied on survey data, specifically from the Turkish automotive industry, to understand management practices. While we did consult a broad survey dataset and qualitative interview feedback to confirm our findings, these perspectives might not fully represent the entire industry.

As a fourth, this research highlighted a critical consideration for policymakers and industry leaders alike: assessing digital maturity is not a one-size-fits-all endeavor. Our findings, particularly the observed inconsistencies between the BWM ranking and CC bi-clustering results, underscore the need for a more nuanced and comprehensive evaluation approach. Hence, we recommend adopting a multifaceted assessment strategy such that incorporates both quantitative and qualitative dimensions:

i. Embrace Multiple Analytical Approach: Relying solely on a single metric, such as the BWM ranking, can provide a skewed perspective.
   Instead, our approach integrated complementary analytical tools like bi-clustering to gain a more holistic understanding of digital maturity. This approach allowed for the identification of potential imbalances where a company might demonstrate high performance in certain areas while lagging in others.
ii. Contextualize Results: Avoid direct, one-to-one comparisons between different analytical outputs. Instead, researcher may interpret the results within the broader context of each company's specific quantifiable data. As a result, this contextualization may provide a more accurate and actionable assessment of their true digital maturity level.

Table 23 – Further Research Title and Policy Recommendation

Further Research Title	**Explanation of Potential Research**	**Policy Recommendation (in brief)**
Awareness Level	• While automotive companies generally demonstrate a *strong* understanding of the benefits of digital transformation, there is room for improvement in areas like product development speed, new lean methods. • This study directs us to a planned approach to address emerging digitalization needs and emphasize the importance of raising awareness	• Promote sectoral and company-specific research on digital transformation within the automotive industry to foster broader awareness
Digital Compliance Policies and Governance Intervention	• While companies generally believe they are prepared in terms of digital compliance policies and risk management, the study reveals a crucial need for forward-thinking approaches in both areas.	From the company perspective: • Develop a comprehensive roadmap encompassing digital compliance policies, risk management, and relevant legal processes. • Establish a dedicated institutional framework to manage the digital transformation process through a lean manufacturing perspective • • Strengthen internal digital transformation coordination mechanisms through training and other capacity-building initiatives.

Table 23 – Further Research Title and Policy Recommendation (Continued)

Further Research Title	Explanation of Potential Research	Policy Recommendation (in brief)
Digital Compliance Policies and Governance Intervention	• This highlights a vital role for government intervention in guiding the Turkish automotive industry's digital transformation. Specifically, the government should prioritize developing future-oriented policies and sector-wide coordination	From the government perspective: • Adapt a comprehensive policy framework that anticipates future trends and fosters innovation in the sector. • Foster collaboration, facilitating knowledge sharing, and establishing industry-wide standards for digitalization.
Human Resources	• The study highlights the lack of a qualified workforce capable of meeting the demands of Industry 4.0 technologies as a major obstacle to digital transformation. • Addressing this skill gap by investing in education and training programs is crucial for both achieving and sustaining digital transformation within the industry.	• Conduct thorough skills gap analyses to identify the specific competencies required for digital transformation. • Develop targeted training programs and initiatives to cultivate a qualified workforce equipped with the necessary digital skills
New Technologies	• While companies express a strong interest in adopting new technologies, affordability and accessibility remain significant barriers.	• Prioritize investments in research and development to bolster technological and innovative capacity

Table 23 – Further Research Title and Policy Recommendation (Continued)

Further Research Title	Explanation of Potential Research	Policy Recommendation (in brief)
New Technologies	• The study emphasizes the need for qualified personnel, comprehensive training programs, and readily available external technical support. Furthermore, it underscores the importance of strengthening technological and innovative capabilities	• Foster the development of new capabilities specifically geared towards supporting digitalization efforts
Infrastructure	• Although the existing technical infrastructure is generally deemed sufficient, the study identifies areas (sub-criteria) for improvement. • Strengthening data communication infrastructure, establishing data transfer protocols and standards, enhancing data security measures, etc. are crucial steps. • Aligning a company's IT infrastructure and organizational framework with the demands of digital transformation is another critical factor for successful implementation.	• Invest in upgrading and expanding data communication infrastructure to support the growing demands of digitalization. • Encourage companies to adapt their IT architecture and systems to meet the specific needs of digital transformation.
Digital Technology Suppliers	• Leveraging domestic digital technology suppliers is deemed crucial for the automotive industry's digital transformation.	• Implement measures to enhance the capacity and capabilities of digital technology suppliers, particularly in technology acquisition and development.

Table 23 – Further Research Title and Policy Recommendation (Continued)

Further Research Title	Explanation of Potential Research	Policy Recommendation (in brief)
Digital Technology Suppliers	• Strengthening these suppliers' capabilities and ensuring access to cost-effective services will be vital for companies' successful adoption of new Industry 4.0 practices	• Improve accessibility to digital technology suppliers' products and services for companies within the automotive industry
Collaboration in the Value Chain	• While collaboration exists between some of the NGOs and companies within the value chain, the study highlights the need for increased collaboration with universities, digital technology suppliers, and other value chain stakeholders specifically in the context of digital transformation. • Fostering a stronger culture of collaboration and knowledge sharing within the industry is crucial	• Encourage and facilitate collaborative initiatives between various stakeholders within the automotive industry ecosystem, including universities, digital technology suppliers, and other relevant entities

iii. Prioritize Targeted Interventions: Recognizing that digital maturity is not monolithic, policymakers and industry leaders should develop targeted interventions and support programs. These initiatives should address specific areas of weakness identified through the multifaceted assessment, fostering a more balanced and sustainable digital transformation journey for companies.

By embracing this nuanced approach, we can move beyond simplistic rankings (current and target rankings) and create a more effective framework for evaluating and supporting digital maturity across diverse industries and organizational contexts.

Moreover, when the CC algorithm replaces bi-cluster elements with random values, it essentially "masks" those elements from further consideration. In this regard, important patterns involving the masked elements might be missed in subsequent iterations (Imagine a scenario where two overlapping bi-clusters exist. Masking elements from the first one might prevent the algorithm from discovering the second one accurately). As a result of this masking behavior of the model, CC algorithm might be biased towards finding larger bi-clusters early on, as they mask more elements, potentially obscuring smaller but significant patterns later. In addition, lack of generalizability is possible while one dataset might not be suitable for another. This makes it difficult to apply the algorithm consistently across different datasets without prior knowledge or tuning.

Finally, in order to overcome this masking behavior, researchers may be depicted to define a threshold. However, this attitude can also be somewhat arbitrary. Different thresholds can lead to the discovery of different bi-clusters, introducing subjectivity into the analysis. Finally, the diverse professional backgrounds and perspectives of the surveyed participants introduce potential variability in their understanding and interpretation of key concepts like "digitalization" and "Industry 4.0."

The self-selection of interview participants interested in digitalization and Industry 4.0

might also create a bias in the findings, as companies less engaged with these topics might hold different perspectives. Hence, this variation could influence the research outcomes and limit the ability to draw definitive conclusions.

6.3. Further research

As depicted in Section 6.2, based on some of this thesis' limitations, future research could address the use of different quantitative methods (CC, quest, plaid, etc.) with a larger, statistically significant sample of companies to allow for more generalizable findings.

This research can be further strengthened and expanded upon in several key ways:

i. Enhancing Interview Data Consistency: Future studies may benefit from a more homogenous group of participants. Selecting surveyor's similar levels of knowledge and experience, ideally working in comparable roles or departments within their respective companies, would enhance the consistency and comparability of responses. This approach minimizes variations in understanding and interpretation, ensuring everyone approaches the questions from a similar knowledge base.

ii. Industry-Specific Deep Dives: While this research provides a valuable overview of digital maturity in the Turkish automotive sector, future studies may delve deeper into other specific industries within manufacturing. For example, focusing on electronics or aerospace could uncover unique challenges and opportunities related to digitalization within those sectors, leading to more targeted insights and recommendations.

iii. Exploring Causality and Relationships: Another promising avenue for future research is to explore the causal relationships between different digital maturity criteria. Understanding how these factors influence each other may provide a more nuanced understanding of the digital transformation process and enable the development of more effective intervention strategies. This may involve statistically analysing the relationships between criteria or developing system dynamics models to simulate the impact of different interventions.

Finally, comparing companies in the automotive sector to those in other sectors may also be an important area for future research.

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APPENDICES

A. SURVEY QUESTIONS

AUTOMOTIVE INDUSTRY DIGITAL TRANSFORMATION INFORMATION SURVEY

I. Automotive Technology Platform (OTEP) - Brief Information

The Automotive Technology Platform, founded in 2008 with support from TÜBİTAK, seeks to enhance Turkey's long-term competitiveness in the automotive industry. It aims to achieve this by creating a collaborative platform for R&D organizations connected to the industry within Turkey. This platform facilitates the identification and initiation of essential research and development efforts, fostering synergy and leveraging a common-sense approach to bolster the industry's R&D capabilities.

II. About Digital Transformation Knowledge Survey

The purpose of the Digital Transformation Knowledge Survey is to determine the current status of the automotive industry regarding digital transformation and to create information that will form the basis for defining the roadmap for the future.

III. Privacy Policy

OTEP undertakes not to share the answers given by the companies to the questions with other companies, institutions and organizations.

This survey prepared for the OTEP Automotive Technology Platform cannot be used, copied, translated, published or distributed, in whole or in part, through any printed or digital medium or tool without the permission of OTEP.

Please rate your level of agreement with the following questions and statements on a scale of 1-5, considering your current situation and your estimated future situation. Please also indicate the year you are aiming for when rating your future target *estimation. (1- Strongly Disagree, 2- Disagree, 3- Neither Agree nor Disagree, 4- Agree, 5- Completely Agree)*

IV. Questions (Company Info)

i. Which of the following options describes your company?
   a. Main Industry or Supplier
   b. Membership Status:
      i. Member of TAYSAD or Member of OTEP or Member of OSD

ii. Company Information:
   a. Trade Name:
   b. Neighbourhood:
   c. Address:
   d. District:
   e. City:
   f. Postal code :
   g. Name and Surname: Position / Duty:
   h. Telephone
   i. Email:
   j. Company Establishment Year:
   k. Company activity (In which areas does your company operate? - Please specify briefly):
   l. Target markets:
      i. Domestic or Abroad
   m. Please specify the shareholding structure of your company:
      i. or Family Business or Significant Non-Family or Domestic Partners or Significant Foreign Partners International

iii. Change in your turnover in the last three years
   a. 2015 to 2020

iv. Profitability of Sales= (Gross Profit/ Sales) Indicate the percentage change in the equivalent in the last three years.

a. 2015 to 2020

v. Have you exported in the last three years?

vi. Have you exported your own R&D products?

vii. Number of Employees in the last three years

a. 2015 to 2020

viii. Could you please distribute the total number of employees in 2017 by units and education levels?

V. Questions (Survey)

1. R&D and innovation policy is satisfactory. (rate from 1 to 5)
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
2. Digital capabilities add value to our company's products and services.
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
3. The products produced by our company are/will be digitalized (e.g. RFID identification, sensors, IoT connectivity, smart products, etc.).
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
4. The lifecycle of your products is digitalizing. (digitalization and integration of design, planning, engineering, production, services, recycling)
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
5. Data usage and analysis is important for your business model (customer data, product and equipment based data)
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
6. In the context of product and service development, we maintain a high level of cooperation with our business partners, suppliers and customers.
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm

7. In the context of digitization of product development, please rate your opinion on the following propositions ("Current/present" and "Target Future" choices are asked separately) (*1 = not important, 2= less important, 3= neither important nor unimportant, 4= important 5= very important)*
    a. Collecting technical information (know-how) such as production, product and maintenance digitally and sharing it within the company through a knowledge management system
    b. Rapid prototyping using digital technologies (e.g., using a 3D printer)
    c. Conducting preliminary trials using digital technologies (e.g., simulation software)
    d. Simultaneous consideration of different stages in product development, such as production and procurement, which will come later with the help of digital technologies (e.g., concurrent engineering, design for production)
    e. Advanced analytics in product development to understand customer behaviour and needs (e.g., by identifying what customers value through big data analytics)
    f. Utilizing specialized software and technologies for product development (e.g., simulation software, intelligent algorithms for design optimization)
8. Within the scope of digitalization, which issue or issues related to human resources are currently experiencing problems in your company, and how important do you think the following problems are? ("Current/present" and "Target Future" choices are asked separately) *(1 = unimportant, 2 = less important, 3 = neither important nor unimportant, 4 = important, 5 = very important)*
    a. *Qualified workforce on digital technologies*
    b. *Unwillingness of the labour force qualified in digital technologies to work in the manufacturing industry (e.g. working environment, career prospects)*
    c. *Difficulty in creating financial attractiveness for the employment of skilled labour in digital technologies Lack of qualification of the existing workforce to develop digital solutions*

d. *Lack of trainings to equip the existing workforce with the qualifications to use digital technology or develop digital solutions*
e. *Quality of trainings to equip the existing workforce with qualifications to use digital technology or develop digital solutions*
f. *Digital education system is implemented in the company*
g. *Employee training through digital tools (Virtual Reality, Enriched Reality, etc.)*

9. In which areas of digitalization do you currently need qualified manpower the most, and what is the importance of these areas according to your needs ("Current/present" and "Target Future" choices are asked separately) *(1 = not important, 2 = less important, 3 = neither important nor unimportant, 4 = important, 5 = very important)*
    a. *Big Data*
    b. *Internet of Things Enriched Reality*
    c. *Horizontal - Vertical Software Integration*
    d. *Cloud Technologies Cyber Security Smart Robots*
    e. *Additive Manufacturing*
    f. *Simulation*
    g. *Artificial Intelligence - Intelligent/ Learning Systems Detection Systems*
    h. *Computer Vision Design*
    i. *Computer Aided Design (CAD)/ Computer Aided Manufacturing (CAM)/ Computer Aided*
    j. *Engineering (CAE) Manufacturing Energy*
    k. *Supply and Value Chain Management Technology and Innovation Management Artificial Intelligence*
    l. *Management and Social Sciences*
    m. *Education*

    n. *Digital Procurement Digital Sales*
    o. *Digital Marketing*
    p. *Other ...*

10. In which areas do you currently encounter more infrastructure problems in terms of digital applications? (“Current/present” and “Target Future” choices are asked separately) *(l= Very encountered, 2= Encountered, 3= Moderately encountered, 4= Less encountered, 5= Very little encountered)*
    a. Broadband access and capacity Sufficient network and processing power Data collection and storage
    b. Ensuring data security and establishing measures against cyber-attacks
    c. Standardization of data to ensure compatibility between different systems in data transfer and integration
    d. Energy infrastructure
    e. Other …
11. What are the biggest obstacles to your company's digitalization? (“Current/present” and “Target Future” choices are asked separately) *(1 = Not an obstacle at all, 2= Not an obstacle, 3= Neither an obstacle nor not an obstacle, 4= Obstacle, 5= Major obstacle)*
    a. Lack of sufficient knowledge on the subject (not knowing exactly what kind of benefits digitalization will provide in which areas)
    b. Lack of sufficient suppliers to provide technology and solutions for digitalization Technologies and solutions for digitalization are expensive and the returns do not cover it
    c. Failure to employ the needed qualified manpower
    d. Inadequate government incentives
    e. Insufficient technical infrastructure to support digitalization (e.g. broadband, cloud data centres, cyber security)
    f. Lack of competition that will force our company to digitalize Lack of a customer base that will force our company to digitalize
    g. Legislation and regulations do not support digitalization (e.g., pre-competitive cooperation regulations are an obstacle)

    h. Other …
12. In the ecosystem you are in, which areas do you think should be developed as a priority in terms of digitalization of your company? (“Current/present” and

"Target Future" choices are asked separately) *(l= No need for improvement, 2= Little improvement, 3= Neither improvement nor no improvement, 4= Improvement, 5= Much improvement)*

a. Culture of collaboration with digital technology suppliers Competence of digital suppliers
b. Adequacy of technical and management consultants
c. A culture of collaboration with other players in the value chain (e.g., customers, suppliers) Collaboration with industry players
d. Cooperation with academia
e. Technical competence of the Academy Competitiveness of the business environment Cooperation with NGOs
f. Financing opportunities
g. Other …

13. In the context of your company's needs, which are the priority areas where you think the government should intervene in the current state of digitalization? ("Current/present" and "Target Future" choices are asked separately) *(1 = Cannot intervene, 2= Can intervene a little, 3= Should intervene moderately, 4= Should intervene, 5= Should definitely intervene)*

a. Supporting investments in digitalization
b. Supporting digital technology suppliers Raising awareness of companies and people
c. Increasing digitalization practices and investments by the government, creating demand itself and setting an
d. example
e. Cyber security and protection of personal/corporate data Protection of intellectual property rights
f. Adapting the education system
g. Establishing the necessary technical infrastructure Arrangement of necessary legislation
h. Determining the boundaries and content of legal rights after digitalization
i. An organizational structure dealing with digitalization
j. Other …

14. Evaluate the potential contribution of the value elements that stand out in the context of digitalization in manufacturing to your company ("Current/present" and "Target Future" choices are asked separately) *(1 = No contribution at all, 2= Little contribution, 3= Moderate contribution, 4= Contribution, 5= Very much contribution)*
    a. Labor productivity (e.g., automation of tasks; industrial robots; digital performance management; automation of knowledge-intensive tasks)
    b. Resource/process efficiency (e.g., efficient use of energy; real-time process optimization)
    c. Production machine/equipment/facility efficiency (e.g., production parameter optimization, real-time production monitoring of machines, predictive maintenance)
    d. Effective inventory management (e.g., effective monitoring and optimization of stock quantities and values; use of 3D printers in spare parts production)
    e. Product and production quality (e.g., fully automated quality control systems; advanced and statistical process controls)
    f. Sales and operations planning (forecasting, planning and optimization of sales, procurement, inventory and production
    g. Service offerings related to products sold (e.g., predictive or usage-based maintenance through real- time monitoring of machinery, tools and equipment sold to customers using remote sensors)
    h. Speed of product development (e.g., faster creation of samples/prototypes with 3D printers; co- development of products with customers)
    i. Transparent logistics services
    j. Other …
15. In which of the following areas of "Digital Transformation" do you think your company needs support? You can select more than one option. (Please mark the area(s) where you need support.)
    a. Big Data
    b. Internet of Things Enriched Reality
    c. Horizontal - Vertical Software Integration

d. Cloud Technologies Cyber Security Smart Robots
e. Additive Manufacturing
f. Simulation
g. Artificial Intelligence - Intelligent I Learning Systems Detection Systems
h. Computer Vision Design
i. Computer Aided Design (CAD)/ Computer Aided Manufacturing (CAM) I Computer Aided
j. Engineering (CAE) Manufacturing Energy
k. Supply and Value Chain Management Technology and Innovation Management Artificial Intelligence
l. Management and Social Sciences
m. Education
n. Digital Procurement Digital Sales
o. Digital Marketing

Please rate your level of agreement with the following questions and statements on a scale of 1-5, considering your current situation and your estimated future situation. Please also indicate the year you are aiming for when rating your future target estimation. (1=Strongly Disagree, 2=Disagree, 3=Neither Agree nor Disagree, 4=Agree, 5=Completely Agree)

16. We use multiple integrated sales channels to sell our products to our customers.
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
17. We have integrated multiple channels (website, blog, forum, social media platforms, etc.) to interact with customers to share news, receive feedback, meet their requests, etc.
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
18. Your sales team has advanced digital capabilities (mobile devices, access to all relevant systems at any time and place, completion of sales processes at the customer's location, etc.)
    a. "Current/present" and "Target Future" choices are asked separately

    b. "Target Year" is asked to confirm.

19. Our pricing system is dynamic and customized.
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
20. We analyse customer data in order to increase customer insights (e.g. preparing personalized offers based on customers' personal circumstances, preferences, location, creditworthiness, using data for design and engineering, etc.).
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
21. We cooperate with your business partners to reach customers (sharing customer insights, coordination of marketing activities, etc.)
    a. "Current/present" and "Target Future" choices are asked separately
    b. "Target Year" is asked to confirm.
22. What kind of cooperation have you made with other companies? Please indicate their importance for your company ("Current/present" and "Target Future" choices are asked separately) (1 = unimportant, 2 = less important, 3 = neither important nor unimportant, 4 = important, 5 = very important)
    a. Sharing company knowledge and skills Digital Transformation/Industry 4.0 R&D
    b. Design
    c. Acquiring/developing new technology
    d. Production
    e. New product development Marketing
    f. Education
    g. Financing
    h. Cooperation to benefit from open information sources such as fairs, exhibitions, publications, etc.
    i. Other …
23. In which areas has your company benefited from organizations providing knowledge-based services? Indicate their importance for your company ("Current/present" and "Target Future" choices are asked separately) (1 =

unimportant, 2= less important, 3= neither important nor unimportant, 4= important, 5= very important)

a. R&D
b. Digital Transformation/Industry 4.0 Design
c. Technology development Product development
d. Information technologies and communication systems
e. Marketing
f. Technical consultancy Legal advice
g. Auditing and accounting
h. Other …

24. In the context of Digital Transformation/Industry 4.0, please rate your opinion on the following statements from 1 to 5 (l= Strongly Disagree, 2= Disagree, 3= Neither Agree nor Disagree, 4= Agree 5= Strongly Agree)
    a. Your company can allocate resources to collaborations to develop new products or processes. (“Current/present” and “Target Future” choices are asked separately)
    b. Your company has significantly increased its competitiveness in its sector thanks to the new products/processes developed in the last 5 years. (“Current/present” and “Target Future” choices are asked separately)

Please rate your level of agreement with the following questions and statements on a scale of 1-5, considering your current situation and your estimated future situation. Please also indicate the year you are aiming for when rating your future target estimation. (1=Strongly Disagree, 2=Disagree, 3=Neither Agree nor Disagree, 4=Agree, 5=Completely Agree)

25. How digitalized is our vertical value chain from product development to production? 5 = Fully digitalized - Continuous data flow through the vertical value chain (e.g. direct control of machines with CAD models, integration of ERP and MES) *(l= No digitalization at all - No automated flow of information through the vertical value chain (e.g. manual programming of machines based on paper plans)*
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.

26. We can monitor production in real time and react dynamically to changes in demand.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
27. We effectively carry out end-to-end IT-based planning, sales forecasting, inventory planning and logistics activities.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
28. High level of digitalization of our production equipment (sensors, IoT connectivity; digital monitoring, control, optimization and automation)
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
29. Our horizontal value chain from customer demand to suppliers, from production to logistics services is digitalized
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
30. Our IT architecture meets the requirements of digitalization and Digital Transformation/Industry 4.0.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
31. We are familiar with Industry 4.0 needs in Information Technology architecture.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
32. We use Manufacturing Execution Systems (MES) effectively.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
33. We have a sophisticated IT and data architecture to collect, combine and interpret real-time manufacturing, product and customer data.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
34. Social media, mobile technologies, analytics and cloud computing are important for our company to realize our activities.

a. “Current/present” and “Target Future” choices are asked separately
b. “Target Year” is asked to confirm.

35. Your IT organization is sufficient for you to carry out our activities in the required time, quality and cost.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
36. Our IT integration with our customers, suppliers and business partners is advanced.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
37. Our digital compliance policy includes foresights for the future.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
38. We protect the intellectual property rights of our digital products and services and do not infringe the intellectual property rights of others.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
39. Our risk management practices cover our digital product portfolio, production and facilities.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
40. Digital components of our value chain are successfully managed (location of intellectual property, licenses, patents, etc.)
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
41. The concept of Information Security is taken into account in our production activities.
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
42. Our digital compliance and risk management policies include our business partners and customers
    a. “Current/present” and “Target Future” choices are asked separately

b. “Target Year” is asked to confirm.

43. How would you rate your ability to create high value-added, meaningful outputs from complex masses of data?
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
44. Please rate your resources and capabilities related to Digital Transformation/Industry 4.0 in your organization (e.g. Data Analytics, Internet of Things (IoT), Cyber Physical Systems (CPS), Human Machine Interface (HMI), Manufacturing Security, Digital Product Lifecycle (PLM), etc.).
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
45. To what extent is the senior management interested, supportive and expert in Digital Transformation/ Industry 4.0 in your organization?
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
46. To what extent has your business institutionalized cooperation with external partners such as academia, industry, suppliers and customers in the fields of Digital Transformation/Industry 4.0?
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
47. To what extent would you evaluate your organization's human competence and investment in people in the fields of Digital Transformation/Industry 4.0?
    a. “Current/present” and “Target Future” choices are asked separately
    b. “Target Year” is asked to confirm.
48. What opportunities do you CURRENTLY utilize for your company's employees to be aware of technological developments? Please indicate their importance for your company. (“Current/present” and “Target Future” choices are asked separately) *(l= unimportant, 2= less important, 3= neither important nor unimportant, 4= important, 5= very important)*
    a. Internal information sources and information flow In-house training
    b. External information sources and information flow
    c. External training

d. Technical consultancy service procurement
e. Presence of employees monitoring new products and technologies coming to the market
f. Technological cooperation with other organizations
g. Efforts to regularly identify and increase employees' awareness of technological developments
h. Other …

Please rate your level of agreement with the following questions and statements on a scale of 1-5, considering your current situation and your estimated future situation. Please also indicate the year you are aiming for when scoring your future target. 1=No change/stayed the same, 2=Little change, 3=Moderate change, 4=Change happened, 5=There has been a lot of change

49. To what extent do you think the concept of Digital Transformation/Industry 4.0 is a technological change on a global scale?
50. What problems do you think your company may face in the short/medium and long term in the context of digital transformation?
51. How do you think you can overcome these potential problems?
52. According to your company, what are the practices that automotive industry enterprises at the beginning of the digitalization process in production can implement in a short time and easily and that will have a high impact? (Please explain briefly)
53. Please rank your priority areas when starting digitalization from 1 to 8 (1 = most important, 8 = least important).)
    a. Production line (Machine, Value Stream Mapping)
    b. Data analysis
    c. Production value stream
    d. Maintenance (Predictive maintenance, autonomous maintenance)
    e. Logistics (eKanban, RFID)
    f. Human Resources Management
    g. Company Administrative Management
    h. Facility Management

B. ANALYSIS CODE SAMPLE

Best-Worse Code (Sample)

```
from scipy.optimize import linprog
import numpy as np
from collections import OrderedDict
import pandas as pd

# Calculate Weight Values for BWM #
def calc_weight(compared2best, compared2worst):

    cb = OrderedDict()
    cw = OrderedDict()

    allkeys = sorted(compared2best.keys())

    for key in allkeys:
        cb[key] = compared2best[key]
        cw[key] = compared2worst[key]

    colSize = np.size(allkeys)
    rowSize = 4 * colSize - 5
    mat = np.zeros((rowSize-1, colSize+1), dtype=np.double)
    bloc = 0
    bkey = ''

    wloc = 0
    wkey = ''

    # get the best criteria location
    bkey =  min(compared2best, key=compared2best.get);
    bloc = allkeys.index(bkey);

    # get the worst criteria location
    wkey = min(compared2worst, key=compared2worst.get);
    wloc = allkeys.index(wkey);
    cb_copy = cb.copy();

    cb_copy.pop(bkey, None)
    tmpmat = np.zeros((len(cb_copy.keys()), colSize+1), dtype=np.double)
    tmpmat1 = np.zeros((len(cb_copy.keys()), colSize+1), dtype=np.double)
```

```
for idx in np.arange(len(cb_copy.keys())):
    itmp = allkeys.index(list(cb_copy.keys())[idx])
    tmpmat[idx, bloc] = 1.0
    tmpmat[idx, itmp] = -cb_copy[list(cb_copy.keys())[idx]]

    tmpmat[idx, colSize] = -1.0

for idx in np.arange(len(cb_copy.keys())):
    itmp = allkeys.index(list(cb_copy.keys())[idx])
    tmpmat1[idx, bloc] = -1.0
    tmpmat1[idx, itmp] = cb_copy[list(cb_copy.keys())[idx]]
    tmpmat1[idx, colSize] = -1.0

mat[0:2 * colSize - 2, :] = np.concatenate((tmpmat, tmpmat1), axis=0)

cw_copy = cw.copy()

cw_copy.pop(bkey, None)
cw_copy.pop(wkey, None)

tmpmat  = np.zeros((len(cw_copy.keys()), colSize+1), dtype=np.double)
tmpmat1 = np.zeros((len(cw_copy.keys()), colSize+1), dtype=np.double)

for idx in np.arange(len(cw_copy.keys())):

    # find the location of the key of cw_copy in the keylist list
    itmp = allkeys.index(list(cw_copy.keys())[idx])
    tmpmat[idx, itmp] = 1
    tmpmat[idx, wloc] = -cw_copy[list(cw_copy.keys())[idx]]
    tmpmat[idx, colSize] = -1.0

for idx in np.arange(len(cw_copy.keys())):
    # find the location of the key of cw_copy in the keylist list
    itmp = allkeys.index(list(cw_copy.keys())[idx])
    tmpmat1[idx, itmp] = -1
    tmpmat1[idx, wloc] = cw_copy[list(cw_copy.keys())[idx]]
    tmpmat1[idx, colSize] = -1.0

mat[2 * colSize-2 :, :] = np.concatenate((tmpmat, tmpmat1), axis=0)
Aeq = np.ones((1, colSize + 1), dtype=np.double)
Aeq[0,-1] = 0.

beq = np.array([1])
bub = np.zeros((rowSize-1), dtype=np.double)

cc = np.zeros((colSize+1), dtype=np.double)
cc[-1] = 1;
res = linprog(cc, A_eq=Aeq, b_eq=beq, A_ub=mat, b_ub=bub,
```

```
            bounds=(0, None), options={"disp": False})
    sol1 = res['x']
    outp = dict()
    ii = 0

    for x in allkeys:
        outp[x] = sol1[ii]
        ii += 1

    return((outp, sol1[-1]))

#################################################################
############################################

# Best Worst Method Main Code #
def bwm(data):

    cleaned_data_with_numeric_only = pd.read_excel("DATA_FILE_PATH")

    firma_dict = dict()

    for idx in data.index:

        firma_puani = 0

        for col in data.columns:

            firma_puani = firma_puani + data.loc[idx, col] *
list(weightDF.loc[weightDF["Parameter_Name"] == f"{col}_WEIGHT",
"Value"])[0]

        firma_dict[idx + 1] = firma_puani

    firma_skor = pd.DataFrame(index=firma_dict.keys(),
data=firma_dict.values(), columns=["Score"])

    firma_skor = firma_skor.sort_values(by="Score", ascending=False)

    return firma_skor
```

Bi-Clustering Code (Sample)

```
library("biclust")
library("readxl")
library("ggplot2")
library("tidyr")
library("dplyr")
```

```
################ Read the data ################

data <- as.matrix(read_excel("Rawdata_MEVCUT.xlsx"))
data_df <- read_excel("Rawdata_MEVCUT.xlsx")

################ Read the data ################

################ Draw Correlation Coefficients Heatmap
################

ggplot(melted_upper, aes(x = Var2, y = Var1, fill = value)) +
  geom_tile(color = "white") +
  scale_fill_gradient2(low = "blue", high = "red", mid = "yellow",
                       midpoint = 0, limit = c(-1, 1), space = "Lab",
                       name="Correlation") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, size = 12, hjust = 1),
        axis.text.y = element_text(size = 12)) +
  scale_x_discrete(breaks = levels(melted_upper$Var2)[seq(1,
length(levels(melted_upper$Var2)), by = 5)]) +
  scale_y_discrete(breaks = levels(melted_upper$Var1)[seq(1,
length(levels(melted_upper$Var1)), by = 5)]) +
  coord_fixed() +
  labs(title = "Survey Results Correlation Matrix Heatmap",
       x = "Criteria",
       y = "Criteria")

################ Draw Correlation Coefficients Heatmap
################

################ Apply Cheng and Church Bi-Clustering Algorithm
################

bicluster_result <- biclust(data, method = BCCC(), delta=0.15, number=5)

################ Apply Cheng and Church Bi-Clustering Algorithm
################

################ Draw Bi-Clusters Heatmap ################

heatmapBC(data, bicResult = res, number=1:5)

################ Draw Heatmap ################

################ Get bi-cluster assignments ################

get_assignments <- function(biclust_result) {
  row_assignments <- vector("list", biclust_result@Number)
```

```r
  col_assignments <- vector("list", biclust_result@Number)

  for (i in 1:biclust_result@Number) {
    row_assignments[[i]] <- which(biclust_result@RowxNumber[, i])
    col_assignments[[i]] <- which(biclust_result@NumberxCol[i, ])
  }
  return(list(rows = row_assignments, cols = col_assignments))
}

assignments <- get_assignments(bicluster_result)

map_column_names <- function(column_indices, original_data) {
  colnames(original_data)[column_indices]
}

for (i in 1:length(assignments$rows)) {
  cat("Bicluster", i, ":\n")
  cat("Rows:", assignments$rows[[i]], "\n")
  cat("Columns:", map_column_names(assignments$cols[[i]], data), "\n\n")
}

################ Get bi-cluster assignments ################
```

C. CURRICULUM VITAE

[redacted]

[redacted]

[redacted]

[redacted]

D. TURKISH SUMMARY / TÜRKÇE ÖZET

1. GİRİŞ

Otomotiv üreticilerinin ve tedarikçilerinin bu rekabetçi ve gelişen dijitalleşme çağında başarılı olabilmeleri için, insan kaynaklarına, süreçlere ve teknolojilere yatırım yaparak uyum sağlamaları gerekiyor. Başarı için ise otomotiv üreticilerinin ve tedarikçilerinin dijital dönüşüme bütünsel bir yaklaşım, Endüstri 4.0'ın sunduğu fırsatlardan yararlanma, inovasyonu, rekabet gücünü ve sürdürülebilir büyümeyi yönlendirme kapasitelerini geliştirmeleri gerekiyor. (Drath & Horch, 2014).

Bu tezin amacı, dijitalleşme ve Endüstri 4.0 çağında, dönem uygulamalarının başarılı bir şekilde otomotiv üreticileri ve tedarikçileri tarafından benimsenmesi için en büyük etkiye sahip olan temel kriterleri belirlemektedir. Bu çalışma, Endüstri 4.0 perspektifinden dijitalleşmenin Türk otomotiv sektörünü nasıl etkilediğini incelemektedir. Temelde dijital dönüşüm ve Endüstri 4.0 prensiplerine dayanan araştırma modelini kullanan çalışma, farklı dijitalleşme seviyelerinin sektörü nasıl dönüştürdüğünü analiz etmekte ve Endüstri 4.0 uygulamalarının başarılı bir şekilde benimsenmesini önemli ölçüde etkileyen temel alanları nitelendirmektedir.

1.1. Problem Tanımı

Endüstri 4.0'ın otomotiv sektöründeki uygulamaları ve sektörler arası farklı benimsenme seviyeleri farklı zorluklar yaratmaktadır.

Temel zorluklardan en önemlisi, şirketler veya sektörler içindeki izole uygulamalardan bütünsel bir yaklaşıma geçmektir. Finansal riskler, itici *(driver)* güçler ve engeller *(barrier)* gibi stratejik kriterler dahil olmak üzere benimsemeyi etkileyen kritik faktörlerin analiz edilmesi, Endüstri 4.0 ve dijital dönüşümün tüm potansiyelinin ortaya çıkarılması ve şirketlerin bütünsel bir yaklaşıma geçebilmeleri için çok önemlidir.

Bu araştırma, dijitalleşmenin Türk otomotiv endüstrisi üzerindeki etkisini, Endüstri 4.0 uygulamalarının benimsenmesi ve olgunluk *(maturity)* düzeyine odaklanarak farklı matematik modelleri ile analiz etmektedir. Araştırmada, yerli üretim verimliliğini artırma ve yeni teknolojilerin küresel bir tedarikçisi olma hedefi ile, Endüstri 4.0 ortamında Türk otomotiv sektöründeki mevcut dijital dönüşüm durumunu anlamak için Otomotiv Teknolojileri Platformu (OTEP) tarafından yürütülen bir anketin verileri kullanmaktadır.

Çalışma, Endüstri 4.0 teknolojilerinin benimsenmesini yönlendiren ve engelleyen temel faktörleri belirleyerek bunları farklı olgunluk seviyelerine ayırmaktadır. Ayrıca, bu faktörlerin Türk otomotiv şirketlerinin genel dijital dönüşüm çabalarını nasıl etkilediğini de araştırmaktadır.

Bu kapsamda, analizimiz, OTEP tarafından sağlanan, Türk otomotiv sektörünün endüstriyel gelişimiyle ilgili bir anketten elde edilen kapsamlı bir istatistiksel veri setine odaklanmaktadır. Bunu takiben, özellikle yeni teknolojilerin entegrasyonunu yönlendiren veya engelleyen kriterlere odaklanarak, Türk otomotiv endüstrisi içinde Endüstri 4.0 teknolojilerinin benimsenmesini etkileyen temel faktörleri (kriterler ve alt kriterler) belirlemek için mevcut araştırmaların kapsamlı bir incelemesini gerçekleştirilmiştir. Bu kriterler ve alt kriterler, daha sonra farklı dijital dönüşüm olgunluk seviyelerine göre *(maturity level)* şirketler için ayrıca analiz edilmiştir.

1.2. Hedef

Bu araştırma aşağıdaki temel hedeflere odaklanmıştır:

i. Endüstri 4.0 uygulamaları üzerinde etkisi olan genel dijitalleşme kriterlerini ve olgunluk seviyelerini belirlemek

ii. Ankete katılan Türk otomotiv firmalarında çalışan endüstri uzmanlarından toplanan anket verilerini analiz ederek kriterleri belirlemek

iii. Şirketleri "mevcut/güncel" ve "hedef/gelecek" bakış açılarına göre karşılaştırmak; karşılaştırma yapmak için ise temel dijitalleşme kriterlerini ve alt kriterlerini doğrulayarak kısa liste halinde tanımlamak

iv. En İyi-En Kötü Yöntemi (Best-Worst Model – BWM) kullanılarak kısa listeye alınan kriterler listesinden tanımlanan her bir olgunluk seviyesindeki etkili kriterleri ve alt kriterleri test ederek şirketleri sıralamak

v. Şirketlerin dijital dönüşüm olgunluk seviyelerini (Maturity Level – ML) beş farklı seviyede (ML-1 en zayıf ve ML-5 en kuvvetli seviyeyi gösterecek usulde) belirlemek için dijitalleşme kriterlerini ve alt kriterlerini kategorize etmek ve araştırmak

vi. Şirketlerin ayrı ayrı ve küme halinde dijital dönüşüm olgunluk düzeylerini tanımlamak için Cheng ve Church (CC) çift kümeleme *(bi-cluster)* analizini uygulamak

1.3. Temel Araştırma Başlıkları

Ana araştırma başlıkları aşağıda listelenmiştir:

i. Faktör Analizi

ii. Sıralama Metodolojisi

iii. Dijitalleşme Olgunluk Modeli Değerlendirmesi

iv. Hedef Odaklı Tavsiye

1.4. Araştırma Soruları

Bu tezde aşağıdaki araştırma sorularının cevaplanması hedeflenmiştir:

i. Soru-1: Şirketler dijitalleşme yeteneklerini geliştirmek için ortakları ile nasıl çalışır?

ii. Soru-2: Şirketlerin dijitalleşme süreçlerinin önündeki engellerini aşmak için uyguladıkları stratejiler nelerdir?

iii. Soru-3: Şirketler dijitalleşme sürecinin itici güçlerini nasıl kullanmalıdır?

iv. Soru-4: Şirketlerin dijitalleşme olgunluk seviyesi nedir?

v. Soru-5: Şirketlerin dijitalleşme olgunluk seviyelerini hangi faktörler etkiler?

1.5. Hipotezler

Bu tez, her biri belirli kriterlere ve alt kriterlere dayanan aşağıda listelenen dört temel hipotez etrafında çalışılmıştır:

i. Hipotez-1 (H1): İtici *(driver)* güçler, daha gelişmiş bir dijital olgunluk seviyesine yol açar.

ii. Hipotez-2 (H2): Engellerin *(barrier)* azaltılması, şirketlerin daha yüksek dijital olgunluk seviyelerine gelmesini sağlar.

iii. Hipotez-3 (H3): Yeni yeteneklerin *(capabilities)* geliştirilmesi, şirketlerin dijital dönüşüm süreçlerini ilerletmeye yardımcı olur.

iv. Hipotez-4 (H4): Artan iş birliği *(collaboration)*, şirketlerin daha yüksek dijital olgunluk seviyelerine gelmesini sağlar.

2. TEORİK ÇERÇEVE

2.1. Endüstri 4.0

Bu tez, şirketlerin teknolojik gelişmeyi uzun vadeli üretim gelişiminin itici gücü olarak konumlandıran Endüstri 4.0 uygulamaları merceğinden Türk otomotiv sektörünün endüstriyel gelişimini incelemektedir.

Bu bağlamda, Endüstri 4.0'ın evrensel olarak kabul görmüş bir tanımı bulunmamaktadır. Genellikle, Endüstri 4.0 terminolojisi, imalat sektörünün sürdürülebilir dijital dönüşümünü ifade eder. Dönüşüm süreci, dijital teknolojilerin ürünlere ve sistemlere entegre edilmesini, fiziksel ve sanal dünyaların birleştirilmesini ve üretim süreçlerinde otomasyon, esneklik ve özelleştirmenin artırılmasını içerir. Gömülü sensörler, siber-fiziksel sistemler ve kapsamlı veri analizi ile karakterize edilen bu birbirine bağlı sistem, tüm tedarik zinciri boyunca sorunsuz bilgi akışını mümkün kılar (Rizvi ve ark., 2023'ten uyarlanmıştır) Bu şekilde birbirine bağlılık, artan dijitalleşme ve esnekliğe odaklanan Endüstri 4.0'ın belirleyici bir özelliğidir.

2.2. Tanım

Literatürde, Endüstri 4.0'ın yükselişi genellikle "evrim" olarak tanımlanmaktadır. Araştırmacıların çoğu, tam bir paradigma değişiminden ziyade mevcut teknolojilerin geliştirilmesi ve adaptasyonu olduğunu savunmaktadır.

Endüstri 4.0, yeni, hizmet odaklı iş modellerini mümkün kılmak için gerekli teknolojik temeli ve altyapıyı sağlar (Kagermann, 2015a; Lasi ve ark., 2014). Bu araştırma, Endüstri 4.0'ın hem tedarik zinciri etkinliğini hem de otomotiv endüstrisi uygulamalarının entegrasyonunu olumlu yönde etkilediğini doğrulamaktadır. Ayrıca, çalışma, Endüstri 4.0'ın uygulanmasına dayalı yeni stratejilerin benimsenmesinin daha yüksek olgunluk seviyeleriyle doğrudan ilişkili olduğuna ve yeni yalın üretim uygulamalarının operasyonel performansı ve üretim performansını olumlu yönde etkilediğine dair kanıtlar sunmaktadır.

2.3. Dijitalleşme ve Dönüşüm

Endüstri 4.0, hem yatay hem de dikey değer zincirlerini dijitalleştirerek iş operasyonlarını dönüştürmektedir. Bununla birlikte, "sayısallaştırma (digitization)", "dijitalleşme (digitalization)" ve "dijital dönüşüm (digital transformation)" terimlerinin sıklıkla birbirinin yerine kullanıldığı ve bu durumun kafa karışıklığına yol açtığına belirtmek gereklidir. Aralarında incelikli bir süreç olduğundan, şirketler genellikle bu terminoloji üzerine inşa edilmiş aşamalar halinde evrim geçirirler, ancak bu süreç her zaman doğrusal bir şekilde ilerlemez. Terminoloji ve aşama tanımları, bir imalat şirketi üzerinden bir örnekle Tablo 1'de hızlı referanslar verilerek tanımlanmıştır. Bu bağlamda, bu tezde *dijital dönüşüm süreçleri için* "dijitalleşme" ve "Endüstri 4.0" terimlerinin birbirinin yerine kullanıldığını ayrıca belirtmek gereklidir.

Tablo 1 – Terminoloji

Terminoloji	Tanım	Referans(lar)
Sayısallaştırma *(Digitization)*	Sayısallaştırma, analog bilgi akışlarının dijitale dönüştürülmesinin maddesel sürecidir.	Papathomas & Konteos, (2023); Rooijen (2020); Wee ve ark. (2015)

Terminoloji	Tanım	Referans(lar)
Dijitalleşme ***(Digitalization)***	Dijitalleşme, bir iş modelini değiştirmek ve yeni gelir ve değer üreten fırsatlar sağlamak için dijital teknolojilerin kullanılmasıdır.	Fabbe-Costes & Lechaptois (2022); Papathomas & Konteos, (2023); Syariah & Ilmu, (2016)
Dijital Dönüşüm ***(Digital Transformation)***	Dijital dönüşüm, dijital teknolojinin bir işletmenin tüm alanlarına entegre edilmesi ve kuruluşların nasıl faaliyet gösterdiğini ve paydaşlara nasıl değer sunduğunu derinden değiştirmesi anlamına gelir.	Geissbauer ve ark. (2014); Lundberg ve ark. (2018); Verhoef ve ark. (2021); World Economic Forum, (2016)

2.4. İtici Faktörler

Mevcut Endüstri 4.0 literatüründen yola çıkarak, Endüstri 4.0'ın başarılı bir şekilde benimsenmesi için kritik öneme sahip önemli temel itici faktörler (driver) olarak aşağıda belirtilmiştir:

i. Mevcut süreçlerin dönüştürülmesi için güçlü bir gerekçe

ii. Yeni teknolojilerle ilişkili risklerin kabulü

iii. Teknolojilerin sağlam bir şekilde anlaşılması.

iv. Nitelikli ve motive olmuş bir iş gücü

v. Üst yönetimin desteği

vi. İş ortakları aracılığıyla iş birliği

2.5. Engeller

Dijital dönüşümün önündeki engeller *(barrier)* arasında başlıca şunlar listelenebilir (Geissbauer ve ark., 2014; Kiel ve ark., 2017):

i. Nitelikli iş gücü eksikliği

ii. Kaynak yetersizliği

iii. Düşük standartlaşma dereceleri, Endüstri 4.0'ın uygulanması için yetersiz altyapı.

iv. Endüstri 4.0 için bilgi ve strateji eksikliği

3. ARAŞTIRMA TANIMI

Bu tez aşağıda belirtilen kapsamda hazırlamıştır:

i. OTEP tarafından gerçekleştirilen anket çalışmasına katılan Türk otomotiv endüstrisinde faaliyet gösteren şirketlerin verimliliklerini, rekabet güçlerini ve büyümelerini artırmak için Endüstri 4.0 teknolojilerini ne ölçüde kullandıklarını ve bu teknolojilere ne kadar yatırım yaptıklarını göstermek.

ii. Söz konusu şirketleri ileri üretime yatırım yapmaya motive eden veya engelleyen çeşitli çerçeve koşullarını ve faktörleri (kriterler ve alt kriterler) anket yordamıyla incelemek.

iii. Şirketlerin Endüstri 4.0 uygulamalarına uyum sağlamaya çalışırken mevcut olgunluk seviyelerini (maturity level) analiz etmek.

Genel olarak, bu tez, söz konusu ankete konu olan Türk otomotiv endüstrisinde faaliyet gösteren şirketleri sıralamanın ve Endüstri 4.0 olgunluk seviyelerini tanımlamanın yeni bir yaklaşımını sunmaktadır. Tez, ayrıca, Türk otomotiv endüstrisi içinde Endüstri 4.0'ın benimsenmesi ve uygulanmasıyla ilgili stratejik düşüncelerin, itici güçlerin ve engellerin kapsamlı bir analizini sunmaktadır.

3.1. Anket Bilgisi

Türk Otomotiv Teknolojileri Platformu (OTEP) tarafından yaptırılan (ve Türkiye Otomotiv Yan Sanayii Derneği- TAYSAD ve Otomobil Sanayicileri Derneği - OSD tarafından desteklenen) "Dijital Dönüşüm Anketi" başlıklı çalışma 2018 yılında tamamlanmış ve 2019 yılında raporlanmıştır. Anket, gelişmekte olan Türk otomotiv endüstrisi içinde Endüstri 4.0 uygulamaları için önemli bir büyüme potansiyeli olduğunu ortaya koymuştur.

OTEP, Türk otomotiv üretim sektörü içindeki üye şirketleri arasında dijital dönüşüme odaklanan şirketlerin katılımı ile bu anket çalışmasını gerçekleştirmiştir. Yedi ana tema etrafında yapılandırılan ve 53 sorudan oluşan anket, 200'den fazla üye şirkete dağıtılmıştır. Sorulardan "mevcut/güncel" ve "hedef/gelecek" kriterleri gözetilerek ikili veri sağlanmıştır. Çalışmaya, 6 büyük / ana otomotiv üreticisi ve 41 birinci kademe (first tier) tedarikçi şirket olacak üzere toplam 47 şirket katılım göstermiş ve yaklaşık %20 yanıt oranı elde edilmiştir. 5'li Likert ölçeğine göre yapılandırılan anket, 2019 yılında raporlanmıştır. Sonuç olarak, ankete katılan şirketler genelinde ortalama bir dijitalleşme seviyesi ortaya koymuştur ve ana sanayi oyuncuları olan "üreticiler" için ortalama 3,5, ilk kademe tedarikçi şirketler için ise ortalama 3,2 lik bir dijitalleşme seviyesi puanı öngörülmüştür.

Ek olarak, raporun ilk analizi, hesaplanan dijitalleşme (olgunluk) seviyeleri açısından, özellikle güçlü bir Bilgi Teknolojileri altyapısına ve güçlü bir organizasyon kültürüne sahip olan başlıca üretici ile ilk kademe tedarikçiler arasında önemli bir fark olmadığını göstermektedir. Dolayısıyla, bu tezde, dijitalleşme seviyesi açısından, "üretici (ana sanayi)" ve "tedarikçi" şirketlerinin dijitalleşme performansları birlikte analiz edilmiştir.

3.2. Amaçlar

Bu çalışmanın amaçları şunlardır:

i. Mevcut literatürden dijital dönüşüm genel kriterlerini belirlemek

ii. Genel kriterler arasından *temel* kriter ve *ana* alt kriterleri belirlemek için Türk otomotiv üreticilerinden endüstri uzmanlarıyla anket tabanlı bir araştırma yapmak

iii. Dijital dönüşüm olgunluk modelinin *(maturity model)* seviyelerini tanımlamak

iv. Seçilen kriter ve alt kriterleri 5 (beş) farklı olgunluk seviyesi altında sınıflandırmak

v. Şirketleri, seçilen kriter sınıflarına göre dijitalleşme performanslarına göre sıralamak için En İyi-En Kötü Yöntemi'ni (Best-Worst Model – BWM) uygulamak.

vi. Tanımlanan kriterlerin etkisini bulmak amacıyla, 5 (beş) farklı olgunluk seviyesi altında şirketleri ikili kümeleme *(bi-cluster)* yöntemi ile gruplandırarak, kriter listesindeki her bir olgunluk seviyesi kategorisindeki etkin kriter ve alt kriterleri Cheng ve Church algoritması aracılığıyla belirlemek.

3.3. Aşamalar

Bu araştırmada, öncelikli olarak, örnekleme dahil olan şirketlerin sıralaması için En İyi-En Kötü Yöntemi (BWM) kullanılması planlanmıştır. Devamında, araştırmanın sonuçlandırılması ve BWM yöntemi ile elde edilen sonuçların doğrulanması için, ikili kümeleme yöntemi (bi-clustering) kullanılmıştır. Bu tez, genel olarak, öznel deneyimleri ve yorumlamaları anlamayı vurgulayan *nitel* bir araştırma yaklaşımı benimsemektedir. Bu *çoklu* analiz yaklaşımı, otomotiv endüstrisindeki yönetimsel kararların teknik düşüncelerin ötesinde bir dizi kritik faktörden de (kriter ve alt kriterler) etkilendiğini varsayarak, dijital dönüşümün ve Endüstri 4.0 benimsenmesinin karmaşıklığını tasvir etmektedir.

Bu çalışma, karmaşık dijital dönüşüm pratiklerinin anlaşılması adına, Türk otomotiv endüstrisi içinden seçilen nitelikli üretici ve tedarikçi şirketlerin dijitalleşme olgunluk seviyelerini ve sıralamalarını belirlemeyi amaçlamıştır. Bu amaçla, tezin savunması için dört aşamalı bir yaklaşım tanımlanmış ve uygulanmıştır:

- **Aşama 0-Olgunluk sınıflarının Tanımlandırılması:** Literatürden farklı olgunluk sınıfı tanımları alınarak çalışmanın öznel sınıfları tanımlanmıştır.
- **Aşama 1-Kriterlerin Sınıflandırılması:** Literatürden araştırması sonucunda belirlenen ve anket sonuçları ile desteklenen 8 (sekiz) ana kriter kullanılarak alt kriterlerin belirlenmesi.

- **Aşama 2-Alt Kriterlerin Belirlenmesi:** 84 (seksen dört) alt kriter belirlenmesi ve kullanılması.

- **Aşama 3-En İyi-En Kötü Yöntemi ile Firma Sıralaması:** Şirketlerin "mevcut/güncel" ve "gelecek/hedef" beklentileri temelinde, seçimleri ve Endüstri 4.0 performansları gözetilerek sıralama yapılması.

- **Aşama 4-İkili Kümeleme Yöntemi ile Olgunluk Seviyesi Analizi:** Şirketlerin Olgunluk Seviyelerini ve dijitalleşme kapasitesini değerlendirmek ve tanımlamak için kriter ve alt kriterlerin kümelemesi.

4. METODOLOJİ

Bu tez, Türk otomotiv sektöründe Endüstri 4.0'ın pratiklerinin benimsenmesini etkileyen faktörleri incelemiş, iç ve dış itici güçlerin ve engellerin karar alma sürecini nasıl etkilediğini analiz etmiştir. Çalışmada, şirketleri dijitalleşme başarılarına göre sıralamak için En İyi-En Kötü Yöntemi kullanılmış ve dijitalleşme çabalarında önemli farklılıklar bulunmuştur. Daha derinlemesine bir anlayış ortaya koymak için, çeşitli Endüstri 4.0 kriterleri ve teknolojileri arasında kapsamlı bir olgunluk seviyesi değerlendirmesini mümkün kılan bir ikili kümeleme metodolojisi kullanılmıştır.

Her iki analizin birleştirilmesi, şirketlerin dijitalleşme başarılarının ve olgunluk seviyelerinin *daha doğru* bir şekilde tahmin edilmesini ve şirketlerin yalın üretim prensipleriyle uyumlu olarak dijitalleşme çabalarına göre kategorize edilmesini sağlamıştır.

4.1. Olgunluk Sınıfı Tanımı

Şirketlerin dijital dönüşüm olgunluk seviyelerinin (maturity levels) belirlenmesi, bir şirketin dijitalleşme yolculuğunu ve Endüstri 4.0'ın temel ilkeleriyle uyumunu değerlendirmek için yapılandırılmış bir çerçeve sağlar. Bu tezde, beş farklı olgunluk seviyesi (sınıfı) kısaca aşağıdaki gibi tanımlanmıştır:

i. Olgunluk Sınıfı-1 (ML-1): Öncül Dijitalleşme Becerileri (İkili Küme #5)

ii. Olgunluk Sınıfı-2 (ML-2): Gelişmekte olan Dijital Dönüşüm Becerileri (İkili Küme #4)

iii. Olgunluk Sınıfı-3 (ML-3): Şirket içinde Dijital Dönüşüm (İkili Küme #3)

iv. Olgunluk Sınıfı-4 (ML-4): Üretim ağı genelinde Dijital Dönüşüm (İkili Küme #2)

v. Olgunluk Sınıfı-5 (ML-5): Değer zincirinde gelişmiş / profesyonel Dijital Dönüşüm (İkili Küme #1)

4.2. Çok Kriterli Karar Verme

Çok kriterli karar verme (ÇKKV) problemleri, alternatiflerin çelişkili kriterlere göre değerlendirilmesiyle Tablo 2'de gösterilen ana çerçevede ifade edildiği gibi ifade edilebilir (Malczewski, 1999).

Tablo 2 – ÇKKV Problemi için Ana Çerçeve

	Kriter$_1$	**Kriter$_2$**	**...**	**Kriter$_n$**
Alternatif$_1$	Çıktı$_{11}$	Çıktı$_{12}$	...	Çıktı$_{1n}$
Alternatif $_2$	Outcome$_{21}$	Çıktı$_{22}$	...	Çıktı$_{2n}$
...	...	...	...	...
Alternatif $_m$	Outcome$_{m1}$	Çıktı$_{m2}$	...	Çıktı$_{mn}$
Önem Derecesi	Weight$_1$	Çıktı$_2$	...	Ağırlık$_n$

Sıralama Metotları: Bu yöntem, karar vericinin tercihlerine dayanarak dikkate alınan her kriterin sıralanmasını gerektirir. Örneğin, 'en önemli = 1', 'ikinci önemli = 2' vb. İlgili sıralama belirlendikten sonra aşağıda formülasyonları belirtilen 3 temel yöntem ile ağırlıklar belirlenebilir:

$$w_j = \frac{n - r_j + 1}{\sum_{k=1}^{n} n - r_k + 1} \tag{1}$$

$$w_j = \frac{1/r_j}{\sum_{k=1}^{n} 1/r_k} \tag{2}$$

$$w_j = \frac{\left(n - r_j + 1\right)^p}{\sum_{k=1}^{n}(n - r_k + 1)^p} \tag{3}$$

Karar Verici Tarafından Puan Tahsisi: Uygulamayı kullanacak olan karar verici tarafından kriterler ikili bir şekilde karşılaştırılarak göreli önem dereceleri belirlenerek bir ikili karşılaştırma matrisi elde edilerek 3 adımda ağırlık hesapları gerçekleştirilir: *(a)* her bir sütunda yer alan değerler toplanır, *(b)* her bir matris değeri sütun toplamına bölünür (normalize edilmiş matris) ve *(c)* normalized edilmiş matrisin her bir satırındaki elemanların ortalaması hesaplanarak kriterlerin göreli ağırlık değerleri elde edilir. İlgili yöntem n kriter sayısını ifade etmek üzere, $n(n-1)/2$ karşılaştırma sonucunda göreli ağırlık değerleri elde edilebildiğinden dolayı yüksek sayıda kriter içeren problemlerde uygulanması zorlaşmaktadır ve bu aşamda ileride bahsedilecek olan BWM bu problemin minimum seviyelere indirilmesi planlanmaktadır.

ÇKKV yöntemleri ile ulaşılmak istenen temel hedef, problemde incelenen alternatiflerin kriterler bağlamında değerlendirilerek bir sıralama elde edilmesidir.

4.3. Aşama 1 ve 2 – Kriter ve Alt Kriterlerin Belirlenmesi

Bu tezde benimsenen karma yöntem kapsamında, dijital dönüşüme etki eden kriterleri belirlemek için bilimsel veri tabanlarını ve çeşitli araştırma projelerinden / endüstri raporlarından elde edilen verileri kullanan kapsamlı bir literatür taraması yapılmıştır. Literatür tarama çalışması sonucu, öncelikli olarak, analizimiz için göreceli ana kriter ve alt kriter sınıflarını tanımlamamızı sağlamıştır. Tablo 3'de sunulan ayrıntılı çerçeve kriter ve alt kriter tanımlarını listelemektedir:

Tablo 3- Kriter ve Alt Kriter Tanımları

Faktör Sınıfı	**S#**	**AS #**	**Alt Kriter (C#)**	**Alt Kriter Tanımı**
Engeller (BR)			**C1**	
BR-1	8	6	C101	Eğitimlerin kalitesi

Faktör Sınıfı	S#	AS #	Alt Kriter (C#)	Alt Kriter Tanımı
BR-2	11	1	C102	Eksik bilgi
BR-3	11	2	C103	Tedarikçi eksikliği
BR-4	11	6	C104	Eksik teknik altyapı
BR-5	11	5	C105	Eksik teşvikler
BR-6	11	7	C106	Eksik rekabet
BR-7	11	8	C107	Eksik mevzuat
BR-8	14		C108	İşbirliklerine kaynak ayırma
İşbirliği (CL)				
CL-1	22	3	C201	Ana işbirliği kapsamı - Ar-Ge
CL-2	6		C202	İşbirliği
CL-3	21		C203	İşbirliği ortakları işbirliği
CL-4	46		C204	Dış Ortaklar ile Kurumsal İşbirliği
CL-5	48	7	C205	Başka Kuruluşlar ile Teknolojik İşbirliği
CL-6	12	1	C206	Tedarikçi İşbirliği kültürü
CL-7	12	5	C207	Sektör işbirliği
CL-8	12	6	C208	Akademi işbirliği
CL-9	12	9	C209	STK işbirliği
CL-10	22	4	C210	Ana işbirliği kapsamı - Tasarım
CL-11	22	5	C211	Ana işbirliği kapsamı - Yeni teknoloji edinme/geliştirme
CL-12	22	6	C212	Ana işbirliği kapsamı - Üretim
CL-13	22	7	C213	Ana işbirliği kapsamı - Yeni ürün
CL-14	22	8	C214	Ana işbirliği kapsamı - Pazarlama
CL-15	12	4	C215	Değer zinciri işbirliği kültürü
CL-16	22	1	C216	Bilgi ve beceri paylaşımı
CL-17	22	2	C217	Dijital dönüşüm ve endüstri 4.0
Yetenekler (CP)				
CP-1	26		C301	Talep değişikliklerine reaksiyon
CP-2	12	7	C302	Akademinin teknik yetkinliği
CP-3	43		C303	Veri yönetimi ve big data yorumlama
CP-4	37		C304	Dijital dönüşüm politikaları
CP-5	42		C305	Ortak Dijital dönüşüm politikası ve

Faktör Sınıfı	S#	AS #	Alt Kriter (C#)	Alt Kriter Tanımı
CP-6	36		C306	Müşteriler ile IT entegrasyonu
CP-7	45		C307	Üst düzey yönetim uzmanlığı / yetenekleri
CP-8	20		C308	Müşteri veri analizi
CP-9	38		C309	Dijital hakların FSMH koruması
CP-10	18		C310	Satış ekibi dijital yetenekleri
Alt yapı (IR)			**C4**	
IR-1	13	2	C401	Tedarikçi desteklenmesi
IR-2	3		C402	Ürünlerin Dijitalleşmesi
IR-3	4		C403	Yaşam döngüsü (life cycle) Dijitalleşmesi
IR-4	28		C404	Üretim Ekipmanlarının dijitalleşme Seviyesi
IR-5	17		C405	Bütünleşik iletişim kanalları
IR-6	30		C406	Bilgi teknolojileri altyapı yeterliliği
IR-7	31		C407	Bilgi Teknolojileri ihtiyaçlarına hakimlik
Devlet Desteği (GI)			**C5**	
GI-1	13	1	C501	Dijitalleşme için Yatırım destekleri
GI-2	13	4	C502	Talep oluşturma
GI-3	13	8	C503	Teknik altyapı oluşumu
GI-4	13	9	C504	Mevzuat düzenleme
GI-5	13	10	C505	Yasal haklar düzenleme
GI-6	13	11	C506	Organizasyonel yapılanma
GI-7	13	6	C507	FSMH koruma
İtici Güç (DR)			**C6**	
DR-1	7	1	C601	Bilgi yönetim sistemi kullanımı
DR-2	14	8	C602	Ürün geliştirme hızı
DR-3	14	9	C603	Lojistik Hizmetleri
DR-4	48	1	C604	Firma içi bilgi kaynakları ve bilgi akışı
DR-5	48	2	C605	Firma içi eğitim
DR-6	48	3	C606	Firma dışı bilgi kaynakları
DR-7	48	4	C607	Firma dışı eğitim
DR-8	48	5	C608	Teknik danışmanlık eğitimi
DR-9	48	6	C609	Yeni ürün varlığı ve çalışanlar

Faktör Sınıfı	S#	AS #	Alt Kriter (C#)	Alt Kriter Tanımı
DR-10	48	8	C610	Farkındalık çalışmaları
DR-11	14	2	C611	Kaynak süreç verimliliği
DR-12	14	5	C612	Üretim kalitesi
DR-13	14	6	C613	Satış ve operasyonel planlama
DR-14	14	7	C614	Hizmet sunumları
DR-15	7	2	C615	Firma Hızlı prototipleme
DR-16	5		C616	Veri kullanımı ve analizi
İnsan Kaynağı (HR)			**C7**	
HR-1	8	2	C701	Nitelikli işgücü çalışmak istememe
HR-2	8	3	C702	İşgücü Finansal zorluklar
HR-3	8	5	C703	İşgücü eğitim eksikliği
HR-4	14	1	C704	İşgücü verimliliği
HR-5	9		C705	IK ihtiyacı - Büyük veri
HR-6	9		C706	IK ihtiyacı - Nesnelerin interneti
HR-7	9		C707	IK ihtiyacı - Zenginleştirilmiş gerçeklik
HR-8	9		C708	IK ihtiyacı - Siber güvenlik
HR-9	9		C709	IK ihtiyacı - Akıllı robotlar
HR-10	9		C710	IK ihtiyacı - Simülasyon
HR-11	9		C711	IK ihtiyacı - Yapay zeka
HR-12	9		C712	IK ihtiyacı - Tasarım
HR-13	9		C713	IK ihtiyacı - Üretim
HR-14	9		C714	IK ihtiyacı - Tedarik zinciri
HR-15	9		C715	IK ihtiyacı - Dijital satın alma
HR-16	9		C716	IK ihtiyacı - Dijital pazarlama
HR-17	11	4	C717	Nitelikli işgücü istihdam edememe
Değer Zinciri (VC)			**C8**	
VC-1	25		C801	Dikey Değer Zinciri dijitalleşmesi
VC-2	29		C802	Yatay değer zinciri dijitalleşmesi
VC-3	40		C803	Değer zinciri yönetimi
VC-4	15		C804	Tedarik ve Değer Zinciri Yönetimi / Dönüşüm

Kısaltmalar:

S#: Anket soru numarası
AS#: (varsa) ilgili soru için alt madde numarası (örneğin; dokuzuncu soru için “büyük veri” seçeneğinin sırası “1” olarak belirtilmiştir.)

4.4. Aşama 3 – En iyi-En Kötü Yöntemi (Best-Worst Method - BWM)

En İyi – En Kötü metodu iki temel aşamada gerçekleştirilmektedir: *(a)* en iyi ve en kötü kriterler belirlenir ve *(b)* en iyi kriter diğer kriterler ile ve diğer kriterler en kötü kriterler ile karşılaştırılır.

En İyi – En Kötü Metodunun Adımları:

1. Karar verme kriterini belirle
2. En iyi ve en kötü kriteri belirle
3. En iyi kriteri diğer kriterler ile 1-9 arasında değişen değerleri kullanarak karşılaştır ve bir en iyi – diğerleri vektörü elde et
4. Diğer kriterleri en kötü kriter ile 1-9 arasında değişen değerleri kullanarak karşılaştır ve bir diğerleri – en kötü vektörü elde et
5. Aşağıdaki matematiksel modeli çözerek optimum ağırlıkları elde et:

$$min\ \zeta$$
$$kısıtlar\ altında$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \zeta \quad \text{bütün } j\ için$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \zeta \quad \text{bütün } j\ için$$

$$\sum_j w_j = 1;\ w_j \geq 0 \quad \text{bütün } j\ için \tag{5}$$

Yukarıda ifade edilen Eş. (5) matematiksel modeli çözüldüğünde optimum ağırlık vektörü elde edilerek problemin devamında kullanıcak olan, bu tez özelinde basit eklemeli ağırlık, skor elde etme yöntemlerinde girdi olarak kullanılabilmektedir.

En İyi – En Kötü metodunda bahsedilmesi gereken bir diğer konu tutarlılık oranıdır (consistency ratio).

Bir karşılaştırma, bütün j için $a_{Bj} \times a_{jW} = a_{BW}$ koşulunu sağladığı takdirde tamamen tutarlı olarak adlandırılır fakat bu durum gerçek hayat problemlerinde nadir olduğundan dolayı tutarlılık oranının değerlendirilmesi önem taşımaktadır. Bu doğrultuda, aşağıda gösterilen eşitlik ile tutarlılık oranı hesaplanabilmektedir:

$$Tutarlılık\ Oranı = \frac{\zeta^*}{Tutarlılık\ İndeksi} \tag{6}$$

Yukarıdaki eşitlikte yer alan *Tutarlılık İndeksi*, Tablo 4'de gösterilmiştir:

Tablo 4 - Tutarlılık İndeksi Tablosu

a_{BW}	1	2	3	4	5	6	7	8	9
Tutarlılık İndeksi	0	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Eş. (6)'de görülebileceği gibi, ζ^* ne kadar büyükse, tutarlılık oranı o kadar yüksek olmakta ve karşılaştırmalar o kadar az güvenilir hale gelmektedir.

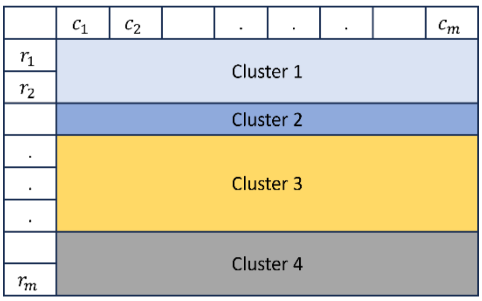
Karşılaştırma sayısının kayda değer bir şekilde düşürülmesine yardımcı olduğundan dolayı En İyi – En Kötü yöntemi birçok alanda başarıyla kullanılarak gerçek hayat problemlerine çözümler üretmiştir. En İyi-En Kötü Yöntemi, karar vericilerin yalnızca en ve en az önemli kriterleri belirlemelerini, ardından en iyi kriteri diğerlerine ve diğer tüm kriterleri en kötüye göre karşılaştırmalarını isteyerek kriterlerin ağırlıklandırılması sürecini basitleştiren çok kriterli bir karar verme yaklaşımıdır.

4.5. Aşama 4 – İkili Kümeleme Yöntemi (Bi-Clustering Method)

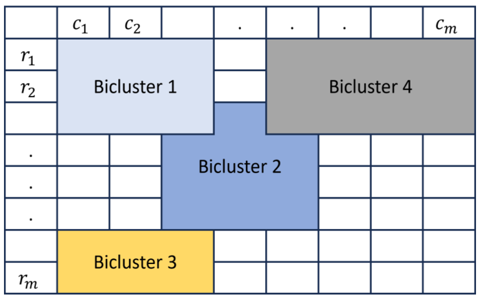
En İyi - En Kötü Yöntemi, tercihleri belirlemek ve ağırlıkları türetmek için çiftler arası karşılaştırmalar temelinde şirketleri sıralamak için kullanılmaktadır fakat bu yöntem şirketlerin seçimlerine dayalı olarak doğrudan karşılaştırmalar yapılmasına izin vermemekte ve kümeleme için gerekli olan benzer alternatifleri gruplama yeteneğinden yoksundur. Ayrıca, BWM, verileri doğrudan analiz etmek yerine karar vericilerden elde edilen tercih bilgilerine dayanmaktadır. Bu sınırlamaları aşmak ve yöntem ile elde edilen sonuçların doğrulanması amacıyla ikili - kümeleme yöntemi kullanılmıştır. Bu yöntem, firmalar arasındaki farklı olgunluk seviyelerini etkileyen temel mekanizmaların ve kriterlerin incelenmesinde yardımcı olarak ve elde edilen bulguların güçlendirilmesini sağlamaktadır.

İkili-kümeleme, hem satırları hem de sütunları aynı anda kümeleyerek veri organizasyonunun ve yapısının daha kapsamlı bir şekilde anlaşılmasına yardımcı olmakla birlikte ayrıca aksi takdirde fark edilmeyen gizli ilişkileri ortaya çıkarmaktadır.

Özetlenen bu fark, Şekil 1 ve Şekil 2 de gösterilen geleneksel kümeleme yöntemi ve ikili kümeleme yapılarına örnek oluşturabilecek bazı temsillerden de anlaşılabilmektedir.



Şekil 1 - Geleneksel Kümeleme Yöntemi



Şekil 2 - Bir Adet İkili Kümeleme

İkili kümeleme, ilk olarak Hartigan tarafından 1972 yılında tanıtılmış ve 2000 yılında Cheng ve Church'un çalışmasıyla önem kazanmıştır. Bu tarihten itibaren *Bimax, Plaid, Quest, xMotif ve Spectral* gibi çeşitli algoritmalar geliştirilmiştir. Bu algoritmaların ortaya çıkması, ikili kümeleme alanını önemli ölçüde ilerletmiş ve araştırmacıların iki boyutlu verilerdeki karmaşık ilişkileri daha iyi keşfetmelerine olanak tanımıştır.

İkili kümeleme, özellikle büyük veri setlerinde optimal çözümler bulmada kapsamlı arama süreçlerinde zorluklarla karşılaşmaktadır. Meta-sezgisel teknikler ile kalite ölçütlerine dayalı olarak aday çözümleri iteratif bir şekilde rafine ederek pratik bir yaklaşım sunar ve kesin en iyi çözümü garanti etmemesine rağmen yakın optimal sonuçlar elde edilmektedir. Ayrıca, her bir bireysel ikili kümenin kaliteleri, farklı modeller aracılığıyla çeşitli desenleri değerlendirerek, tanımlayıcı özelliklerine göre kategorize edilmektedir.

ÇKKV problemlerinin karmaşıklığı göz önüne alındığında, daha etkili yöntemler hayati öneme sahiptir. İkili kümeleme, daha düşük hesaplama gereksinimleri ile, özellikle bulanık küme gibi tekniklerle birleştirildiğinde kayda değer bir alternatif sunmaktadır. Çoğu ikili kümeleme modeli, her adımda yerel optimumları hedefleyerek küresel optimum bulmaya çalışmakta ve bu da onları karmaşık problemleri çözmek için uyumlu hale getirmektedir. Bu tez, veriler içindeki iki kümeleri belirlemek için Cheng ve Church (CC) algoritmasını kullanmaktadır.

Türk otomotiv sanayisi bağlamında, üreticiler ve tedarikçiler arasında karmaşık karşılıklı bağımlılıkların bulunduğu bir ortamda, ikili kümeleme, Endüstri 4.0 kriterleri ile ilgili gizli ilişkileri ortaya çıkarmak için bir veri madenciliği tekniği olarak hizmet eder. Şirketleri ve ilgili niteliklere ikili kümeleme yöntemleri uygulanarak farklı olgunluk seviyeleri arasında benzer güçlü ve zayıf yönlere sahip gruplar tanımlanmakta ve stratejik karar alma sürecini kolaylaştırdığından dolayı her bir şirket için kriterleri optimize etmektedir.

İkili Kümeleme Yapıları:

İkili kümeleme yöntemleri temel olarak sabit ve sabit olmayan olmak üzere ikiye ayrılmaktadır.

Bu iki temel gruplandırma kendi içerisinde üçer alt gruba ayrılarak toplamda altı adet ikili kümeleme yapısını oluşturmaktadır:

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

(a)

1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

(b)

1	1	1	1	1
2	2	2	2	2
3	3	3	3	3
4	4	4	4	4
5	5	5	5	5

(c)

Şekil 3 - Sabit İkili Kümeleme Yapıları

1	2	0	3	2
2	3	1	4	3
3	4	2	5	4
4	5	3	6	5
5	6	4	7	6

(a)

1	2	6	3	9
2	4	12	6	18
3	6	18	9	27
4	8	24	12	36
5	10	30	15	45

(b)

1	3	7	5.3	15
2	5	13	7.3	21
3	7	19	9.3	27
4	9	35	11	32
5	11	31	13	28

(c)

Şekil 4 - Sabit Olmayan İkili Kümeleme Yapıları

Yukarıda gösterimi yapılan yapılarda görüldüğü üzere sabit ikili kümeler tamamen sabit, sütun sabit ve satır sabit olmak üzere üç grupta karşımıza çıkarken sabit olmayan ikili kümeler eklemeli, çarpımlı ve eklemeli – çarpımlı kombinasyon olmak üzere üç başlıkta incelenmektedir. Tez çalışmasında Cheng ve Church (CC) algoritması kullanılmıştır. Bu algoritmaya en üst seviyeden bakıldığında, bir mesafe hesabı ile farklı parametreleri dikkate alarak (α ve β) mümkün olan en yakın satır ve sütun kombinasyonunu bir araya toplamak olarak özetlenebilmektedir. Bu algoritmada kullanılan eşitlikler aşağıda özetlenerek temel mantığının açıklanması hedeflenmektedir:

$$H(I,J) = \frac{1}{|I||J|} \sum_{i \in I, j \in J} \left(a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}\right)^2 \tag{8}$$

Eş. 8 ortalama hata kare ortalamasını göstermektedir. Bu eşitlikte kullanılan bileşenler aşağıda gösterilmiştir:

$$a_{iJ} = \frac{1}{|J|}\sum_{j\in J} a_{ij}\,, \quad a_{Ij} = \frac{1}{|I|}\sum_{i\in I} a_{ij} \tag{9}$$

$$a_{IJ} = \frac{1}{|I||J|}\sum_{i\in I, j\in J} a_{ij} = \frac{1}{|I|}\sum_{i\in I} a_{iJ} = \frac{1}{|J|}\sum_{j\in J} a_{Ij} \tag{10}$$

Eş. 9'da a_{iJ}, a_{Ij} ve a_{IJ} sırasıyla satır ortalamasını, sütun ortalamasını ve matris ortalamasını ifade etmektedir.

CC algoritması, tek düğüm silme, çoklu düğüm silme ve düğüm eklemeyi içeren üç aşamalı bir süreçtir ve bir veri setindeki en büyük kare biçimli ikili kümeyi bulmak amacıyla tasarlanmıştır. Üç algoritmanın uygulanmasıyla beraber bir problem için arzu edilen ikili küme sayısı elde edilerek süreç tamamlanmış olur. Özetlemek gerekirse tekli düğüm silme satır (sütun) değerlerini inceleyerek en büyük mesafeye sahip olan satırı (sütunu) original matristen kaldırmaktan, çoklu düğüm silme tekli düğüm silme sürecini 1'den fazla sayıda yapmaktan ve düğüm ekleme süreci ise tekli ve çoklu düğüm silme algoritmalarından elde edilen matrisleri ele alarak belirli şartlarda düğüm eklemekten sorumludur. Bütün süreçler tamamlandığında 5 adet ikili küme, firmaların mevcut durumda anket sorularına verdiği cevapları girdi olarak alıp 5 adet olgunluk seviyesini temsil etmek üzere elde edilmiştir. Elde edilen ikili kümeler olgunluk seviyelerinde kriterlerin etkisinin firmalar özelinde incelenmesinde yardımcı olarak yalnızca 1 - 5 arasında değerlerden oluşan bir matriste görülemeyen ilişkilerin ısı haritaları ile ortaya çıkarılmasında kullanılmıştır.

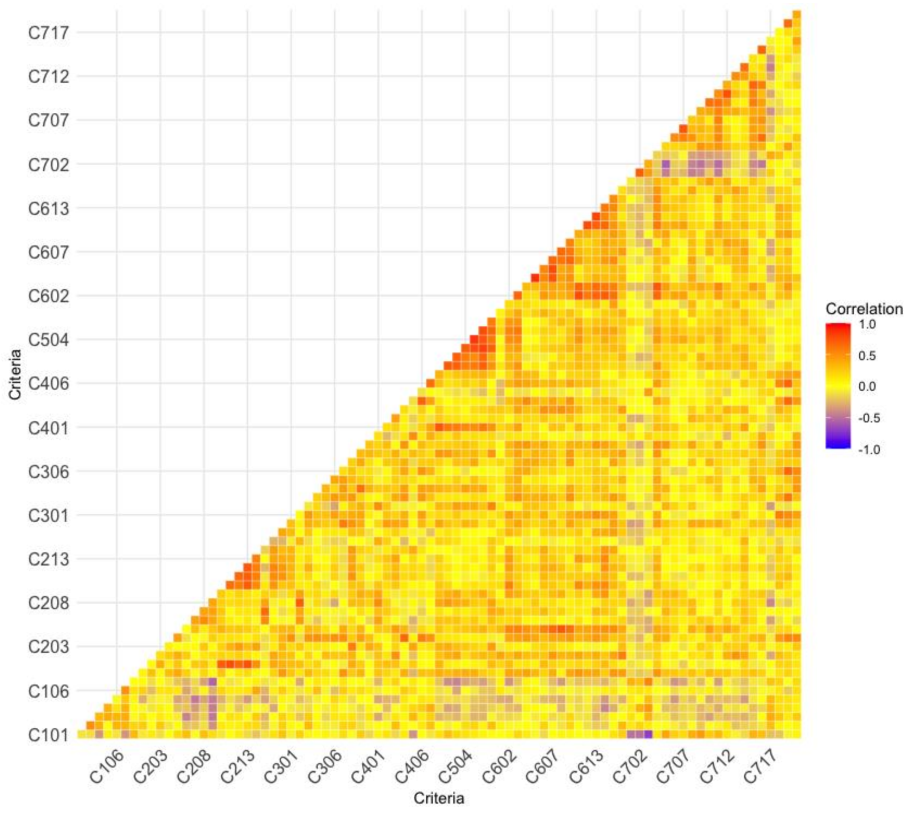
5. ANALİZ SONUÇLARI

Bu tezde yürütülen veri analizinin amacı, karmaşık veri kümelerindeki gizli kalmış yapıları ortaya çıkarmak ve anlamlı bilgiler elde etmektir. İki farklı ancak güçlü metodoloji olan BWM ve CC ikili kümeleme yaklaşımlarının *birlikte* kullanımı, söz konusu yapıları göstermek ve farklı içgörüleri keşfetmek için benzersiz bir yaklaşım sunmaktadır.

Bu tez, veri analizinde BWM, ikili kümeleme ve tanımlayıcı istatistiklerin sinerjik uygulamasını sağlamıştır. Her yöntemin güçlü yönlerinin, sınırlamalarının ve uygun uygulamalarının kapsamlı bir incelemesini sunarak, birlikte kullanımlarının faydaları ayrıca vurgulanmıştır. Bu yaklaşımların birlikte çalıştırılması yoluyla, anket verisi nezdinde şirketlerin dijital dönüşüm statülerinin kapsamlı bir şekilde anlaşılmasını nasıl sağlayabileceğini göstermeyi amaçlanmıştır. Bu amaç doğrultusunda ise, şirketlerin dijital dönüşüm performans seviyelerine ilişkin içgörüleri ortaya çıkarmak ve farklı olgunluk seviyelerini karakterize eden temel kriterleri belirlenmiştir.

Veri analizinin önemli bir ilk adımı olarak, alt kriterler arasındaki ilişkileri anlamak için temel bir ölçüt sağlamak amacıyla korelasyon katsayılarını analiz edilmiştir.

Şekil 5'de gösterilen ısı haritası, veri kümesi içindeki değişkenler arasında yüksek derecede bir *bağımsızlık* olduğunu ve toplanan yanıtlarda *düşük* derecede bir korelasyon olduğunu göstermektedir.



Şekil 5 - Korelasyon Dağılımı Isı Haritası

İki değişkenli verilerimizin analizi için kriterlerin sıklığını iki veya daha fazla nominal veya kategorik değişken kombinasyonuyla ayrıca gösterilmiştir:

- A Sınıfı: Cevaplar arasında Likert ölçeği 1-2 seviyesi birlikte değerlendirilmiştir. Bu bağlamda, 1 (bir) cevabının "kesinlikle katılmıyorum" ve 2 (iki) cevabının "katılmıyorum" anlamına geldiği durumlarda, değişkenlerin (örüntülerin) ortak dağılımına ilişkin verileri içeren bir senaryo ele alınmıştır. Bu sayede, cevaplar, görüşmeciler arasında benzer veya farklı olarak "en kötü cevaplar" olarak kategorize edilmiştir ve sınıf tanımlanmıştır.

- B Sınıfı: Cevaplar arasında Likert ölçeği 3 seviyesi tek başına değerlendirilmiştir. Bu bağlamda, 3 (üç) ile verilen cevapların, anket aracılığıyla analiz üzerinde *doğrudan* etkisi olmayan (görüşmecinin seçimi hakkında hiçbir ipucu verilmeyen) cevaplar için "nötr" olarak kategorize edilip edilemeyeceği senaryosunu değerlendirilmiştir ve sınıf tanımlanmıştır.

- C Sınıfı: Cevaplar arasında, likert ölçeği 4-5 seviyesi birlikte ele alınmıştır. 4 (dört) cevabının "zayıf olumlu" ve 5 (beş) cevabının "son derece olumlu" anlamına geldiği durumlarda, değişkenlerin (örüntülerin) ortak dağılımına ilişkin verileri içeren bir senaryoyu ele alınmıştır. Söz konusu cevaplar, görüşmeciler arasında benzer veya farklı olarak "en iyi cevaplar" olarak kategorize edilmiştir ve sınıf tanımlanmıştır.

Tablo 5'de alt kriterlerin frekansını cevap sınıflarına göre gösteren ortak dağılım sunulmuştur:

Tablo 5 – Sınıflara göre Cevap Sıklığı

Kriter Adı	#	Kısaltma	A Sınıfı	B Sınıfı	C Sınıfı
Engeller	C1	BR	19.13	13.13	14.75
İşbirliği	C2	CL	9.29	10.29	27.41
Yetenekler	C3	CP	11	11.40	24.60
Altyapı	C4	IR	12.86	16.14	18
Devlet Desteği	C5	GI	3.86	2.86	40.29
İtici Faktörler	C6	DR	6.60	9.40	31
İnsan Kaynağı	C7	HR	15	7.76	24.24
Değer Zinciri	C8	VC	11.33	17.67	18

Kriter Adı	#	Kısaltma	A Sınıfı	B Sınıfı	C Sınıfı
		Min	*3.86*	*2.86*	*14.75*
		Max	*15.00*	*17.67*	*40.29*

5.1. BWM yöntemi ile Sıralama Sonuçları

BWM analizi sonucunda, katılımcı şirketlerin dijital olgunluklarına göre sıralaması belirlenmiştir. Analiz sonuçları, ikili kümeleme yönteminin uygulanması için temel oluşturmuştur. Bu *ikili* yöntem, bulguların güvenilirliğini güçlendiren bir doğrulama biçimi olarak işlev görmüştür.

Tablo 6 en iyi ve en kötü kriter eşleştirmeleri ile kriterlerin ağırlığını göstermektedir.

Tablo 6 – BWM En İyi-En Kötü Kriter Listesi

Criteria Name	C#	Ağırlık	En İyi	En Kötü
Engeller	C1	0.11300	C104	C105
İşbirliği	C2	0.17125	C202	C206
Yetenekler	C3	*0.30930*	C303	C308
Altyapı	C4	0.08316	C403	C404
Devlet Desteği	C5	0.03396	C501	C503
İtici Faktörler	C6	0.15523	C609	C614
İnsan Kaynağı	C7	0.11254	C703	C706
Değer Zinciri	C8	*0.02156*	C801	C804

Sonuç olarak:

- Ankete katılan şirketlerin dijitalleşme performansını "mevcut/güncel" ve "hedef/gelecek" seçimlerine göre BWM yöntemi sıralama sonuçları Tablo 7'de gösterilmiştir:

Tablo 7 – BWM Sıralama Listesi

Şirket #	"Mevcut" Sıra #	"Hedef" Sıra #	Şirket #	"Mevcut" Sıra #	"Hedef" Sıra #
40	1	11	**23**	25	29

Şirket #	“Mevcut” Sıra #	“Hedef” Sıra #	Şirket #	“Mevcut” Sıra #	“Hedef” Sıra #
3	2	43	**46**	26	16
6	3	9	**13**	27	39
15	4	5	**24**	28	44
19	5	1	**38**	29	35
11	6	10	**29**	30	30
16	7	12	**47**	31	17
37	8	13	**17**	32	34
35	9	18	**43**	33	41
42	10	21	**4**	34	27
44	11	8	**18**	35	36
41	12	7	**26**	36	33
12	13	32	**10**	37	45
2	14	4	**20**	38	25
31	15	20	**36**	39	40
1	16	12	**21**	40	38
45	17	19	**25**	41	2
9	18	15	**28**	42	6
7	19	26	**14**	43	37
33	20	14	**22**	44	42
34	21	24	**27**	45	46
39	22	31	**30**	46	47
32	23	23	**8**	47	22
5	24	3			

Kendall Tau İstatistiği:

Bölüm 5.1'deki sonuçlara göre listemizdeki sıralamanın korelasyonunu doğrulamak için ek olarak, faktör yükleri (sıralamalar) arasındaki tutarlılığı değerlendirmek ve doğrulamak için Kendall'ın tau istatistiği kullanılmıştır.

Sonuç olarak analizimiz, Kendall'ın tau istatistiği 0.474560 ve p değeri ($p<0.001$ koşulu) 0.0000025456 olarak hesaplanmıştır. Bu sonuca göre, istatistik değeri 0,45'ten büyük olduğu için, sıralamalar arasında *güçlü pozitif uyum* olduğu varsayılabilir. Bu sonuç, ayrıca faktör yapısının nispeten istikrarlı olduğunu göstermektedir.

5.2. İkili Kümeleme Yöntemi ile Olgunluk Seviyelerinin Tespiti

Bu tezdeki analizimizin dördüncü aşamasında, seçilen temel alt kriterlere uygulanan bir iki kümeleme yöntemi kullanılmıştır. Bu yaklaşım, her biri dijital dönüşüm yolculuklarında ortak özellikler taşıyan şirketlerin benzersiz bir gruplaşmasını temsil eden beş farklı ikili kümeyi başarıyla tanımlamaktadır. Her küme farklı bir olgunluk aşamasını temsil etmektedir (bkz. Bölüm 4.1). Bu yaklaşım neticesinde oluşturulan ısı haritaları ise, karmaşık verileri görselleştirmek için çeşitli endüstriyel analizlerde yaygın olarak kullanılan bir araçtır. Isı haritasında, her hücrenin rengi, alt kriterlerin oluşum sıklığını temsil eder. Daha parlak renkler (örneğin sarı), daha düşük bir oluşumu gösterirken, daha koyu renkler (örneğin kırmızı) daha yüksek bir oluşumu göstermektedir.

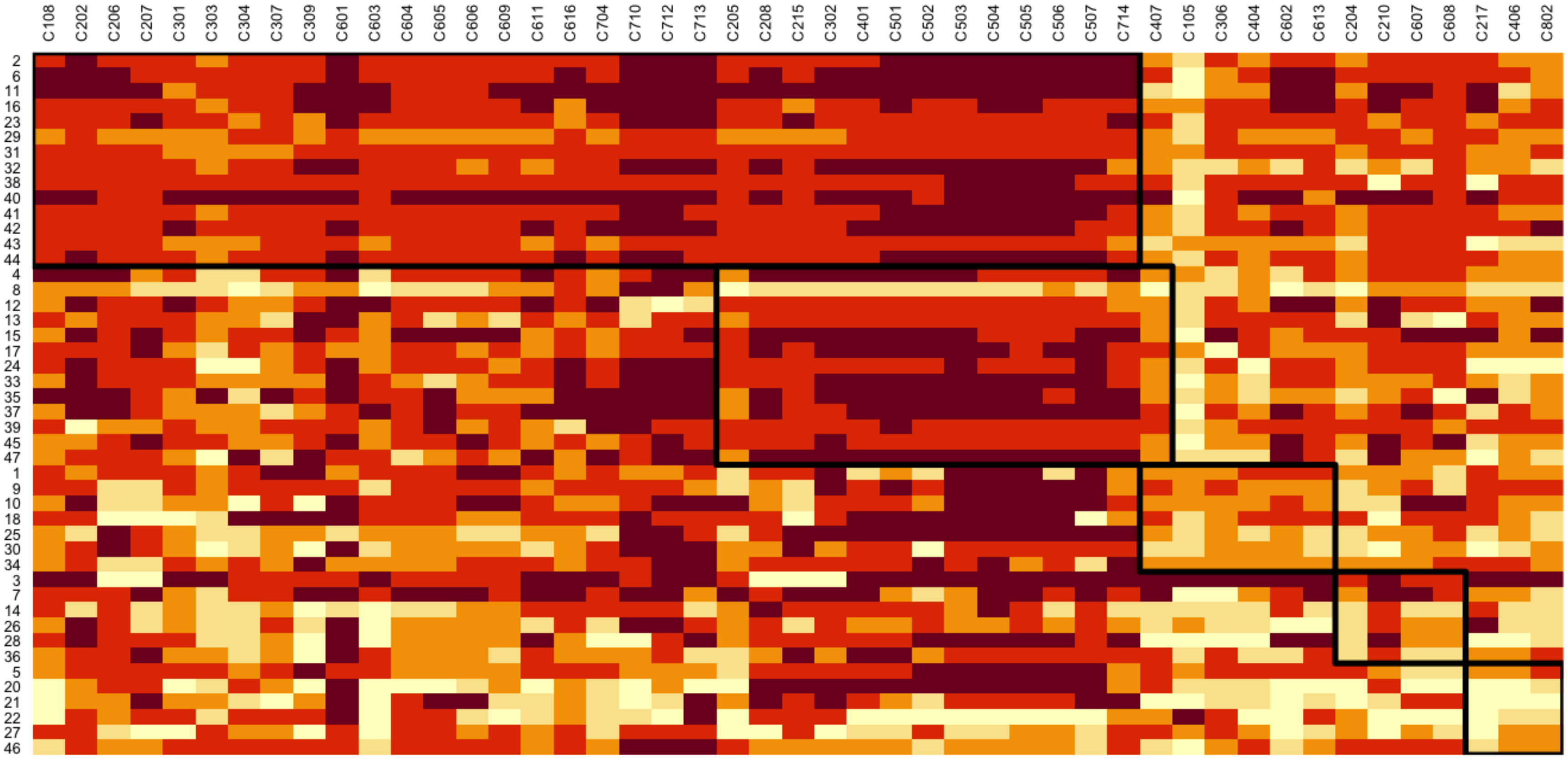
CC ikili kümeleme analizi sonucunda elde ettiğimiz CC ikili kümeleme ısı haritası Şekil 4'de sunulmuştur. Tablo 8'de ise Şekil 6'da sunulan ısı haritasında tanımlı ikili kümeler içinde değerlendirilen alt kriterler birlikte sunularak, her grubun belirleyici özellikleri değerlendirilmiştir.

Sonuç olarak, ikili kümeleme analizi sonucunda ilgili şirketlerin temel olgunluk düzeyleri tespit edilmiştir. Analizde, beş adet ikili küme ve 84 alt kriteri oluşturan alt kriterlerin içerik analizi, ankete katılan 46 şirketle ilişkilendirilmiştir.

5.3. Doğrulama Çalışması (BWM ve CC İkili Kümeleme)

Bu tezde, araştırma çalışmasına katılan şirketlerin dijitalleşme başarısını beş seviyeli bir olgunluk modeli kullanarak değerlendirilmiştir. Bunu yapmak için, önce şirketleri dijitalleşme seçimlerine göre sıralamak için En İyi-En Kötü Yöntemi ile genel bir model oluşturulmuştur. Ardından, benzer olgunluk seviyelerine sahip şirketleri gruplandırmak için ikili kümeleme yöntemini kullanılmıştır. BWM ve ikili kümelemeden elde edilen sonuçları karşılaştırmak için, katılımcıların "mevcut/güncel" BWM sıralamalarına bakılmıştır.

Bu aşamada, başlangıçta, bazı veri noktalarının neden eksik olabileceğini anlamak da önemlidir. Ankete katılan şirketlerin verilerinin bütünü için "Rastgele Eksik" tanımlaması yapılabilir.



Şekil 6 – CC İkili Küme Isı Haritası (ML-1 ve 5 sınıfları)

Tablo 8 – İkili Küme Olgunluk Seviyeleri ve Temsilci Kriter Tablosu

İkili Küme No.	**Olgunluk Sınıfı**	**Küme Elemanları (Şirket Numaraları)**	**İkili Kümede Listelenen Ana Kriter Sınıfları**	**İkili Kümede Listelenen Alt Kriter Sınıfları**
İkili küme #5	ML-5	2, 6, 11, 16, 23, 29, 31, 32, 38, 40, 41, 42, 43, 44 (%30,43)	C1, C2, C3, C4, C5, C6, C7	C108, C202, C205, C206, C207, C208, C215, C301, C302, C303, C304, C309, C401, C501, C502, C504, C505, C506 C507, C601, C603, C604, C605, C606, C609, C616, C707 C710, C712, C713, C714
İkili küme #4	ML-4	4, 8, 12, 13, 15, 17, 24, 33, 35, 37, 39, 45, 47 (%28,26)	C2, C3, C4, C5, C7	C205, C208, C215, C302, C401, C407, C501, C502, C503, C504, C505, C506, C507, C714
İkili küme #3	ML-3	1, 9, 10, 18, 25, 30, 34 (%15,21)	C1, C3, C4, C5, C6	C105, C108, C306, C307, C404, C407, C503, C504, C602, C604, C605, C613, C616

İkili Küme No.	Olgunluk Sınıfı	Küme Elemanları (Şirket Numaraları)	İkili Kümede Listelenen Ana Kriter Sınıfları	İkili Kümede Listelenen Alt Kriter Sınıfları
İkili küme #2	ML-2	3, 7, 14, 26, 28, 36 (%13,04)	C2, C3, C5, C6, C7	C204, C205, C210, C304, C307, C505, C507, C605, C606, C607, C608, C609, C616, C712
İkili küme #1	ML-1	5, 20, 21, 22, 27, 46 (%13,04)	C2, C4, C6, C7, C8	C202, C217, C406, C611, C616, C704, C802

Bu durum, eksik veri noktalarının, özellikle belirli alt kriterlerdeki eksik şirket yanıtlarının, diğer veri noktalarıyla muhtemelen ilgili olmadığı anlamına geldiği öngörülmüştür. Ancak bu, diğer alt kriterler gibi gizli faktörlerin, bu veri noktalarının neden eksik olduğunu etkileyebileceğini göstermektedir. Örneğin, analizimiz kapsamında diğer alt kriterlerin değerlendirilme şekli, eksik yanıtlarla bağlantılı olabilir. Bu nedenle, bazı eksik değerleri nedeniyle 19 numaralı şirket analizden çıkarılmıştır. Önemli değişkenlerde çok sayıda eksik değerin bulunması, onu aykırı bir değer haline getirdiği için ve ikili kümeleme algoritmasının anlamlı gruplandırma yeteneğini bozmuştur.

Tablo 9'da şirket sıralamalarının olgunluk seviyeleriyle karşılaştırma sonuçları sunulmuştur. Tablo 9'da ayrıca şirketlerin olgunluk seviyelerini en güçlü tanımlayıcı kriter ve alt kriterler ayrıca listelenmiştir. Yukarıda belirtilen gerekçe kapsamında, genel olarak, şirket sıralamalarını olgunluk seviyeleriyle karşılaştırma yaklaşımı, olgunluk değerlendirmelerinin farklı yönlerindeki tutarsızlıkları belirlememize yardımcı olmuştur.

Tablo 9 – BWM sıralama sonuçlarına göre olgunluk seviyesi karşılaştırması

Şirket #	BWM Sıra (M)	BWM Sıra (H)	ML Sınıfı	Tanımlayıcı Kriter	Tanımlayıcı Alt Kriter
40	1	11	ML-5	C3, C6, C7	C302, C605, etc.
3	2	43	ML-2	C2, C5	C210, C505, etc.
6	3	9	ML-5	C5, C7	C501, C710, etc.
15	4	5	ML-4	C2, C5	C215, C501, etc.
19	5	1	N/A	N/A	N/A
11	6	10	ML-5	C1, C5, C7	C108, C202, etc.
16	7	12	ML-5	C7	C712, etc.
37	8	13	ML-4	C3, C5	C502, C503, etc.
35	9	18	ML-4	C3, C5	C502, C503, etc.
42	10	21	ML-5	C5	C504, C505, etc.
44	11	8	ML-5	C5	C504, C505, etc.
41	12	7	ML-5	C2, C5	C207, C501, etc.
12	13	32	ML-4	C2, C7, C3	C208, C714, etc.
2	14	4	ML-5	C5, C7	C505, C710, etc.

Şirket #	BWM Sıra (M)	BWM Sıra (H)	ML Sınıfı	Tanımlayıcı Kriter	Tanımlayıcı Alt Kriter
31	15	20	ML-5	C2, C5, C6	C206, C606, etc.
1	16	12	ML-3	C3, C5	C506, C307, etc.
45	17	19	ML-4	C2, C4, C5	C504, C505, etc.
9	18	15	ML-3	C1, C5, C6	C504, C604, etc.
7	19	26	ML-2	C2, C6, C5	C205, C605, etc.
33	20	14	ML-4	C4, C5	C401, C502, etc.
34	21	24	ML-3	C5	C504, C503, etc.
39	22	31	ML-4	C2, C3, C5	C215, C504, etc.
32	23	23	ML-5	C5	C505, C506, etc.
5	24	3	ML-1	C2, C6	C202, C616, etc.
23	25	29	ML-5	C2, C7	C207, C710, etc.
46	26	16	ML-1	C2, C8	C202, C802, etc.
13	27	39	ML-4	C2, C3, C4	C208, C302, etc.
24	28	44	ML-4	C2, C3, C4	C215, C401, etc.
38	29	35	ML-5	C5, C7	C505, C704, etc.
29	30	30	ML-5	C5, C6, C7	C503, C712, etc.
47	31	17	ML-4	C2, C3, C4	C215, C302, etc.
17	32	34	ML-4	C2, C3, C7	C208, C714, etc.
43	33	41	ML-5	C3, C5, C6	C207, C505, etc.
4	34	27	ML-4	C2, C3, C4	C302, C401, etc.
18	35	36	ML-3	C3, C5	C307, C504, etc.
26	36	33	ML-2	C3, C6	C307, C607, etc.
10	37	45	ML-3	C3, C6	C307, C604, etc.
20	38	25	ML-1	C2, C6	C202, C616, etc.
36	39	40	ML-2	C2, C6, C7	C210, C712, etc.
21	40	38	ML-1	C2, C6	C202, C616, etc.
25	41	2	ML-3	C1, C5	C105, C503, etc.
28	42	6	ML-2	C2, C7	C210, C505, etc.
14	43	37	ML-2	C2, C6, C7	C616, C712, etc.
22	44	42	ML-1	C2, C6	C202, C616, etc.
27	45	46	ML-1	C2, C6	C202, C616, etc.

Şirket #	BWM Sıra (M)	BWM Sıra (H)	ML Sınıfı	Tanımlayıcı Kriter	Tanımlayıcı Alt Kriter
30	46	47	ML-3	C5	C503, C504, etc.
8	47	22	ML-4	C5, C7	C506, C714, etc.

M: Mevcut/güncel kriterler
H: Hedef/gelecek kriterler

Şirketlerin "Mevcut/Güncel" seçimlerine göre ortalama sıralamalarını, ikili kümeleme analizinden elde edilen atanmış olgunluk seviyeleriyle karşılaştırdığımızda, açık ve mantıklı bir model ortaya çıkmaktadır. Bunun nedeni, her kümenin (olgunluk sınıfı) çalışmada listelenen kriterlerimiz tarafından belirlendiği gibi, her kümenin ortak temel dijitalleşme yeteneklerine sahip farklı bir şirket grubunu temsil etmesidir.

Destekleyici biçimde, Tablo 10'da listelenen her bir olgunluk sınıfı için belirlenen sıralama ortalamaları, analizimizin ve bulgularının geçerliliğini desteklemekte ve güçlendirmektedir.

Sonuç olarak, her bir olgunluk sınıfı içindeki ortalama sıralamalar, her sınıf ile ilişkili alt kriterleri arasında benzersiz bir ilişki gösterirken, sonuçları daha yakından incelediğimizde daha geniş bir model ortaya çıkmaktadır. Özellikle analiz, ML-3, ML-2 ve ML-1 olgunluk sınıflarının istatistiksel olarak ayrılamaz olduğunu göstermektedir. Bunun nedeni, bu üç sınıf için sıralama puanlarının birbirine çok yakın olması ve bu da seçilen alt kriterlerindeki farklılıklara rağmen genel dijital olgunluk seviyelerinde önemli bir fark olmayabileceğini düşündürmektedir. Bu bulgu, bu sınıfların yeniden tanımlanması gerekip gerekmediğini veya gözlemlenen bu benzerliğe katkıda bulunan başka faktörler olup olmadığını belirlemek için olası bir araştırma alanını vurgulamaktadır.

Tablo 10 – Olgunluk sınıflarının BWM sıralama ortalamaları ile karşılaştırması

Olgunluk Sınıfı	Sınıfa Dahil Firma Sayısı ve Yüzdesi (%)		Sınıfa Dahil Alt Kriter Sayısı ve Yüzdesi (%)		BWM sıralama ortalaması
ML-5	14	30.43%	34	41.46%	15.64
ML-4	13	28.26%	14	17.07%	22.46
ML-3	7	15.22%	13	15.85%	30.57

ML-2	6	13.04%	14	17.07%	30.16
ML-1	6	13.04%	7	8.54%	36.16
KÜM. TOPLAM	46	100%	47	100%	

Öte yandan, CC algoritması, yeni tanımlanan bir ikili küme içindeki orijinal veri noktaları yerine rastgele değerler koyarak, farklı ikili kümelerin çakışmasını önler. Bu değiştirme işlemi, aynı veri noktalarının gelecekteki herhangi bir ikili kümeye dahil edilmesini mümkün kılmaz. Ayrıca, CC algoritmasının *maskeleme* (bazı çakışan kriterleri hesaplamama) unsuru, sonuçlarda potansiyel olarak bir yanlılığa neden olabilir. Bunu azaltmak için, anket verilerine dayanarak ikili kümelerin alt kriterlerin en az %50'sini içermesini gerektiren bir eşik değeri uygulanmıştır. Ek olarak, anketteki veri seyrekliği analiz sürecinde zorluk oluşturmuştur ve neticede çok sayıda eksik değere sahip bazı alt kriterlerin analizde söz konusu algoritma tarafından hariç tutulmuştur. Neticede, veri sınırlamaları nedeniyle, analizde *en yüksek görünürlüğe* sahip toplam 47 adet alt kriterden oluşan konsolide bir kriter grubuna odaklanılmıştır.

6. SONUÇ ve TARTIŞMA

Bu tez, dijital dönüşüm ve Endüstri 4.0 ekseninde Türk otomotiv endüstrisine odaklanmaktadır. Öte yanda, bu tezde örneklem olarak kullanılan şirketlerin dijital dönüşüm süreçlerini değerlendirmek için her seviyesi belirli ikili kümeyle tanımlanan beş seviyeli bir olgunluk modeli sunulmuştur. Araştırma, farklı olgunluk seviyelerine göre üretici ve tedarikçi şirketlerle yapılan görüşmelerden yola çıkarak temel kriterlerin ve alt kriterlerin dijital dönüşüm üzerindeki etkisini analiz etmektedir. Temel bulgular, büyük şirketlerin stratejik fırsatlar tarafından yönlendirildiğini, daha küçük şirketlerin ise operasyonel faydalara odaklandığını ortaya koymaktadır. Ancak tüm firmaların beceri eksiklikleri, finansal kısıtlamalar ve bilgi engelleri gibi zorluklarla karşı karşıya olduğu da öngörülebilir.

Bu çalışma, Türk otomotiv şirketlerinin Endüstri 4.0'ın önemini kabul etmelerine rağmen, hala dijital dönüşümün erken aşamalarında (1-3 arası olgunluk sınıfında olanlar) olduğunu ortaya koymaktadır. Çalışmaya katılan hiçbir şirket için, dijital teknolojileri tam olarak entegre etmese de, dijitalleşmeye uzun vadeli bir strateji olarak güçlü bir bağlılık gösterdikleri öngörüsü yapılabilir. Ayrıca, büyük veri ve tedarik zinciri yönetimi gibi alanlarda beceri gelişimini önceliklendiren şirketlerin rekabet avantajına sahip oldukları da söylenebilir.

6.1. Polika Önerileri

Bu tez, çalışmaya katılan şirketlerin dijital dönüşüm olgunluğu ile Endüstri 4.0 uygulamalarını benimseme kapasitesi arasındaki güçlü ilişkiyi doğrulamaktadır. Araştırma, Türk otomotiv endüstrisinde başarılı bir dijital dönüşüm için kritik öneme sahip temel kriterlerin önemini belirlemektedir. Endüstri 4.0 pratiklerinin ve teknolojilerinin daha hızlı özümsenmesini sağlamak için değerlendirme, iş birliği, yönetişim ve yeni nesil insan kaynakları uygulama aşamalarını öne çıkaran bir yaklaşım önermektedir. Ayrıca, devletin teknolojik inovasyona olan destek gereksinimi vurgulanmakta ve şirketlerin değişen ortama uyum sağlama ihtiyacı üzerinde durulmaktadır.

6.2. Çalışma Kısıtı

Bu tez için aşağıda listelenen bazı birkaç kısıt ve bu kapsamda gelecek çalışma kapsamı öngörülebilir:

i. Veri Yaşı: Çalışmanın nispeten eski verilere dayanılması ve teknolojinin hızla gelişmesi, bulguların mevcut Endüstri 4.0 ortamı değerlendirmesini sınırlayabilir.

ii. Sınırlı Örneklem Büyüklüğü: Görece gerçekleştirilen az sayıda görüşme, sonuçların genelleştirilmesi için kısıtlı kalabilir. Ancak, bu çalışmada katılımcı şirketleri arasında en büyük / önemli üreticiler analize alınmıştır. Bu nedenle, sonuçlar sektör genelinde genelleştirme yapılabilmesi için yeterlidir.

iii. Endüstriye Özgü Odaklanma: Otomotiv sektörüne odaklanma, dijital dönüşüm zorluklarıyla karşı karşıya kalan diğer sektör firmaları için geçerli olmayabilir.

iv. Çok Yönlü Değerlendirme İhtiyacı: BWM sıralaması gibi tek bir ölçüt, dijital olgunluğu değerlendirmek için yetersizdir. Bu sebeple, ikili küme analizi de tamamlayıcı olarak çalışılmıştır. Tezde ele alınan bu çok yönlü yaklaşım, dijital olgunluk seviyelerinin daha doğru bir değerlendirmesini sağlamayı ve etkili politika ve endüstri kararlarına rehberlik etmeyi amaçlamaktadır.

6.3. Gelecek Öngörüsü

Gelecekteki araştırmalar bu tezin sonuçları değerlendirilerek aşağıda tarif edildiği şekilde inşa edilebilir:

i. Farklı nicel yöntemler ve daha büyük bir örneklem büyüklüğü kullanmak: Bu yöntem ile daha genelleştirilebilir bulgular sağlanabilir.

ii. Görüşme verilerinin tutarlılığını artırmak: Benzer bilgi ve deneyime sahip katılımcıları seçmek, yanıtların karşılaştırılabilirliğini artırabilir.

iii. Farklı endüstrilere özgü derinlemesine araştırmalar yapmak: Elektronik veya havacılık gibi diğer imalat sektörlerine odaklanmak, dijitalleşme zorluklarını

ve fırsatlarını ortaya çıkarabilir.

iv. Nedenselliği ve ilişkileri keşfetmek: Farklı dijital olgunluk kriterleri arasındaki nedensel ilişkileri araştırmak, dijital dönüşümün daha derinlemesine anlaşılmasını sağlayabilir.

v. Otomotiv sektörünü diğer sektörlerle karşılaştırmak: Bu sayede, sektörler arası dijital olgunluğa ilişkin daha geniş bir bakış açısı sunulabilir.

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