IMPLEMENTING REAL-TIME DATA ANALYTICS METHODS FOR PREDICTIVE MANUFACTURING IN OIL AND GAS INDUSTRY: FROM THE PERSPECTIVE OF INDUSTRY 4.0

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ABSTRACT

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With the recent developments in statistics and computer science, digitalization has become more important for manufacturing companies. Thanks to the progress made in the area of information technologies, it has become possible for all production systems to communicate with each other by transmitting and receiving data digitally in order to manage the decision-making process in the best manner. Several studies suggest that production processes that are based on full automation will be compulsory for companies to survive in the future. According to field experts, the new industrial revolution which covers Big Data and the Internet of Things will be a process of digital manufacturing, known as Industry 4.0. In this revolution process, computers can analyze the data collected from the digital components placed in the production area and decide the best action to take automatically. This study conducts a comprehensive review of Industry 4.0 technologies and the contribution of these technologies to the oil and gas sector.

Keywords: Industry 4.0, Oil and Gas Sector, Big Data, Data Analytics.

ÖZ

PETROL VE GAZ SEKTÖRÜNDE TAHMİNE DAYALI ÜRETİM İÇİN GERÇEK ZAMANLI VERİ ANALİTİĞİ YÖNTEMLERİNİN UYGULANMASI: ENDÜSTRİ 4.0 PERSPEKTİFİ

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İstatistik ve bilgisayar bilimlerindeki gelişmelerle birlikte dijitalleşme, imalat şirketleri için daha önemli hale geldi. Bilgi teknolojileri alanında kaydedilen ilerleme sayesinde, tüm üretim sistemlerinin, karar verme sürecini en iyi şekilde yönetebilmesi amacıyla dijital olarak veri alışverişinde bulunarak birbiriyle iletişim kurması mümkün olmuştur. Bazı çalışmalar, tam otomasyona dayalı üretim süreçlerinin, şirketlerin gelecekte hayatta kalabilmeleri açısından zorunlu olacağını göstermektedir. Alan uzmanlarına göre, Büyük Veri ve Nesnelerin İnterneti'ni kapsayan yeni sanayi devrimi, Endüstri 4.0 olarak bilinen bir dijital üretim süreci olacak. Bu devrim sürecinde, bilgisayarlar üretim alanında konumlanmış dijital bileşenlerden toplanan verileri analiz edebilir ve en uygun aksiyonu otomatik olarak alabilir. Bu çalışma dahilinde Endüstri 4.0 teknolojileri ve bu teknolojilerin petrol ve gaz sektörüne olan katkısı hakkında kapsamlı bir inceleme yapılmaktadır.

Anahtar Kelimeler: Endüstri 4.0, Petrol ve Gaz Sektörü, Büyük Veri, Veri Analitiği.

To my beloved family and my love Hande.

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
CDU	Crude Oil Distillation Unit
EMP	Employees interviewed for the thesis
E&P	Exploration and Production
ICT	Information and Communication Technologies
IoT	Internet of Things
IIoT	Industrial Internet of Things
IT	Information Technologies
LNG	Liquefied natural gas
PdM	Predictive Maintenance
R&D	Research and Development
STPS	Science and Technology Policy Studies

CHAPTER 1

INTRODUCTION

Companies have missed important opportunities due to the fact that they have not been able to realize the transformation of the industry from the past industrial revolutions (Stock & Seliger, 2016). In this thesis, technology policies necessary to manage Industry 4.0 transition with real-time data analytics in process manufacturing industry will be investigated based on the example of oil and gas industry in Turkey.

1.1. Digitalization

Digitalization is drastically changing manufacturing processes, from production methods to customer expectations and distribution channels. Through digitalization, companies are making significant gains (Legner et al., 2017). Digitalization plays a critical role in improving production performance and achieving manufacturing goals, and most importantly in enhancing competitiveness. Digitization, on the other hand, is a method of converting information into a computer-readable digital form. That is to say, the method of transforming data into a digital format is known as digitization. Digitalization performs digitization of information, making it more convenient to archive, easily access and share information (Gray & Rumpe, 2015). All these developments bring industries to a new phase and cause countries to enter a digital transformation race. Digitalization is at the center of the transformation in the industry by undertaking the task of driving force. Digital technologies such as Big Data and real-time data analytics can be used by companies to respond to changing customer demands as well as operational improvements (Bloomberg, 2018).

1.2. Industry 4.0 and Rise of the Internet of Things

Industry 4.0 and digitalization are generally used as synonyms (Gray & Rumpe, 2015). In this thesis, I frequently prefer to use the term Industry 4.0 instead of the terms digital transformation and digitalization to provide clarity. While the first industrial revolution was based on water and steam power with mechanical innovations, it was followed by the second industrial revolution, the electrification of the factories and mass production. In Industry 2.0, Frederick Taylor published the scientific management principles. In this era, the demand was in two dimensions; volume and variation. The Taylor Theory was pursued by two innovators, Henry Ford, and Taiichi Ohno. Ford addressed the supply shortage using mass production assembly lines in product quantities. On the other hand, by creating the Toyota manufacturing system, Ohno tackled multiple client interests in product variants (Yin et al., 2018). Then, the digital revolution, the third industrial revolution, brought computerization. Automation, computers, and electronics are introduced in this stage. The third industrial revolution is the crossroads between Ford's move to higher productivity and the smart procedures under Industry 4.0 stage. Not only were procedures simplified as they were at Ford but also automation increased the efficiency of essential components for the manufacturing process. Lastly, Industry 4.0 aimed to define Germany's research and development investments related to production in the coming years (Almada-Lobo, 2016). Development and production processes in Industry 4.0 are increasingly flexible, effective and customized. Using the latest intelligent information and communication technologies, production, logistics, and customers are intermeshed. Industry 4.0 includes a variety of technologies (Rüssmann et al., 2015). Some of these technologies are Big Data and data analytics, digital automation with sensors, additive manufacturing, robotics and cloud services (Dalenogare et al., 2018). In this thesis, the main focus is on the effects of Big Data and real-time data analytics on the oil and gas sector from the perspective of Industry 4.0. In this way, I focus on how to produce more valuable information from data in process manufacturing companies having a pre-established sensor infrastructure.

Low-cost production, minimum energy use, time-saving, high-speed operation, higher yields, and better quality products are among the objectives of Industry 4.0 (Yin et al., 2018). Industry 4.0 technologies can facilitate the problematic parts of industries such as faulty production, stock waste, and equipment failure by using the power of Big Data and the Internet of Things (IoT) (Yin et al., 2018). Big Data and Internet of Things concepts are among the main topics in Industry 4.0. Big Data definition is generally associated with a very big amount of data to be analyzed. Big Data is defined as high-volume, high-speed and high-variability data that requires innovative solutions for processing (Jagadish, 2015). In order to transform the data into information, it is necessary to record the data collected in accordance with a certain order and systematic. Thus, data warehouses have gained importance, especially with the concept of Big Data. Depending on the type of the data, different techniques have come to the forefront, such as collecting, processing, presenting, storing and analyzing the data. Figure 1 shows the journey of data within a firm (Becker, 2016). Big Data starts with the acquisition of the data, then requires the analysis of the data, verification of the data, storage of the data and finally usage of the data. The users can be executives who make decisions using the data. To illustrate the importance of Big Data, Airbus, a leading aircraft manufacturer, uses Big Data analysis to accelerate its product testing processes. In fact, each test flight produces terabytes of data showing the performance of the aircraft. Big Data analysis has reduced testing time by 30 percent by accelerating data analysis processes for Airbus analysts (Oracle 2016).

Big Data Value Chain				
Data Acquisition	**Data Analysis**	**Data Curation**	**Data Storage**	**Data Usage**
• Structured data • Unstructured data	• Machine Learning • Cross-sectional data analysis	• Data Quality • Data Validation	• In-Memory Databases • Cloud storage	• Decision support • Prediction

***Figure 1*. Data usage in the Big Data value chain**

The Internet of Things, on the other hand, includes adding digital sensors and network technologies to the devices. It deals with the control of systems that can be monitored by computers or smartphones. When we think about the manufacturing, we can understand the importance of continuously monitoring and analyzing the data from production lines monitored by the sensors. Industry 4.0 aims to bring the industrial revolution to the business with the help of advanced information systems. Therefore, digitalization for companies corresponds to the utilization of their Big Data and use of the Internet of Things to make fast decisions. After the Internet of Things and Big Data platforms are established, analysis can be performed with real-time data analytics methods (Matt el al., 2015). In order to make decisions, manufacturing companies need data from their production systems. With the decreasing costs of bandwidth, storage and sensors, IT systems can support monitoring of industrial machines. This means that industrial machinery can be monitored on enterprise-scale thanks to the Big Data and Internet of Things. However, the smooth monitoring of the machines is directly related to the quality of the incoming data. Thus, the quality of the data is critical in order to create valuable information. As seen in Table 1, the quality of data from the production line should be questioned by each institution in order to provide useful information.

Table 1

Dimensions of data quality

Data Quality Dimension	Description
Accuracy	Are the data free of errors?
Timeliness	Are the data up-to-date?
Consistency	Are the data presented in the same format?
Completeness	Are required data missing?

Source: Hazen (2014).

Enterprise data warehousing and quality data processing have a crucial role in the digitalization of companies and their transition to Industry 4.0 applications.

Incomplete or inaccurate data causes waste of time and loss of decision-making opportunities. In recent years, companies in nearly all industries have taken a number of initiatives to explore and benefit from new digital technologies. This often involves changes in key business operations and affects products and processes, as well as organizational structures and concepts of management. Companies can utilize new technologies such as Big Data management software tools and get the maximum benefit from productivity opportunities when they use them to solve problems they did not foresee (Lee et al., 2013). These new technologies for manufacturing companies are the Big Data and Internet of Things (Cecchinel et al., 2014).

The way to increase productivity in manufacturing is to have full control over the processes such as the production and post-production phases. In these processes, if there are neglected parts, there will be a loss of efficiency. In order to prevent this loss, it would be wise to control every phase of the production process. For instance, Smart Factories will be the next generation of production facilities, where machines are communicating among themselves. Thus, efficiency will be controlled through information extracted from Big Data at every stage of production. It is supposed that digital transformation with Big Data and statistical learning methods will enable real-time examination of industry processes with cheaper, more sustainable and efficient production (Matt el al., 2015). For instance, in light of an overview of more than 4,000 information technology experts from 93 nations and 25 ventures, the IBM Tech Trends Report (2011) distinguished Big Data analysis as one of the four noteworthy innovations in the 2010s.

With the Internet of Things, the data produced by machines can communicate with each other. In fact, these systems are currently in use. For example, there are applications that collect data from the human body. These applications are aware of the steps that people take in the day and tell them what needs to be done to be healthier. These applications can exchange data between each other, make suggestions to people and analyze the person in a better way. The places where people travel, the energy they spend in the day and their physical movements are collected with the help of sensors and mobile applications can make predictions for individuals to lead a healthier life (Zubair et al., 2016). The same situation will now be observed in production systems. The machines will communicate with each other and set up their own intelligent environments. In the oil and gas sector, the data obtained via sensors can be used to improve operations, increase efficiency and prevent failure mechanisms. As Big Data systems increase the speed of operation, they can be used to work with suppliers under better conditions and to optimize the costly parts of production (OECD, 2017). The expectation of the digital transformation in the manufacturing industry is to increase the value-added by improving the manufacturing processes in such a way that they can make maximum use of their applications that increase the speed, efficiency, flexibility, and quality brought by digital technologies. Fortunately, the use of Big Data to gain the advantages from analytics to enhance operational processes seems a reachable target (Zikopoulos et al., 2012). Predictive maintenance, for instance, is aimed at predicting when a failure of the equipment can occur and preventing failure before the problem occurs by analyzing Big Data gathered from manufacturing systems (Lee at al., 2013). Big Data can be analyzed by using real-time data analytics techniques. Generally, the methods in analytics are composed of finding parameters that best explains the relationship between inputs and outputs. Computer Engineering and Statistics are the two most important research areas used in analytical studies. In general, most of the industrial companies directly target predictive maintenance by using Big Data as it yields the fastest return on investment and results (Gilchrist, 2016).

Digitalization in the manufacturing industry has the potential to create value through productivity increase at every stage of the value chain. While digitalization offers significant opportunities for countries and businesses that have made progress in this regard, they pose a major threat to the countries and enterprises that have not taken steps in this area. In the digital transformation process of the manufacturing industry, in order to be in a competitive position, digital technologies must be utilized efficiently and effectively.

1.3. Data Analytics and Machine Learning

In order to reach Industry 4.0, I have indicated that manufacturing companies must have large amounts of data and monitor them continuously. I also emphasized that companies should be able to process and store their data in real-time with high-processor-powered computers. The meaning extracted from the data produced by sensors, which are in communication with each other, is the real valuable information for the companies. These insights can be captured with data analytics and machine learning methods which are the intersection of statistics and computer engineering.

Data Analytics is a field of study that aims to unleash the potential of information by integrating statistical science and modern numerical calculation methods to create business value from high volume data (Jagadish, 2015). Data analytics is a collection of fundamental values that encourage and guide fundamental information extraction. Data analytics may be the closest notion to information science which is the real extraction of information by means of statistical techniques. In fact, there are hundreds of algorithms and field methods in data analytics (Provost & Fawcett, 2013). Machine learning, on the other hand, aims to model a situation using historical data so that when new data arrives, it can be labeled with the learned system. Machine learning has become one of the most significant subjects in order to find creative methods to use the information to assist the company to achieve a higher level of knowledge. The machine learning models are continuously updated as data is continually added. The value is that firms can have the opportunity to predict the future since they use the best and ever-changing data sources in the context of their real-time data with machine learning (Simeone, 2018).

1.4. Objectives and Scope of the Study

This study will investigate the contribution of Big Data and real-time data analytics which are two major components of Industry 4.0 to the oil and gas sector. While there exist studies on the concepts of Big Data and real-time data analytics in the literature, there are key questions and notions that are still not discussed in the literature in terms of cost reduction, equipment uptime, operations speed, product quality and workplace safety in the manufacturing sector. The aim of this thesis is to design technology policies for companies in the oil and gas industry to make better use of Big Data and data analytics technologies.The rest of this thesis is structured as follows. Chapter 2 starts with a literature review on Industry 4.0 applications in manufacturing. In Chapter 3, the methodology conducted to investigate the Industry 4.0 effect in manufacturing in terms of cost reduction, equipment uptime and availability, operations speed, product quality, and safety is unveiled. In Chapter 4, findings from the questionnaire and interviews are explained and the results are discussed. Finally, in Chapter 5, the contributions of this thesis to the literature are outlined and discussed.

CHAPTER 2

LITERATURE REVIEW

This section reviews the literature related to Industry 4.0 in manufacturing industry. I discuss the academic literature about the importance of digitalization for the oil and gas sector. The aim of this thesis is to understand how to optimize production operations by implementing real-time data analytics in oil and gas industry and propose technology policies for manufacturing sector to assist decision-makers to achieve their business outcomes. Thus, this thesis addresses the importance of Big Data and real-time data analytics for process manufacturing companies. In the previous literature studies, the impact of data analytics and Big Data has been assessed only to a very limited extent. However, this thesis examines the contribution of data analytics and Big Data concepts to the production sector in more detail.

2.1. The Growing Significance of Big Data in the Industry

Big Data is different compared to previous data management systems. Increasing use of the Internet and the decreasing cost of computer data storage made Big Data distinct in terms of its volume, velocity, and variety (McAfee & Brynjolfsson, 2012). Volume represents the amount of data generated by enterprise IT systems. Velocity pertains to the speed at which data is produced. Variety alludes to all structured and unstructured data that can be generated by computer systems (Zikopoulos et al., 2012). A series of recent studies have indicated that the growth rate of data is anticipated to increase twice every two years (Nagorny et al., 2016). This trend is also valid in the field of manufacturing. The vision of Industry 4.0 aims to establish an industrial infrastructure in which manufacturing processes can exchange information through a network compatible with the architecture of enterprise information technologies, and as a result, it will be easier to find significant implications for manufacturing processes (Nagorny et al., 2016). Hence, Industry 4.0 requires companies to gain instant insights with the help of real-time data analytics. By using Industry 4.0 applications, manufacturing companies can improve their production processes, product quality, and supply chain performance. In this way, they can determine the inefficiencies in production and carry out preventive actions with real-time data analytics (Almada-Lobo, 2016). Furthermore, it is estimated that the potential benefits gained from the use of Big Data, as well as the challenges it will pose, will differ from sector to sector. It is expected that manufacturing industries, government organizations as well as finance and insurance sectors will benefit from the use of Big Data (Yin & Kaynak, 2015). The analysis implies that the Internet of Things can benefit global gross domestic product up to $ 15 trillion over the next twenty years (Evans & Anninziata, 2012).

2.2. Expected Benefits of Transitioning to Industry 4.0

The terms “Industry 4.0” and “Big Data” are utilized to depict advances empowering the collection, management, and analysis of datasets that are too large for conventional database systems (Tambe, 2014). Industry 4.0 technologies are not only billboards that show production data in real-time, but also a management module, where stored data can be analyzed to find trends, carry out forecasts for operations in manufacturing processes (Snatkin et al., 2013). With the transformation of Industry 4.0, improvements are expected in the area of productivity, growth, investment and employment in industry (TÜSİAD, 2016). Table 2 lists the ten types of technologies commonly associated with the fourth industrial revolution. Some of these technologies are Computer-Aided Design, Integrated engineering systems, flexible manufacturing lines and Big Data analysis. In this thesis, analyses will be made on the contribution of real-time data analytics methods from Big Data systems.

Table 2

Technologies of the Industry 4.0

Technologies	**Definition**
Computer-Aided Design and Manufacturing	Development of projects manufacturing, based on computerized systems (Scheer, 2012).
Integrated engineering systems	Integration of IT support systems for information exchange in product development and manufacturing (Kagermann et al., 2013).
Digital automation with sensors	Automation systems with embedded sensor technology for monitoring through data gathering (Saldivar et al., 2015).
Flexible manufacturing lines	Digital automation with sensor technology in manufacturing processes (e.g. radio frequency identification – RFID – in product components and raw material), to promote Reconfigurable Manufacturing Systems (RMS) and to enable the integration and rearrangement of the product with the industrial environment in a cost-efficient way (Brettel et al., 2014).

Table 2 (cont'd)

Manufacturing Execution Systems (MES) and Supervisory control and data acquisition (SCADA)	Real-time data collection using SCADA and remote control of production, transforming long-term scheduling in short term orders considering restrictions, with MES (Jeschke et al., 2017).
Simulations/analysis of virtual models	Finite Elements and Computational Fluid Dynamicsfor engineering projects and model-based design of systems, where synthesized models[1] simulate properties of the implemented model[2] (Saldivar et al., 2015).
Big Data collection and analysis	Correlation of great quantities of data for applications in real-time data analytics, data mining and statistical analysis (Gilchrist, 2016).
Digital Product-Service Systems	Incorporation of digital services in products based on IoT platforms, embedded sensors, processors, and software enabling new capabilities (Porter and Heppelmann, 2014).

[1] Synthesized models are designed to automatically generate a large model that resembles a small example model provided by the user.
[2] Implemented models are true representation of the mathematical model.

Table 2 (cont'd)

Additive manufacturing, fast prototyping or 3D impression	Versatile manufacturing machines for flexible manufacturing systems, transforming digital 3D models into physical products (Garrett, 2014).
Cloud services for products	Application of cloud computing in products, extending their capabilities and related services (Porter and Heppelmann, 2014).

Source: Dalenogare et al. (2018).

Current industrial revolution is guiding the industry toward maximum leverage from the benefits of interconnected systems in Big Data environment. Companies with a more futuristic vision that establish new methodologies in their culture will have the opportunity of being significantly profitable in the recent future (Bagheri et al., 2014). Many production systems are not ready to manage Big Data because of the lack of analytical tools (Matt el al., 2015). Thus, embedded intelligent software systems integrated into industrial systems can go even further with predictive technologies and machine learning algorithms. These technologies can be used to anticipate degradation in product performance. (Lee et al., 2014). To illustrate the benefits of Big Data analysis, a case study was investigated for the company named SPEC which is an integrated engineering, design, project management, and construction service provider for various sectors. In their article, Tan et al. (2015) stated that a real-time data analytics infrastructure is needed to help managers use their existing Big Data to gain competitive advantage in the sector. It is pointed out in the article that the greatest need is to interconnect the large datasets to create a consistent picture of a particular manufacturing problem. The CEO of the company remarked that with the Big Data and Internet of Things, the company SPEC has used their maximum production capacity (Tan et al., 2015). Furthermore, IoT enables manufacturing companies that collect data via sensors to better monitor the status of their products and thus make better decisions using real-time operations data (OECD, 2017). One of the world's biggest truck body producer uses Internet of Things to oversee the maintenance of their trailers (OECD, 2017). This helps its customers to minimize downtimes (OECD, 2017). Moreover, IoT is used by power generation equipment manufacturers to anticipate unexpected situations in their complex operations (Chick, Netessine and Huchzermeier, 2014). In addition, estimates from Japan indicate that the use of real-time data analytics in companies can cover maintenance costs by JPY 5 trillion (OECD, 2017). More than JPY 45 billion can be earned with cost savings related to electricity by using Big Data and real-time data analytics (MIC, 2013). Estimates for Germany show that improved IoT use in manufacturing can increase productivity by 5% to 8% (OECD, 2017). Manufacturing companies are anticipated to achieve the greatest productivity gains (Rüssmann et al., 2015). With Industry 4.0, it is predicted that up to 78 billion euros could be generated by 2025, particularly in the mechanical, automotive, chemical and IT sectors as potential contributions in German Industry. (OECD, 2017).

In the manufacturing industry, business gains are achieved with reduced unplanned downtimes (Gilchrist, 2016). To illustrate, Industrial Internet of Things (IIoT) provides a way to bring visibility into the company's operations and assets through the integration of machine sensors, analytics and storage systems. Therefore, it provides a method for transforming operational processes using advanced real-time data analytics (Matt el al., 2015). IIoT focuses specifically on manufacturing industry (McClelland, 2016). Manufacturers in every sector have an important opportunity not only to monitor but also automate many complex manufacturing processes. Although systems are able to monitor progress in the production plant, IIoT technology gives the managers much more detailed information. According to the survey of Aberdeen Group, it is stated that the most important benefit of IIoT is cost reduction. Equipment uptime, increased operations speed, improved product quality, and improved safety are among the other benefits that can be reached via IIoT (Aberdeen Group, 2017). Therefore, companies need to have well-designed IT infrastructure resources on their digitalization path. Indeed, fast operational transactions, Big Data storage, and high-performance analysis require significant IT investments (Gilchrist, 2016). Besides, with the development of technology, manufacturing companies do not have to obtain the infrastructure required for the transition to Industry 4.0 through their own information systems. Cloud technologies can provide processing power and storage space for the manufacturing industry in order for them to store the combination of all sensor data (Dillon et al., 2010).

Cloud computing provides access to computing resources on a flexible demand with low management effort (OECD, 2014). To clarify, cloud computing provides access to a pool of common computing resources, which can be quickly configured and provided with low levels of management effort (Dillon et al., 2010). Lots of advanced industrial applications, such as autonomous machines and systems, require supercomputers (OECD, 2017). Cloud computing addresses remote data storage problems, such as the cost of saving Big Data sets. Cloud providers also supply analytical tools to process huge quantities of information. These technologies are maturing and becoming increasingly available, and it seems that this is a major development in order to bring firms to Industry 4.0 (Gilchrist, 2016). Cloud computing has played an important role in expanding the availability and capacity of highly scalable computing resources, especially for startups and SMEs (OECD, 2017). This is because cloud computing services can easily be scaled, used on-demand and paid for per-user or capacity used (OECD, 2017). Thus, firms can have cloud computing to sharpen their business agility and reduce IT investment costs (OECD, 2017).

Cloud computing services can be a software (SaaS as a service) or can be extended to platforms (PaaS as a service) or infrastructure (IaaS as a service), and can be deployed for private use, public use or under a hybrid format of PaaS and SaaS (OECD, 2017). In a SaaS service model, cloud consumers distribute their applications into a hosting environment accessible by various clients. PaaS service model, on the other hand, is the software lifecycle development platform that allows cloud users to develop IT services directly on the PaaS cloud. Lastly, in the IaaS service model, virtualized computing resources such as processing power and computer data storage are provided over the Internet (Dillon et al., 2010). In order to understand the strategic importance of cloud computing, a survey was conducted by cloud computing technology provider VMware (2011). It was found that 57% of all respondents consisting of 373 business leaders pointed out that speeding up the execution of projects is one of the most common reasons for adopting cloud computing. In addition, 56% of the leaders prefer cloud computing because they can quickly adapt to market opportunities and 55% of them choose cloud technologies because of its ability to scale costs relative to revenue (OECD, 2017).

2.3. Oil and Gas Industry Outlook

The natural substances of crude oil and natural gas are found in earth's crust. Oil and gas are biological substances produced through compression of sedimentary rock remains of plants and animals, such as sandstone and calcite. The sedimentary rock is a product of deposits in old oceans and other water systems. Crop layers and sedimentation residues of ocean animals were included in the rock because the sediment layers were deposited at the ocean floor. After exposure to certain temperatures and pressures in the depths of the earth, the organic matter ultimately turns into oil and gas (McClay, 2019).

Oil and gas industry can be divided into two parts according to their functions in the supply chain. Upstream activities include natural resource development whose output is a primary commodity through production which are crude oil and natural gas. Downstream activities, on the other hand, create added value in products that constitute a final commodity (Singer & Donoso, 2008). In comparison, the downstream method includes processing the collected materials into a completed item during the upstream phase. In addition, the downstream phase involves the sale of items such as gas and diesel.

The oil and gas industry can also be defined more broadly. The main mechanisms used in the oil and gas industry are exploration, upstream, midstream, refining and petrochemical (Devold, 2006). Above all, the upstream industry includes raw material exploration and production (E&P). The downstream sector focuses on oil and gas refining, processing, transportation, marketing, and distribution. As shown in Table 3, oil and gas industry operations mainly include locating, extracting, processing, and refining crude oil.

Table 3

An overview of the oil and gas industry production stream

Exploration
Includes prospecting and seismic activities beneath the ground.
Upstream
Usually refers to all oil and gas production and stabilization facilities. Includes bringing the crude oil to the surface. The upstream stage can include petroeum processing from the wellhead. Together, exploration and production are called E&P.
Midstream
Oil and gas pipeline systems. It can include processing, storage and transportation of crude oil and natural gas.
Refining
Where oil and gas are converted into commercial products with defined specifications, such as gasoline, diesel or jet fuel.
Petrochemical
They are chemical products in which hydrocarbons are the main feedstock. Mainly produces plastics and cosmetics.

Source: Devold (2006).

The oil and gas industry is a complex, data-driven business with exponentially increasing data volumes (Baaziz & Quoniam, 2014). In terms of production monitoring, large datasets generated by oil and gas companies are invaluable. Real-time data analysis for the oil and gas industry contains all of the Big Data terminologies which are volume velocity, variety, and veracity (Khodabakhsh et al., 2017). Structured and unstructured data are being used simultaneously with oil and gas operations. Oil and gas industry must analyze more data than ever before in order to obtain meaningful information from Big Data (Baaziz and Quoniam, 2014). Under these circumstances, traditional analytical methods such as basic statistical analysis from small dataset may not be enough. Oil and gas sector can gain insights from their operations data through the appropriate infrastructure and tools associated with Big Data and IoT (Baaziz & Quoniam, 2014).

Data-driven methods are therefore robust instruments for converting data into knowledge in the oil and gas sector. Because of the lack of well-organized data, Big Data was not effectively used in analyzing processes, where there is an enormous potential to convert terabytes of data into knowledge. Thus, complex processes within the oil and gas industry can only be revealed by using proper Big Data analytics methods (Baaziz & Quoniam, 2014).

2.4. Digital Technologies to Optimize Operations in the Oil and Gas Industry

Previous studies have emphasized that with the help of digital technologies, firms can reduce their costs and improve their equipment uptime by converting their Big Data into knowledge. In their paper, Baaziz, and Quoniam (2014) state that "Big Data is the oil of the new economy". Their study emphasized that Big Data is similar to crude oil. To have a value, it has to be broken down and analyzed. The oil and gas companies use tens of thousands of data collection sensors for the purpose of real-time monitoring of their assets. Their findings remarked that the understanding and use of Big Data allows oil and gas companies to remain competitive in the sector.

In the past, information technologies was used in oil and gas production, but employees had limited ability to process the vast amounts of data produced by a drilling plant because its storage was expensive and not feasible (Baaziz and Quoniam, 2014). Industry 4.0 has changed this process. Now drilling plants are able to return huge amounts of the raw data collected from production sensors for cloud storage. In order to discover new reservoirs in upstream operations, the oil and gas industry relies on the real-time data analytics technologies. In order to explore newly discovered oil and gas resources, modern sensors, analytics and automation processes are necessary (Baaziz & Quoniam, 2014). The oil and gas industry is furthermore able to obtain data related to the status of the machinery and process condition. These technological breakthroughs, such as high bandwidth communications, wireless sensor technology, cloud data storage, and advanced analytical tools enable production systems to be more understandable. Fortunately, Industry 4.0 technologies can provide the necessary computing, data storage, and industrial scalability to deliver real-time data analysis for the oil and gas industry (Gilchrist, 2016).

It is important to understand that Big Data and the concepts of Industry 4.0 promise to change what oil companies can do and how they can operate (Baaziz & Quoniam, 2014). The overall reason for the excitement created in relation to the Big Data has long been something that manufacturing organizations desire: better decision-making (Regalado, 2014). For many years, the petroleum and gas industry has confronted massive data, yet Big Data is a relatively new concept that is capable of significantly reforming the industry. In the past, a large proportion of the data collected in the oil and gas sector tended to be discarded or ignored (Perrons & Jensen, 2015). Actually, modern oil and gas companies could have data centers that contain up to 20 petabytes of information that is roughly 926 times the size of the United States Congress Bibliothèque. When this information was copied into papers in the bookshelf, it would go roughly six times around the Earth equator (Beckwith, 2011).

Big Data differs from traditional databases in terms of volume, velocity, and variety of data (McAfee & Brynjolfsson, 2012). Decreasing data collection and storage costs have led to a fundamental change in the way data quality and volume are evaluated. In the past, the collection of data was based on the sampling of a subset of the general population. The shift towards Big Data, on the other hand, led to greater tolerance for imprecision since companies can have a lot of information about their processes. Greater numbers of data make firms become more comfortable with uncertainty (Mayer-Schönberger & Cukier, 2013).

Contrary to popular belief, Big Data systems have been intensely used in the oil and gas industry (Perrons & Jensen, 2015). However, the oil and gas sector is becoming highly competitive and regulated. Thus, oil companies are striving to access hidden information in their core assets by using their data (Holdaway, 2014). Oil and gas companies must increase production, optimize cost and reduce the impact of environmental hazards against fluctuating demands and price volatility (Baaziz & Quoniam, 2014). Oil and gas industry, therefore, needs to synthesize diverse data sources into a unified set in order to support real-time decisions (Holdaway, 2014).

2.5. Manufacturing Problems and Industry 4.0

In oil and gas companies, as in other manufacturing companies, the operational continuity and the functioning of the equipment are of great importance in terms of costs. By monitoring data collected continuously from the equipment and making predictions on the basis of these data, problems in production stage can be prevented which may bring a big cost burden (Perrons & Jensen, 2015). After the initial purchase, the lifetime costs of maintaining important equipment can be materially shocking in the oil and gas sector (Perrons & Jensen, 2015). Refineries have routine maintenance procedures, no matter how different their flowchart is. Planned closures mean that production equipment are paused, so maintenance teams stop and inspect the machine according to the manufacturer's recommended programs even if the machines are in perfect working condition. Here, the importance of data is revealed with the benefits of predicting planned maintenance to be done at the right time and increasing production profitability or by avoiding uncontrolled maintenance. However, the main issue is that the conditions affecting the equipment life are not the same in every refinery, and thus the proper data analytics methods can extend the service life of the equipment. The recommended maintenance programs included in the equipment manuals are based on faulty statistics and do not take into account that equipment in the real world cannot always fail at an average speed (Holdaway, 2014).

Corrosion and fouling are two of the important factors affecting the life of equipment in refineries (Prabha, 2014). There are a variety of corrosive environments in the petroleum sector. Corrosion problems can occur in the production, transportation and refining process of oil and gas (Prabha, 2014). There are serious corrosion challenges in oil and gas sector. In general water, carbon dioxide and hydrogen sulfide cause internal corrosion in the oil and gas industry (Rahuma & Bobby, 2014). Similar to corrosion, any undesired material is called fouling on equipment surfaces. The thermal and mechanical performance of equipment may be significantly affected by fouling. Thus, oil and gas companies are looking to extend the lifetime of their assets beyond their original design life. This makes life extension an even more critical and highly discussed subject in the petroleum and gas industry with the goal of improving economic viability and increasing profitability (Rahuma & Bobby, 2014). The other situation can be the fouling of equipment. The preheating heat exchanger in the crude oil distillation unit (CDU) is costly in terms of operation and is difficult to deal with due to uncertainty in the fouling process (Mozdianfard and Behranvand, 2015). Fouling in the preheating system for crude oil distillation has become one of the most challenging issues in the refinery industry (Loyola-Fuentes et al., 2017). For a single crude oil distillation unit, the pollution-related cost can reach millions of dollars a year. Given a contamination pattern, the accumulation can be reduced by manipulating the heat exchanger tube wall temperatures, the wall shear stress and the cleanliness of the heat exchangers. Pollution models can be developed from laboratory tests, but such experimental studies require significant amounts of time. In addition, conditions controlled during a test can not be reliably calculated for field operations. Modeling of contamination threshold also shows hazards. Each pollution rate model is developed for a specific mechanism and every parameter in these models can change significantly when the type of crude oil changes. To overcome these problems, a new methodology for identifying pollution models is proposed from on-line data and removes the need for laboratory experiments. When the heat transfer coefficients are combined with the different contaminant mechanism models for the individual heat exchangers, the resulting information is used to estimate the foiling behavior in a heat exchanger network (Mozdianfard & Behranvand, 2015). One of the key parameters for providing an effective distillation process is the thermal efficiency of the preheating train, which can be influenced by the undesired accumulation of solid heat transfer in the heat transfer surface of each heat exchanger. The precipitation process (Epstein, 1983), known as pollution, is one of the most challenging problems of researchers and industries. Different mechanisms and dynamic behavior of pollution are not fully understood (Lemke, 1999). The cost of losses can be as high as USD $ 1.5 million over a 3-month period (Bories & Patureaux, 2003) in terms of total pollution costs in crude oil refining. Pollution can be reduced by correcting or manipulating a certain process and design parameters (Loyola-Fuentes et al., 2017). However, by using Big Data systems in refineries, an analytical model can be developed that use machine learning methods which can predict the rate of pollution in heat exchangers and achieve a decrease in heat transfer efficiency. This can be calculated by using artificial intelligence algorithms on the Big Data that comes from the moment when the expensive equipment needs for maintenance. This prediction model can then be integrated into a preventative maintenance diagnostic tool to plan the cleaning of the heat exchanger to remove contaminants and maximize the efficiency of the heat exchanger. Thus, oil and gas companies can gain great profitability using Industry 4.0 technologies (Gadalla et al. 2003).

On the whole, predictive maintenance (PdM) can help oil and gas companies become agile, flexible, faster and better equipped to adapt their operations. The dissemination and exploitation of predictive maintenance estimates with Data Analytics methods have the potential to save billions of dollars in the oil and gas industry every year. As income can vary considerably in the oil and gas industry due to the changing crude oil prices, it is extremely important to plan the maintenance budget and increase the profitability by controlling the downtimes. Moreover, with the increase in efficiency and safety, the prevalence of accidents and costs is reduced, which benefits business, customers and the environment. In short, oil and gas companies have a huge opportunity to improve efficiency and reduce operating costs through better asset tracking and forecast maintenance (Gadalla et al. 2003).

2.6. A Wrap up of the Literature Review

In Chapter 2, I first tried to provide a review of what digitalization is. I studied the meaning of digitalization and the importance of real-time Big Data analytics. Secondly, I emphasized the benefits of Industry 4.0 for manufacturing firms. Thirdly, I provided a review of how the oil and gas industry works. Fourthly, I focused on the literature covering the motivations of using digital technologies to optimize operations in the oil and gas industry. Lastly, I put forward the literature explaining the problems in manufacturing that can be solved with Industry 4.0. On the whole, I tried to underline the importance of manufacturing by examining its relation with Industry 4.0 technologies. In the next chapter, I will describe the materials and methods used to investigate the benefits of Industry 4.0 technologies to manufacturing sector based on observations in the oil and gas industry.

CHAPTER 3

METHODOLOGY

The main purpose of this thesis is to analyze the effects of Industry 4.0 technologies on the manufacturing sector based on the oil and gas industry. In the previous chapters, I discussed the concept of digitalization, common Industry 4.0 modules and digital applications based on oil and gas industry. This chapter explains the research methodology used in order to examine the contribution of Industry 4.0 applications described in this study.

3.1. The Sequence of Work Carried Out

This thesis has been started by making literature reviews for Industry 4.0 and the oil and gas industry. The concept of Industry 4.0, Big Data, data analytics, and machine learning are examined extensively. Moreover, the expected benefits of moving to Industry 4.0 were explored in depth. After investigating scenarios for the application of Industry 4.0 technologies in the oil and gas industry, the use of digital technologies in the production sector has been found to be significant. However, there are deficiencies in the literature in terms of investigating the contribution of concepts such as Big Data, data analytics, machine learning to the oil and gas industry. Therefore, the contribution of real-time data analytics to the oil and gas sector is explored in this thesis. In this context, qualitative and quantitative studies were conducted. Statistical procedures were applied to test the validity of the findings. Open source programming language R is used for the quantitative part of this thesis. First, online survey questions were prepared and distributed to the participants who are working in oil and gas industry in Turkey. In addition, interviews were conducted with selected participants and in-depth analyses were carried out. In this way, it is aimed to find deeper insights and confirm the results of qualitative and quantitative research. Detailed information about the survey and interviews will be mentioned in Section 3.3.

3.2. Research Objective

Industry 4.0 has been considered as a new industrial stage in which integration and product monitoring in processes can contribute to business performance for manufacturing companies (Dalenogare et al., 2018). However, little is known about potential contribution of Industry 4.0 in terms of cost reduction, equipment uptime, operations speed, product quality and safety in the oil and gas industry. This study aims to analyze the benefits of using Industry 4.0 technologies in the oil and gas industry. In this context, the biggest industrial enterprise of Turkey operating four refineries with a total capacity to handle an annual 28.1 million tons of crude oil, was investigated.

In this thesis, a successful implementation model for real-time data analytics methods for predictive manufacturing in the oil and gas industry is analyzed.

The objective of the thesis is to answer the following question;

- To what extent does the implementation of real-time data analytics technologies to production systems in the oil and gas sector affect cost reduction, equipment uptime, operations speed, product quality, and workplace safety?

3.3. Research Design

It is essential to obtain accurate information in scientific research. Therefore, it is necessary to reach the right information. To do this, generalizable analysis is required. The more generalized the results of a research, the higher its value (Fuller, 2011). It is important to try to obtain information that will be generalizable in a wide area of research (Fuller, 2011). In this manner, a comprehensive online survey has been utilized as an information collection instrument for the questionnaire. With this way, quantitative information about the research question is collected. The sampling method used in the online questionnaire falls under the random sampling method. This inspecting strategy is called probability sampling strategy where all members of the populace contain an equal chance to take part. Using the entire population would be superlative in every type of research, but it is not possible to include every subject in most cases. Random sampling method was used in order to disseminate the results of the questionnaire. Hence, random sampling is a method used to generalize the findings to the population (Fuller, 2011). Participants in the target population were ranked according to their registry numbers. Then, random numbers were generated using the open source statistical analysis software R. According to these randomly generated numbers, it was ensured that the people in the target population were randomly selected through the listed registry number. In this way, the findings of the survey are expected to reveal what needs to be done about Big Data and data analytics in the oil and gas sector. 36 participants from 4 refineries were randomly selected to represent the whole population and a questionnaire was sent to these people. All participants responded to the online questionnaire. The target population of the company is 700 people. The participants selected for the questionnaire consist of white-collar people who have completed university education and who actively use the data analytics systems or play a managerial role in their use. According to formula, having this sample rate over the population, we can say that our confidence level is 95% and margin of error is 16% (Fuller, 2011). With this information, we can state that our findings will be within 16% points of the whole population value 95% of the time. In statistical studies, it is preferred that margin of error is less than 20% (Suresh & Chandrashekara, 2012). Thus, we can state that our findings after quantitative survey analysis will be reliable and generalizable.

Qualitative information is typically descriptive. They are not less precious than numerical data, but in fact, their wealth and their originality contribute to excellent ideas (Walliman, 2017). Therefore, this thesis uses qualitative methods as another research methodology. Face-to-face interviews are qualitative part of this thesis. Thus, observations from quantitative research results will be interpreted with qualitative research results. Purposeful sampling method was used to determine the participants before starting the interview procedure. For the qualitative study, 15 interview candidates were pre-determined. A semi-structured interview method is used. In order to represent the whole population, purposive sampling was performed with high diversity. The interview participants were selected from employees using real-time data analytics systems in the field of engineering and management, and who could provide the most relevant information on this topic. Interview questions can be found in Appendix F.

3.4. Research Method

One of the most important ways to better understand the research topic is to use mixed methods. In this way, the reasons behind the answer to the research question can be better explored based on both qualitative and quantitative data (Creswell & Clark, 2017). It is argued that the mixed method approach is an important milestone in social research. Especially since the early 1990s, mixed-method research has been seen as a distinct field in the social sciences. Literature studies show that mixed methods are referred to as the third methodological movement (Tashakkori & Teddlie, 2003). Methodological studies on mixed-method research paradigm have been published in various articles and books. The research question can be better answered with mixed methods (Creswell & Clark, 2017). In this thesis, both qualitative and quantitative research approaches are employed. Using these two approaches together is called mixed methods research (Creswell & Clark, 2017).

This study has several major hypotheses.

H1: “Real-Time Data Analytics Methods” has a significant and positive impact on “Cost Reduction” in the oil and gas industry.

H2: “Real-Time Data Analytics Methods” has a significant and positive impact on “Equipment Uptime” in the oil and gas industry.

H3: “Real-Time Data Analytics Methods” has a significant and positive impact on “Operations Speed” in the oil and gas industry.

H4: “Real-Time Data Analytics Methods” has a significant and positive impact on “Product Quality” in the oil and gas industry.

H5: “Real-Time Data Analytics Methods” has a significant and positive impact on “Workplace Safety” in the oil and gas industry.

3.5. The Questionnaire

The study items are provided in Appendix A and Appendix B. The online questionnaire consists of 27 questions which are evaluated with distinct scales such as 5-point Likert scale (varying from 1=strongly disagreeing to 5=strongly agreeing), dichotomous (yes / no), metric scale (e.g. working years and company positions) and multiple-choice questions in which respondents are required to choose from a set of answers. Likert scale values were averaged to create continuous variables. According to the literature, if the questions with likert scale variables are grouped and averaged, continuous variables can be obtained and thus parametric tests can be applied (Norman, 2010). Therefore, it is appropriate to take the average of Likert scale variables and analyze them using parametric tests (Carifio & Perla, 2008). Therefore, if a series of Likert-type questions can be grouped using statistical procedures (e.g., calculating the mean), a Likert scale can be created. Means and standard deviations can then be used to make analyses from this scale (Boone & Boone, 2012). In the literature, there are similar studies that produce parametric tests and statistical analyses by producing means from Likert-scale data set (Kroth & Peutz, 2011; Diker et al., 2011; Elizer, 2011). The questionnaire focuses on the benefits of real-time data analytics to the oil and gas industry. To ensure data validity and reliability of the questionnaire, five knowledgeable individuals who are the thesis supervisor and four company employees were involved in an iterative process of personal review before the survey was distributed to the participants. Their remarks helped to enhance the survey's quality. Big Data and real-time data analytics have been implemented in the company for almost five years when the survey was applied. Before the survey is applied, each participant is notified of the research purpose and the survey filling procedure. Thirty-six employees filled the survey which is distributed as an online survey, and each informant completed the survey. In order to achieve the reliable results, at least thirty observations are required, according to Hair et al. (2010). Therefore, this research can said to be adequate for assessment. Moreover, Cronbach's alpha of the items in the survey is greater than 0.70 (see Appendix D, Figure 37). Thus, we can say that all the variables have adequate reliability and convergent validity (Hair et al., 2010).

3.6. Face-to-Face Interviews

It is important to learn the ideas of oil and gas employees in the firm about cost reduction, equipment usage time, operational speed, product quality, and workplace safety through data analytic systems. The findings of questionnaires allow us to achieve statistical results but thorough interviews are still needed in order to examine the details and learn from the interviewees' distinct views (Creswell & Clark, 2017). Using interview methods, it is possible to reveal the real meaning of the ideas. In addition, facial expressions, gestures, body language and tone of voice can provide clues to the researcher in evaluating the answers to the questions. The researcher may feel the sincerity of the participant's answers based on this information. In this case, the researcher can concentrate on these points and ask other questions to reach more realistic information. The interview method can be very useful in terms convenience and short duration as well as obtaining the information clearly (Creswell & Clark, 2017). Therefore, another significant part of this thesis is face-to-face interviews. Because of the limited availability of employees, face-to-face interviews are made with 15 people. The time allocated to each interview varied between 20-40 minutes depending on the availability of time for the employees.

CHAPTER 4

FINDINGS

In this chapter of the thesis, the data obtained from the questionnaire and face-to-face interviews will be analyzed. After the representation of these findings, some policy suggestions are made.

4.1. Analysis of the Questionnaire Findings

A total of 36 people participated in the online questionnaire. Some demographic characteristics of the questionnaire respondents are expressed as a percentage in Figure 2 given below.

Gender

Gender	
Female	22,22%
Male	77,78%

Education

Bachelor's	52,78%
Doctorate	2,78%
Master's	44,44%

Title

C-Level Executive	19,44%
Chief Engineer	5,56%
Coordinator	11,11%
Engineer	5,56%
Manager	11,11%
Senior Engineer	30,56%
Specialist	16,67%

Age

21-30	27,78%
31-40	47,22%
41-50	25,00%

Experience

1-5	16,67%
5-10	33,33%
10-15	13,89%
15-20	16,67%
20+	19,44%

***Figure 2*. Demographic characteristics of the questionnaire respondents**

As seen in Figure 6 above, the questionnaire involved demographic questions and all of the participants answered these questions.

After analyzing the results obtained from the questionnaire, it is found that 77.88 percent of the respondents were male and 22.22 percent were female. Moreover, 52.78 percent of the participants have a Bachelor's degree while 44,44 percent have a Master's degree and 2.78 percent have a doctorate degree.

The questions in the questionnaire were grouped into 9 categories as defined in Table 4 given below. A specific variable name was assigned to each category of question.

Table 4

Question Categories and Assigned Variables Names

Question Category	Variable Name
Industry 4.0 Overview	Industry4.0
Data Analytics Decision Support System Criteria	DecisionMaking
Data Analytics Technical Competency Criteria	TechnicalKnowledge
Evaluating the Contribution of Real-Time Data Analytics	RealTimeDataAnalytics
Evaluating the Contribution of Real-Time Data Analytics on Cost Reduction	CostReduction
Evaluating the Contribution of Real-Time Data Analytics on Equipment Uptime	EquipmentUptime
Evaluating the Contribution of Real-Time Data Analytics on Operations Speed	OperationsSpeed
Evaluating the Contribution of Real-Time Data Analytics on Product Quality	ProductQuality
Evaluating the Contribution of Real-Time Data Analytics on Workplace Safety	WorkplaceSafety

Source: Based on the results obtained from the questionnaire.

In order to measure the impact of real-time data analytics on the variables named above, the questions in the questionnaire were grouped into categories. Respondents are asked to answer the questions on a scale of 1-5. Afterward, the scores given were averaged and the evaluations were carried out according to these results. Descriptive analysis of Industry 4.0 in the oil and gas industry can be found in Table 5.

Table 5

Participants' Perspectives on Industry 4.0 and Digitalization in the Oil and Gas Industry

Question	Answer	Percentage
Did you take part in a data analytics or digitization project in your company?	Yes	72,22%
	No	27,78%
Do you think that real-time data analytics applications have a positive impact on your business processes?	Yes	100%
	No	0%
Can you describe the Oil and Gas industry as one of the Industry 4.0 sectors?	Yes	94,4%
	No	5,6%
Do you think that Industry 4.0 and real-time data analytics services can provide new opportunities for the oil and gas industry?	Yes	100%
	No	0%
Do you think it is necessary to allocate a specific budget for the adoption and dissemination of digital technologies used within Industry 4.0?	Yes	94,4
	No	5,6%

Source: Based on the results obtained from the questionnaire.

4.1.1. Industry 4.0 Overview

In this part of the study, the answers given to the questions related to Industry 4.0 will be examined. This section discusses how close the oil and gas sector is to Industry 4.0 in terms of data analytics applications. As seen in Figure 7, 58.3% of the respondents strongly agreed that the oil and gas sector attaches importance to data analytics and digitalization. 36.1% of the participants stated that they agreed with this proposition.

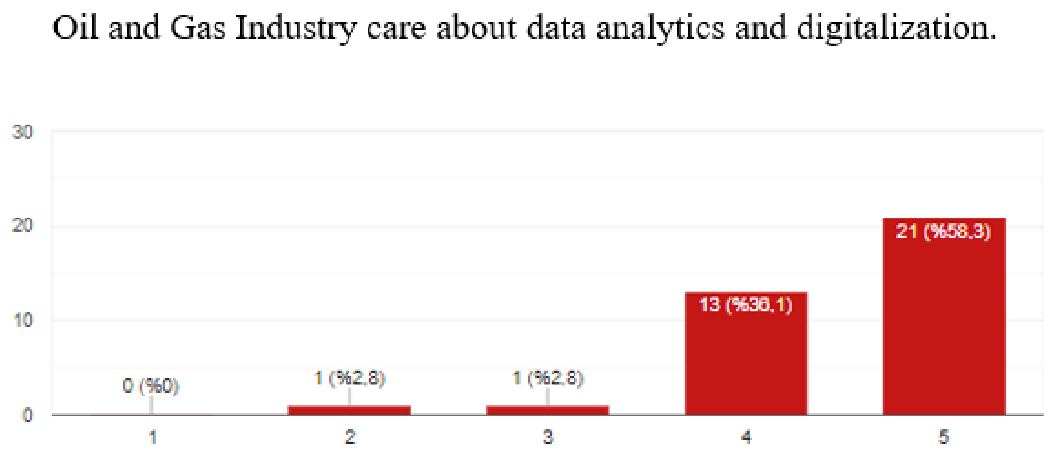

***Figure 3.* Assessment of the importance given to data analytics and digitalization in the oil and gas industry according to respondents' opinions**

According to Figure 3, the level of importance given to digitalization and data analytics in the oil and gas sector, which are very important constituents of Industry 4.0, is assessed as high with a total percentage of 94.4 when a scale of 4 to 5 is considered as high.

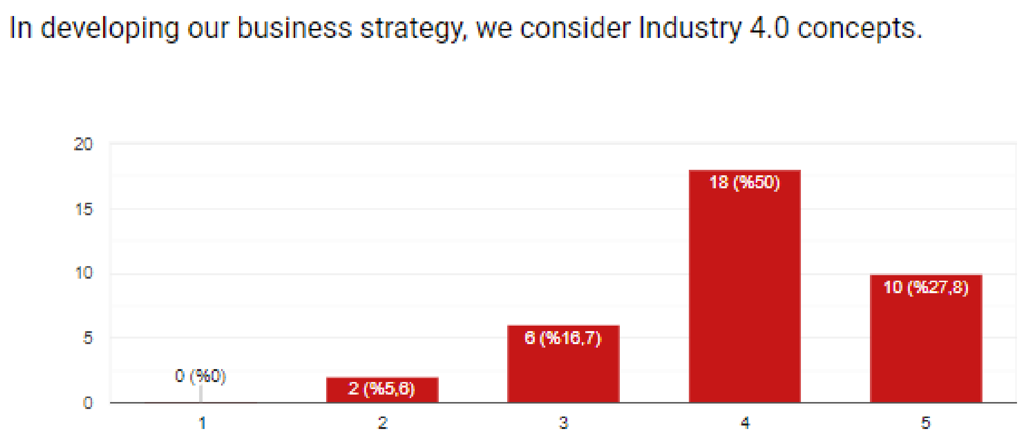

***Figure 4.* Assessment of the Industry 4.0 concept involvement in developing business strategies**

We discussed in previous chapters that a significant part of real-time data analytics depends on the digitalization strategies of manufacturing companies. As seen in Figure 4, 77.8% of the respondents voted that they considered Industry 4.0 concepts when forming their business strategies in the oil and gas industry. This highlights the importance of real-time decision-making for the manufacturing sector. This high ratio shows that the oil and gas industry is a digitally mature sector that follows up with the recent technological developments.

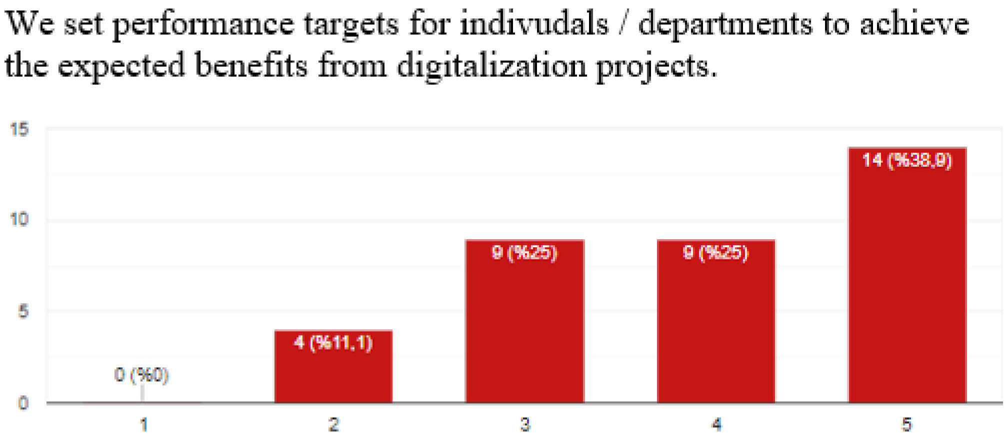

***Figure 5.* Assessment of performance target setting at the individual and department level regarding digitalization**

Looking at Figure 5, we see that the oil and gas sector aims to increase the level of digitization in their business by setting performance targets in related projects to some extent. Although approximately 36% of the participants did not agree that performance targets are set regarding digitization projects, the remaining 64% were encouraged to be involved in digitalization projects and awarded according to their success.

Figure 6 shows how important is to perform instant monitoring on production processes in the oil and gas sector by using digital technologies. 98% of the participants emphasized the importance of instant data monitoring in the oil and gas sector as very high. Therefore, automatic decision-making mechanisms should be incorporated in order to support instant monitoring.

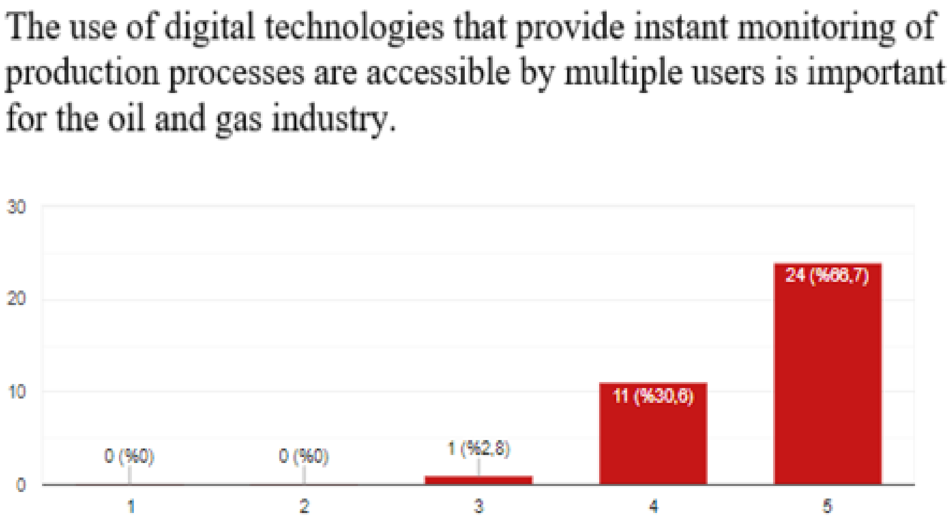

Figure 6. **Assessment of the significance level of instant monitoring by digital technology use and accessibility in the oil and gas industry**

As mentioned in the introductory part of the thesis, one of the main reasons to perform instant monitoring of production may be to increase the speed of operation and reduce the production costs. To be able to make quick decisions here can provide a huge benefit to the oil and gas industry. Further research is made through interview questions regarding this matter and findings are shared in section 4.2.

Having a vision regarding the use of digital technologies is very crucial in the production sector (OECD, 2017). 75% of participants strongly agreed that there is a need to obtain a vision in terms of digital technologies in order to survive in the competitive environment in the oil and gas sector. 25% of them also agreed to some extent with this proposal. Figure 7 shows the corresponding graph.

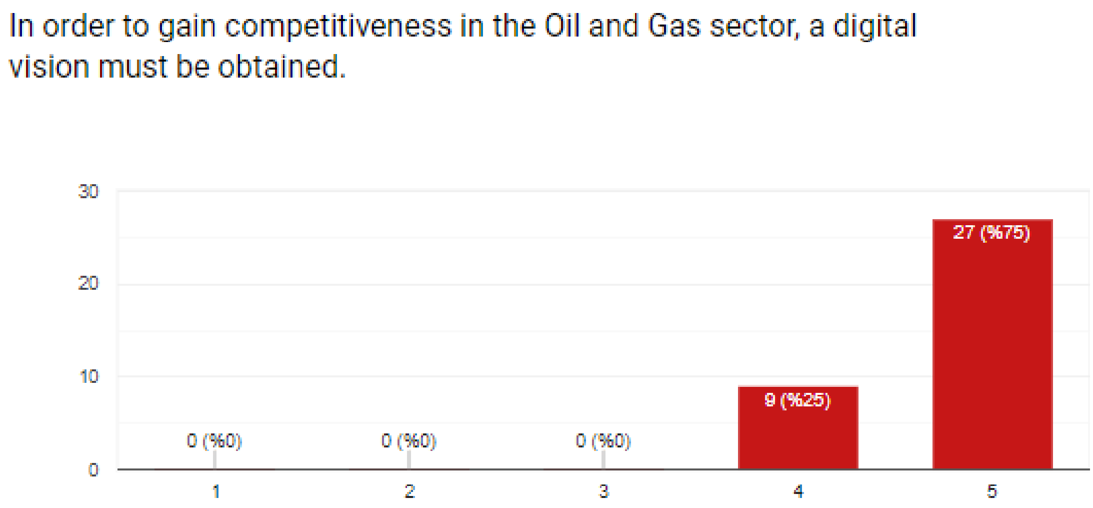

Figure 7. **Assessment of the importance of having a vision regarding digital technology use in the oil and gas sector**

The participants' perspectives on real-time data analytics on a sectoral basis were also evaluated through the online questionnaire. The perspective on real-time data analytics will be explored in detail in the interview section. As seen in Figure 8, participants expressed their trust in the contribution of data analytics applications to the oil and gas sector with a high rate of 72.2%. We can understand that the oil and gas sector has begun to see the benefits of using real-time data analytics in their business operations.

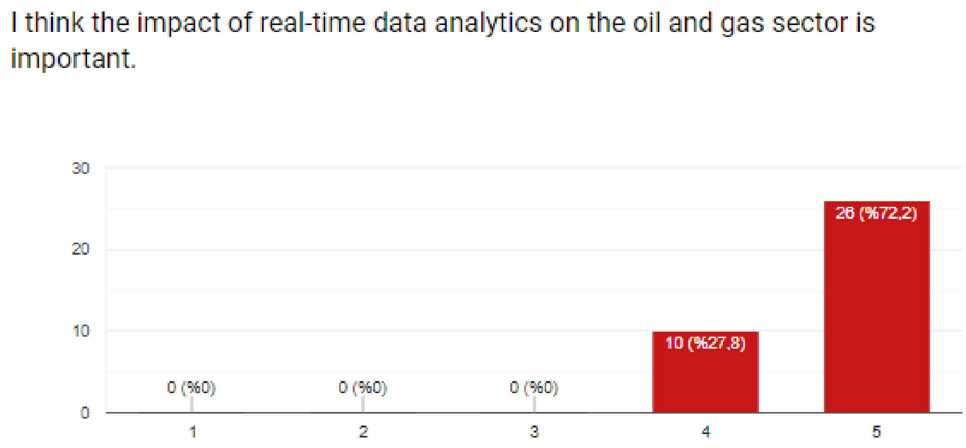

Figure 8. **Assessment of the importance given by the participants to real-time data analytics use in the oil and gas sector**

The questionnaire findings also show that the oil and gas industry is a sector in which digital technologies are extensively used. Employees say that the requirements of Industry 4.0 are widely acknowledged and its impact on business processes is seen as significant. Based on what the participants specified, we can conclude that real-time data can be processed and analyzed automatically in the oil and gas sector. It has been confirmed by the questionnaire responses that having a vision regarding digital technologies is important for remaining competitive and gaining an advantage in the sector. In order to state the findings of the research as clear as possible, we created detailed graphs using statistical analyses based on the questionnaire responses and face to face interviews. Numerical research techniques such as factor analysis, variance analysis and dimension reduction analysis were performed. In the dataset, nonlinear relationship was not detected between variables. Thus, the relationship between the variables is assumed to be linear. Also, no outlier values were detected in the observations. Statistical assumptions were also tested for each statistical test used. First, the differences among the respondents in terms of their demographic characteristics were examined and the results were given by the boxplot method. A boxplot is a way of showing the distribution of the data. It can inform us about outliers, symmetry and skewness of the data. Boxplot shows minimum value, first quartile (the middle number between the smallest number and the median of the dataset), median (the middle value of the dataset), third quartile (the middle value between the median and the highest value of the dataset) and maximum value of the dataset. As seen in Figure 9, the opinions of the respondents about the contribution of Industry 4.0 to the oil and gas sector varies by gender, age, educational background, and title. Findings represented by descriptive visuals and subjected to statistical tests will be further examined in detail by using interview methods.

When we look at Figure 9, while there are no significant differences in terms of gender, age and title, scoring that evaluates the contribution of Industry 4.0 applications differs according to the education level of the employees. One-way ANOVA was used to test this assumption. According to the results of the variance analysis, which can be seen from Table 7 (see Appendix D), there is a difference only according to the education category regarding the contribution of Industry 4.0 to oil and gas sector. This is due to the fact that the p.value is 0.0938. At the statistical significance level of 0.10, the hypothesis that the educational level of the employees does not change their opinions about Industry 4.0 in the oil and gas sector is disproved according to the results of statistical analysis. Differences in the opinions of the employees based on their gender, age, and title could not be determined statistically (see Appendix D, Table 7). When Figure 9 is examined in detail, the contribution of Industry 4.0 to the sector is scored as 4.5 out of 5 on average.

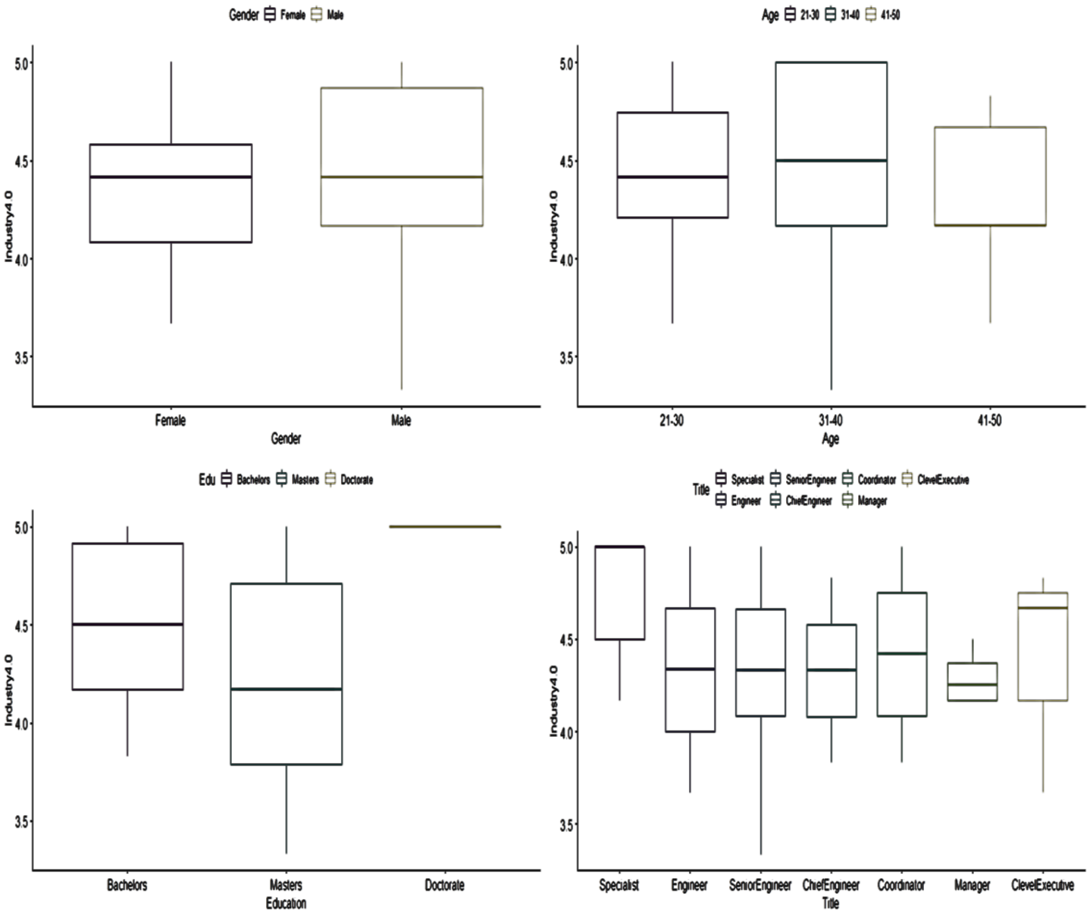

***Figure 9*. Representation of the scoring made by the respondents regarding the contribution of Industry 4.0 to the oil and gas sector based on the respondents' demographic characteristics**

The normality assumption of ANOVA states that the residuals should follow a normal distribution. In order to satisfy this requirement, the Shapiro-Wilk Normality test is used. As we can see it from Table 9 (see Appendix D), we find the corresponding p.value as 0.3316. At the 0,10 level of significance, we can say that errors are normally distributed. Furthermore, Levene's test for homogeneity of variance is found to be 0.3512 (see Appendix D, Table 9). As a result, we can conclude that the assumption of the equality of variances cannot be rejected. Thus, we can state that ANOVA results are reliable based on the significance levels. In addition, according to Table 8 (see Appendix D), we find that most deviances in the level of education variable due to the difference between the number of Master's and Bachelor's degree owners. Therefore, we may conclude that there may be differences in the individuals' perspectives regarding Industry 4.0 in the oil and gas sector based on whether they have a Master's or Bachelor's degree.

4.1.2. Decision Support Systems Overview

Big Data systems are mainly used for decision support systems in the manufacturing sector (Lee et al., 2013). In this part of the thesis, it will be examined how real-time data analytics applications help the decision-making processes in the oil and gas sector.

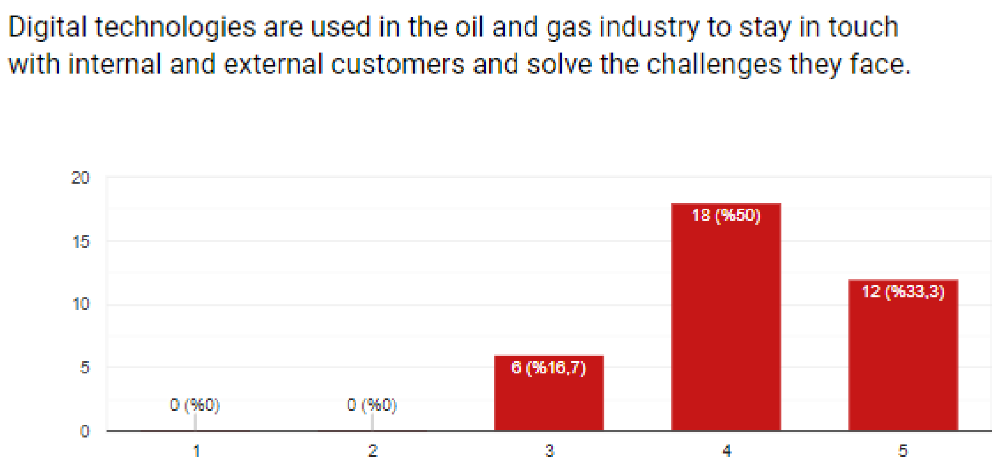

***Figure 10*. Assessment of digital technology use in solving the customers' problems**

As seen in Figure 10, all the participants of the questionnaire stated that they use digital technologies to solve the customers' problems. 33.3% of the employees that fill in the questionnaire strongly agreed that digital technologies solve the problems they face. 50% said that they agree. 16.7% answered the question as they neither agree nor disagree.

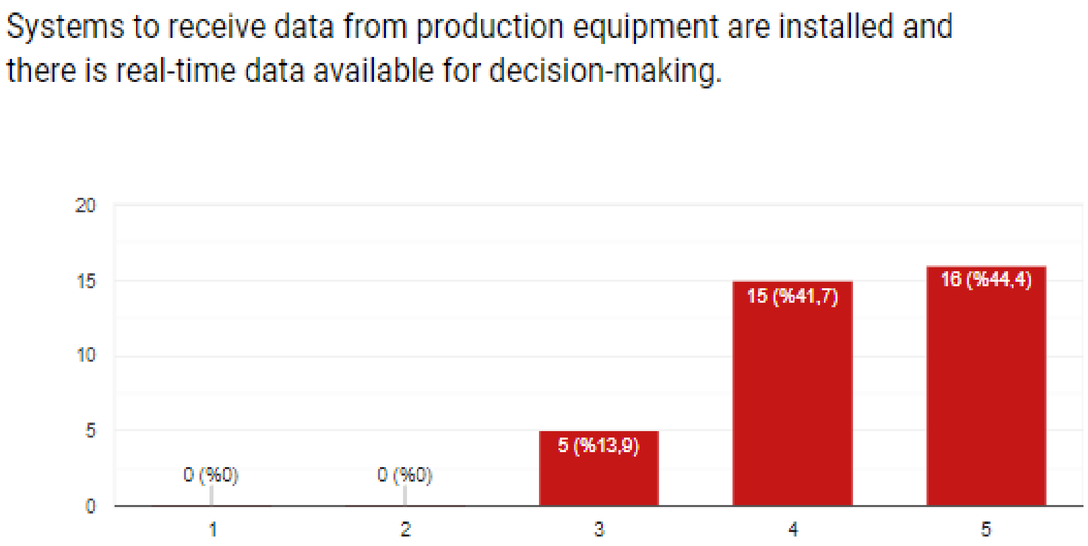

***Figure 11*. Assessment of real-time data use in decision support systems**

Providing real-time data for the automated decision-making process in the manufacturing sector is one of the most important steps of production (Lee et al., 2014). When we look at the oil and gas sector, as we can see from Figure 11, the responses to the use of real-time data in decision-making seem highly positive. Approximately 86% of the respondents indicated that real-time data can be used in decision-making in the oil and gas sector. Moreover, approximately 92% of respondents strongly agreed that real-time data analytics can be used to improve processes (Figure 12). As can be seen in Figure 12, real-time data analytics methods are used in the improvement of production processes. Thus, we can state that findings found in the survey are similar to the studies in the literature. This result also shows that process-based manufacturing companies should use real-time data analytics methods and establish decision support mechanisms.

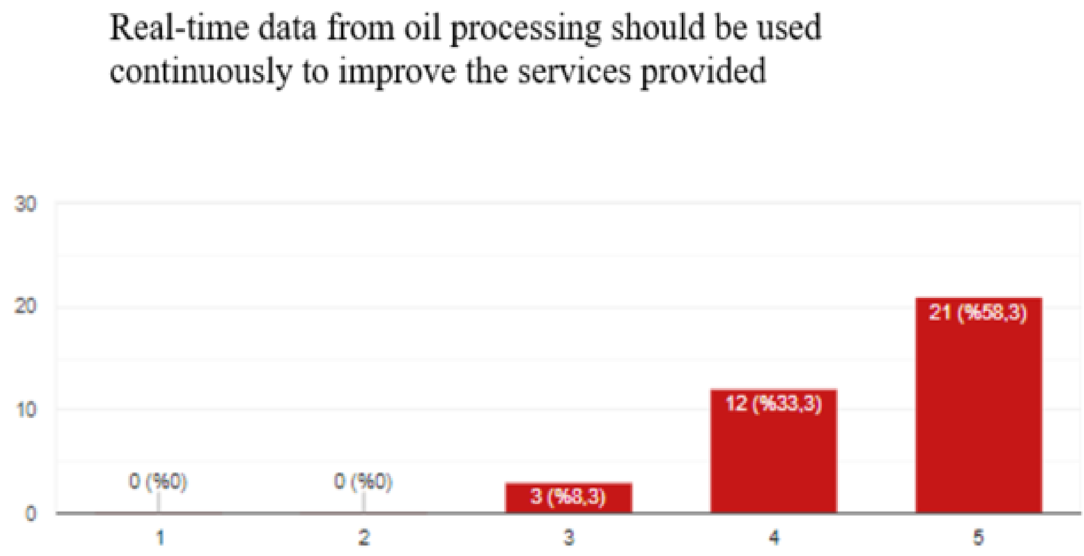

Figure 12. **Assessment of the necessity of real-time data use in oil processing in order to improve the services provided**

As can be seen in Figure 13, participants' views on the contribution of real-time data analytics applications to oil and gas sector in the decision support phase vary according to gender, age, educational status, and title. When we look at Figure 13, although there is no significant difference in terms of age, education, and title, it is seen that the perception of the respondents differs according to gender classes. One-way ANOVA was used to test this assumption. According to the variance analysis results which can be seen from Table 10 (see Appendix D), a difference occurs only according to gender classes. This is because the p.value is 0.0524. At the statistical significance level of 0.10, the assumption that gender differences of employees do not change their opinion regarding decision support systems in the oil and gas sector can be rejected according to the results of statistical analysis. Effect of the differences in age, education, and title could not be determined statistically (see Appendix D, Table 10). Therefore, it can be concluded that there is no difference in terms of age, education and title variables in decision support phase.

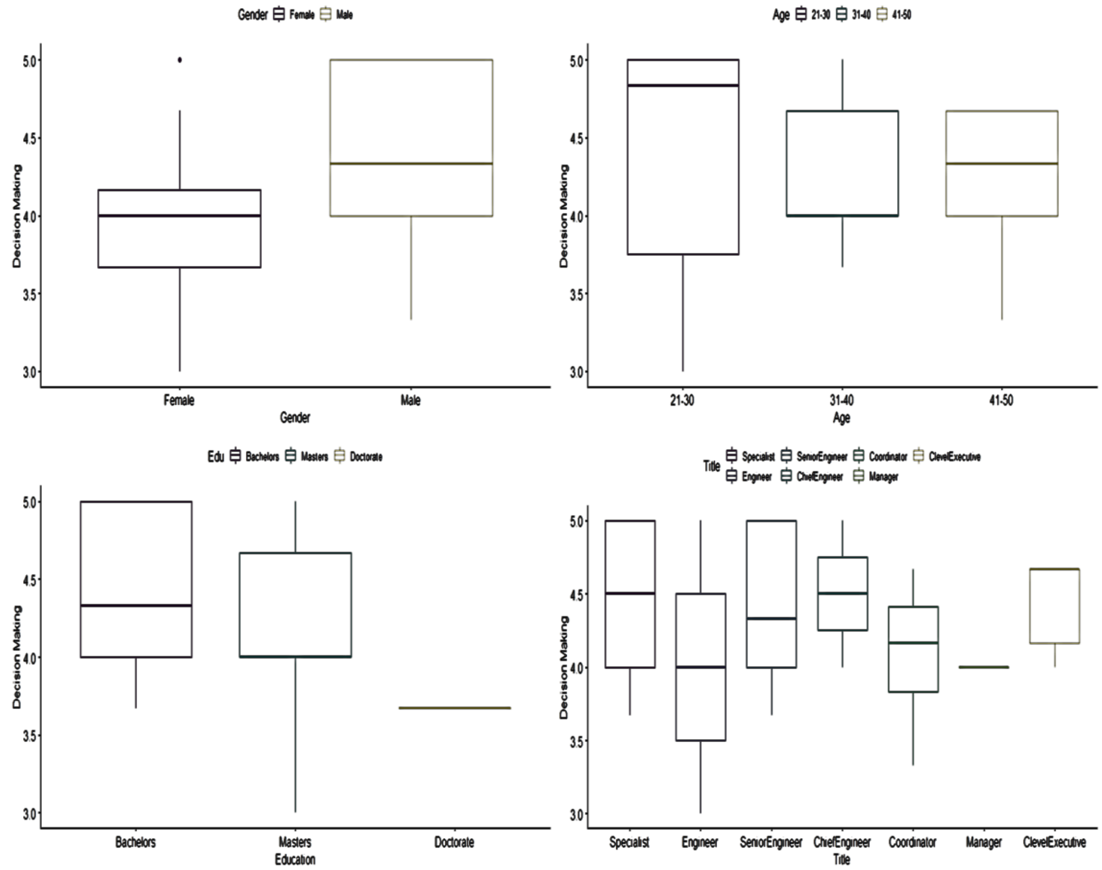

Figure 13. **Representation of the scoring made by the respondents regarding the contribution of real-time data analytics applications to the oil and gas sector in the decision support phase based on the respondents' demographic characteristics**

The normality assumption made while using ANOVA can be checked from Table 11 (see Appendix D). The corresponding p.value is 0.05092. At the 0,01 level of significance, we can say that errors are normally distributed. In addition, according to Table 11, we find that variances are equal among groups with a p.value of 0.9917. Based on this information, there seems to be a statistically significant difference among the respondents' assessments of decision support systems used in the oil and gas sector based on gender.

4.1.3. Technical Competence Overview

Technical competence can be defined as the ability of an enterprise to have the necessary applications for the successful execution of a business and to use them at the desired level with the required knowledge and skills (Epstein, 2003). In this part of the thesis, the technical adequacy of real-time data analytics applications in the oil and gas industry will be examined. The aim is to explore how the necessary technological infrastructure should be developed to better meet the needs of employees.

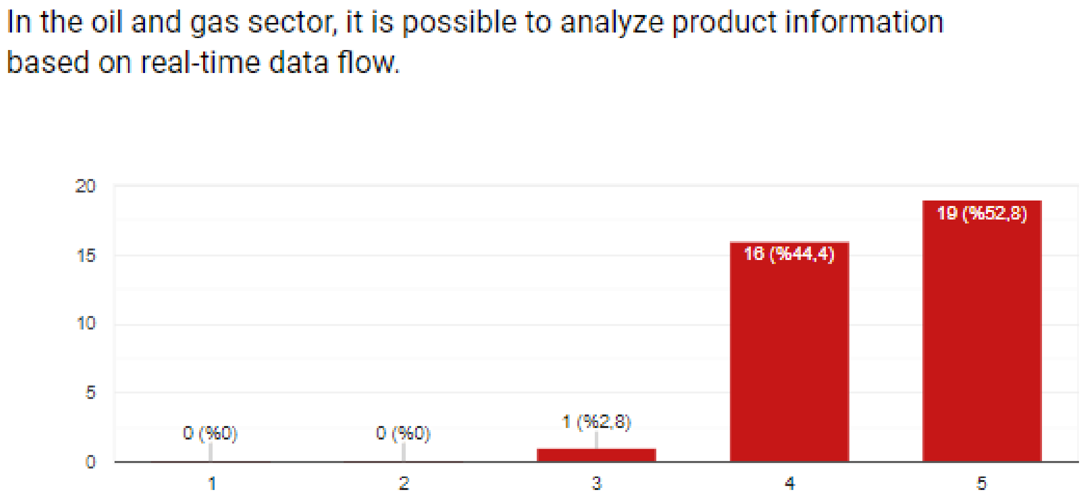

Figure 14. **Assessment of data analytics use in product information analysis in the oil and gas sector**

When we examine Figure 14, we see that 98% of the respondents stated that it is possible to analyze the product information by using real-time data. 3% of the participants said that they do not agree or disagree with this statement. In the oil and gas sector, another criterion used in evaluating the technical competence was whether the effect of real-time data analyses was observable or not. A brief representation of the answers given to the corresponding question is provided through Figure 15. As it is seen in the figure, 25% of the employees stated that they neither agreed nor disagreed with this proposal. The remaining 75% stated that the effects of the analytical studies using real-time data can be observed better compared to the ones using past data.

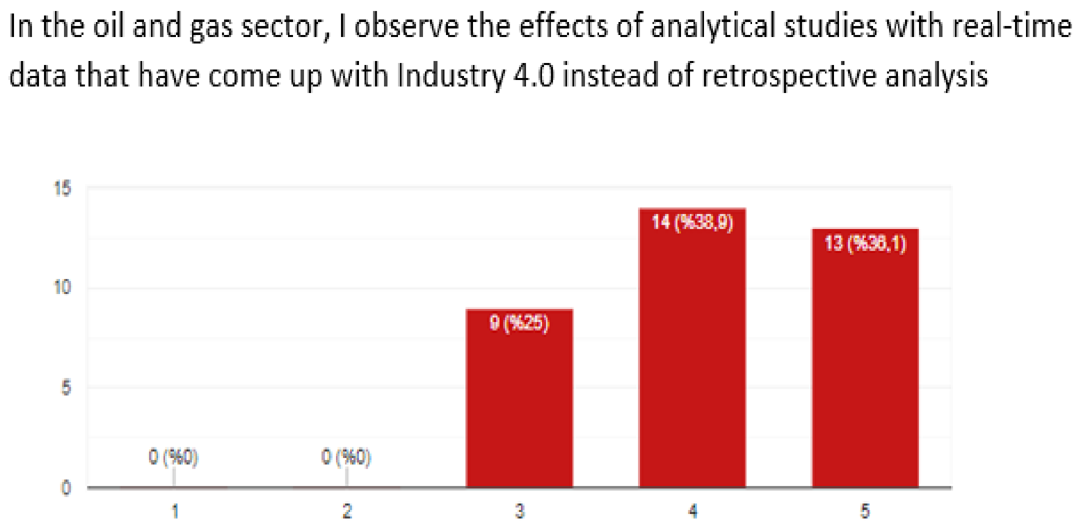

***Figure 15.* Assessment of the effectiveness of analytical studies that employ real-time data as compared to the ones based on past data**

There are studies suggesting the necessity of having technically competent employees that would be able to use digital technologies, to ensure these technologies are extensively used within the organization and to handle data analytics through these technologies (Viktor and Arndt, 2000). In Figure 16, we see that 66.7% of the respondents strongly agreed with the proposal that technical experts should be employed in order to carry out data analytics studies in the oil and gas sector. 25% of the participants also agreed with this proposal and the remaining 8.3% said that they neither agree nor disagree. As can be seen from this point, competent data analysts are required to be involved in the transformation of Industry 4.0 in process manufacturing companies.

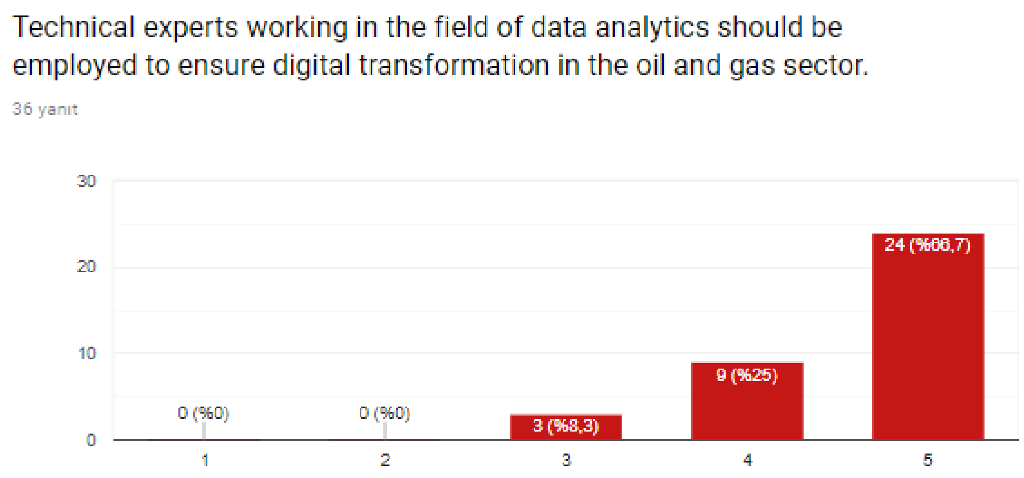

Figure 16. **Assessment of the requirement for technical experts in data analytics in the oil and gas sector**

Information related to the question that assesses the use of technologically sufficient systems in the oil and gas sector to process real-time data analytics can be examined in Figure 17.

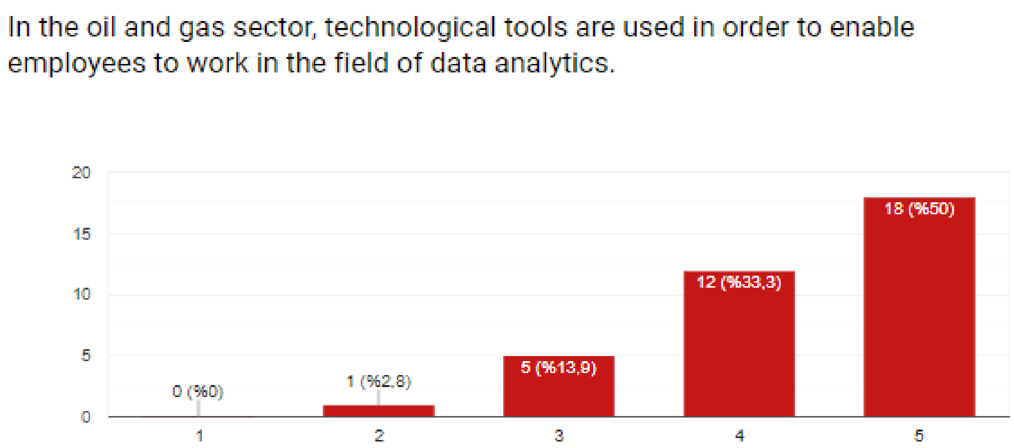

Figure 17. **Assessment of adequate technology use to enable employees to perform data analytics studies**

According to Figure 17, 83.3% of the participants stated that the technology used in the oil and gas sector is sufficient to perform data analysis. In order to do further research about these subjects, more detailed questions will be asked during the interviews and the requirements of the real-time data analytics and Big Data use will be examined from the perspective of the employees.

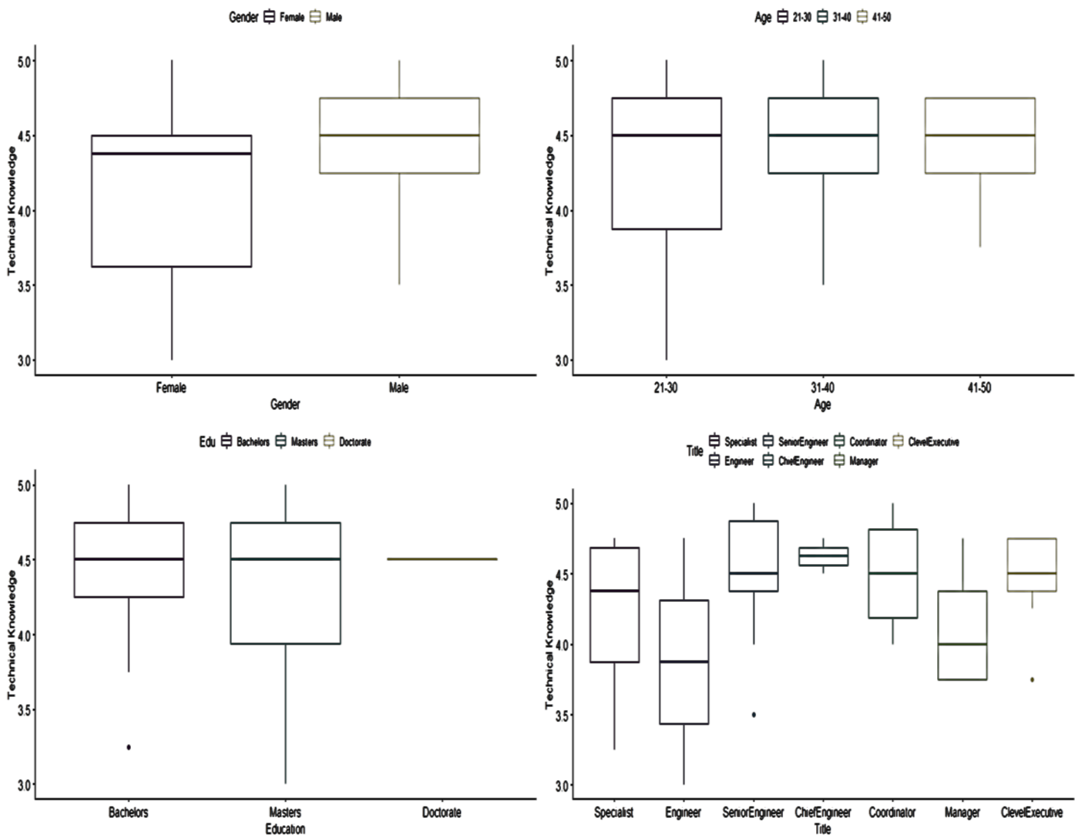

***Figure 18*. Representation of the scoring made by the respondents regarding the technical adequacy in the oil and gas sector based on the respondents' demographic characteristics**

As seen in Figure 18, the status of technical competence in the oil and gas sector varies according to gender, age, educational background, and title. When we look at Figure 18, although there is no significant difference in terms of age, education, and title, we see that the gender of the employees makes a difference. One-way ANOVA was used to test this assumption. According to the results of the analysis of variance, which can be seen from Table 12 (see Appendix D), there is a difference only according to the gender category. This is because the p.value is 0.0737. At the statistical significance level of 0,10, the assumption that gender differences in employees do not change the views of the respondents regarding the technical adequacy criteria in the oil and gas sector can be rejected according to the results of statistical analysis. Differences that may occur due to age, education, and title could not be determined statistically (Table 12). For the ANOVA normality assumption, we found the corresponding value 0.0186. Shapiro-Wilk Normality test results can be seen in Table 13 (see Appendix D). At the 0.01 significance level, we can say that the errors are normally distributed. Levene's variance homogeneity test was also found to be 0.1275% (Table 13). From these results, we can conclude that the assumption of variance equality cannot be rejected. Thus, we can say that ANOVA results are reliable based on the level of significance.

4.1.4. Real-Time Data Analytics Overview

In the previous chapters of the thesis, we stated that real-time data analytics means to perform the analysis of data as soon as it becomes available for use. In other words, real-time data analytics is to build systems so that the data can be collected immediately after data enter the system. In the oil and gas sector, to perform real-time data analysis through Big Data collection methods incorporating sensors placed in the production equipment reduces production costs, extends the life expectancy of the machines and equipment, increases operational speed, improves product quality and enhances workplace safety, which can be inferred from Figure 19. The figure shows that 52.78% of the questionnaire participants stated that the most important area where real-time data analytics systems will contribute to the oil and gas sector is reducing costs. 16.67% of the participants think that product quality is the most important problem that can be solved with real-time data analytics. The other percentages are as follows: 11.11% for equipment life, 13.89% for operating speed and 5.56% for workplace safety.

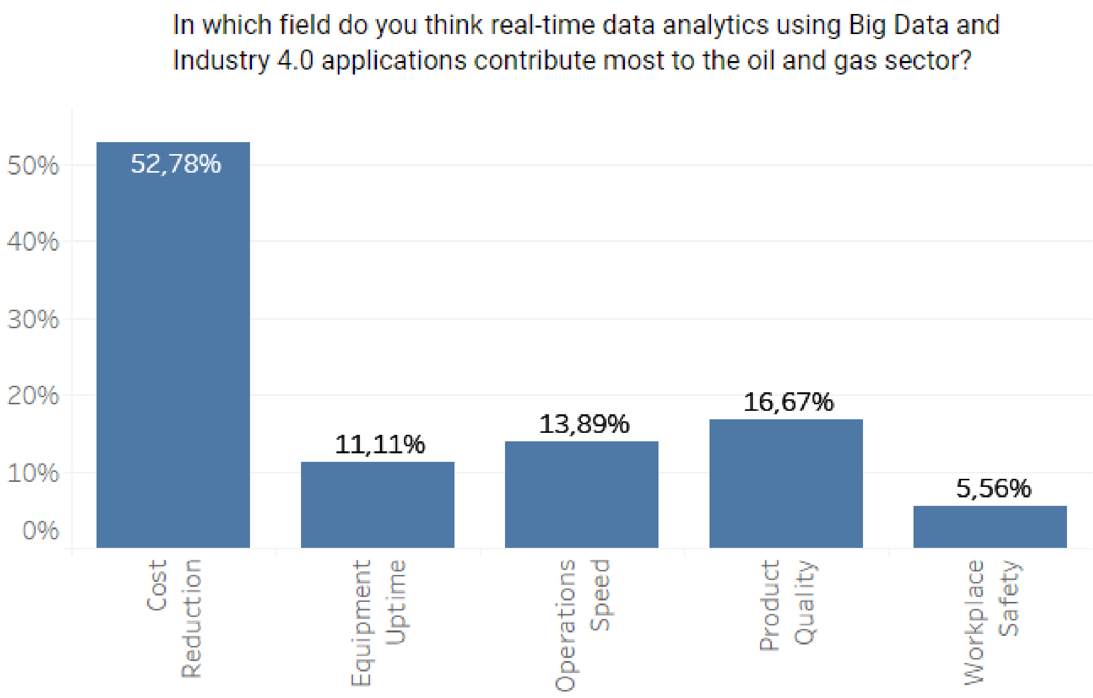

Figure 19. **Assessment of the fields where Big Data and Industry 4.0 applications can be the most beneficial to the oil and gas sector**

Figure 20 shows whether the opinions of the respondents regarding the contribution of real-time data analytics to the oil and gas sector vary according to their demographic characteristics. Although there were differences in the submitted opinions based on the demographic characteristics of the respondents when graphs are considered, no difference was found in that aspect according to the one-way ANOVA test results (see Appendix D, Table 14). Since p.value was higher than the significance level of 0.10 for each demographic variable, we could not reject the hypothesis that the average scoring did not vary among the different demographic groups.

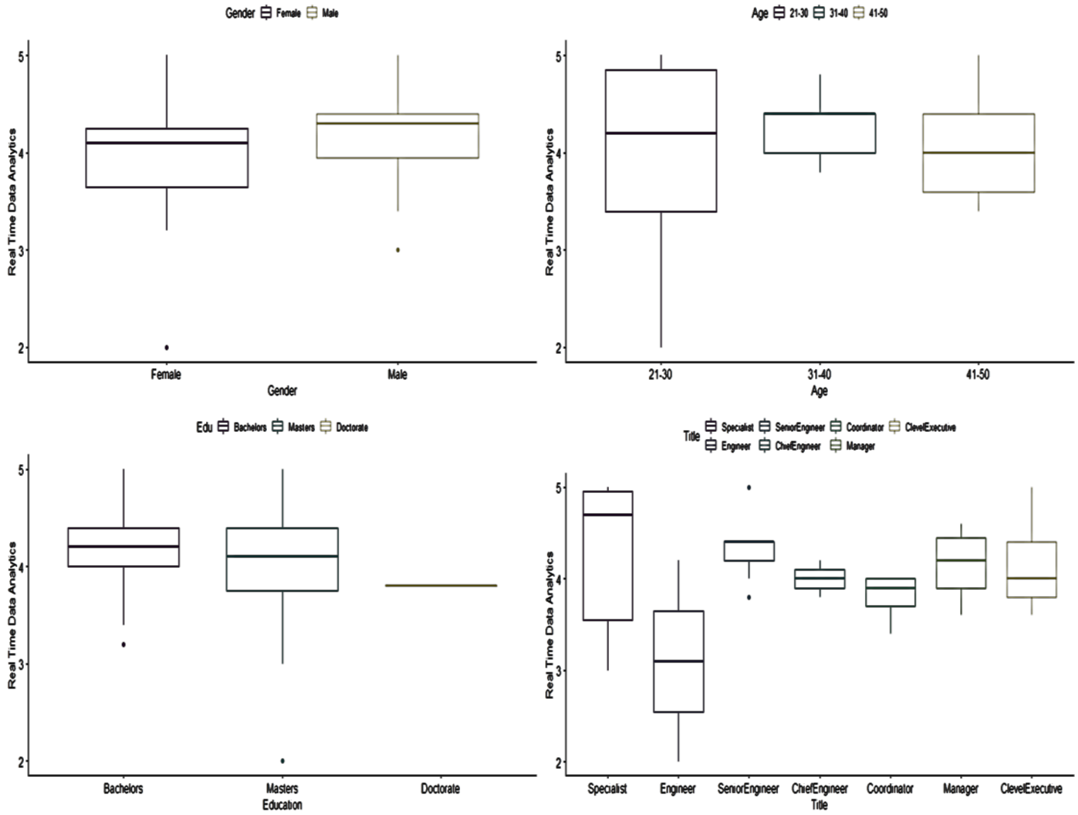

***Figure 20*. Representation of the assessment made by the respondents regarding the contribution of real-time data analytics based on the respondents' demographic characteristics**

When we interpret the graphs in Figure 20 one by one, it is seen that the average score is higher in males than in females on a scale ranging from 1 to 5. The average for the ages between 21-30 seems to be over 4. The results of the questionnaire showed a more stable distribution among the employees between the ages of 41-50 and the average is around 4. For employees between the ages of 31-40, the average seems to be above 4 points. When we look at the results that are provided based on the level of education of the respondents, it is seen that the when the respondents have a bachelor's degree, a more stable distribution is achieved and a score above 4 is observed. On the other hand, it is seen that a more scattered pattern occurs for the respondents who have a master's degree.

4.1.5. Cost Reduction Overview

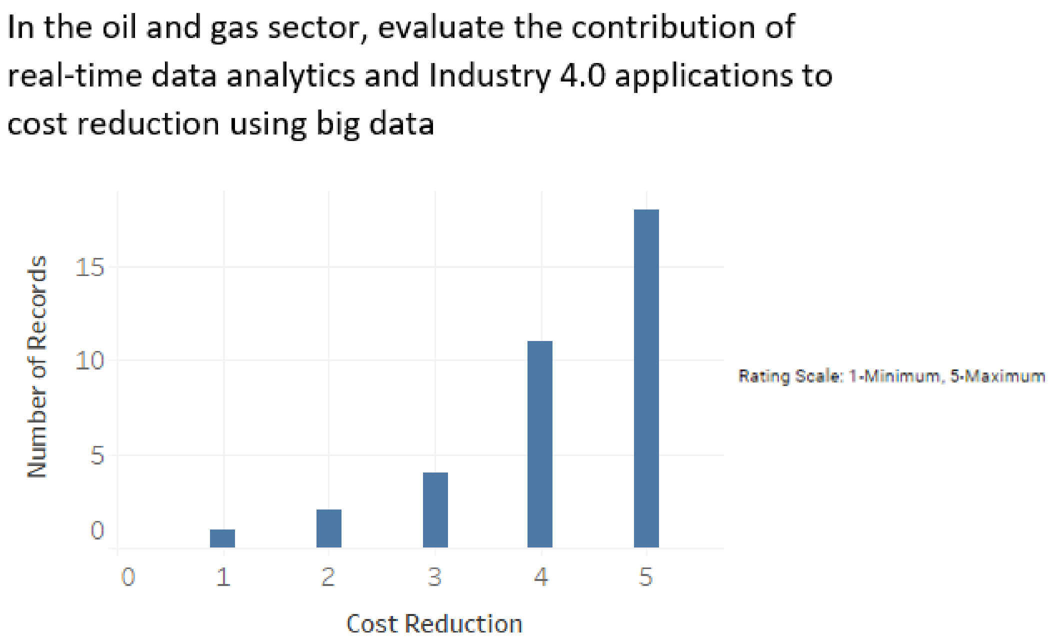

***Figure 21*. Assessment of the real-time data analytics' and Industry 4.0's contribution to cost reduction in the oil and gas sector**

When we look at the scoring made in consideration of the real-time data analytics' contribution to cost reduction in oil and gas sector, it is seen that 18 people gave 5 points, 11 people gave 4 points, 4 people gave 3 points, 2 people gave 2 points and 1 person gave 1 point (Figure 21), which means the majority of the respondents gave high points. From the results, it is inferred that the effect of real-time data analytics on cost reduction is high. It is seen that the information technology systems employing real-time data analytics have an impact on the reduction of production cost in the oil and gas sector.

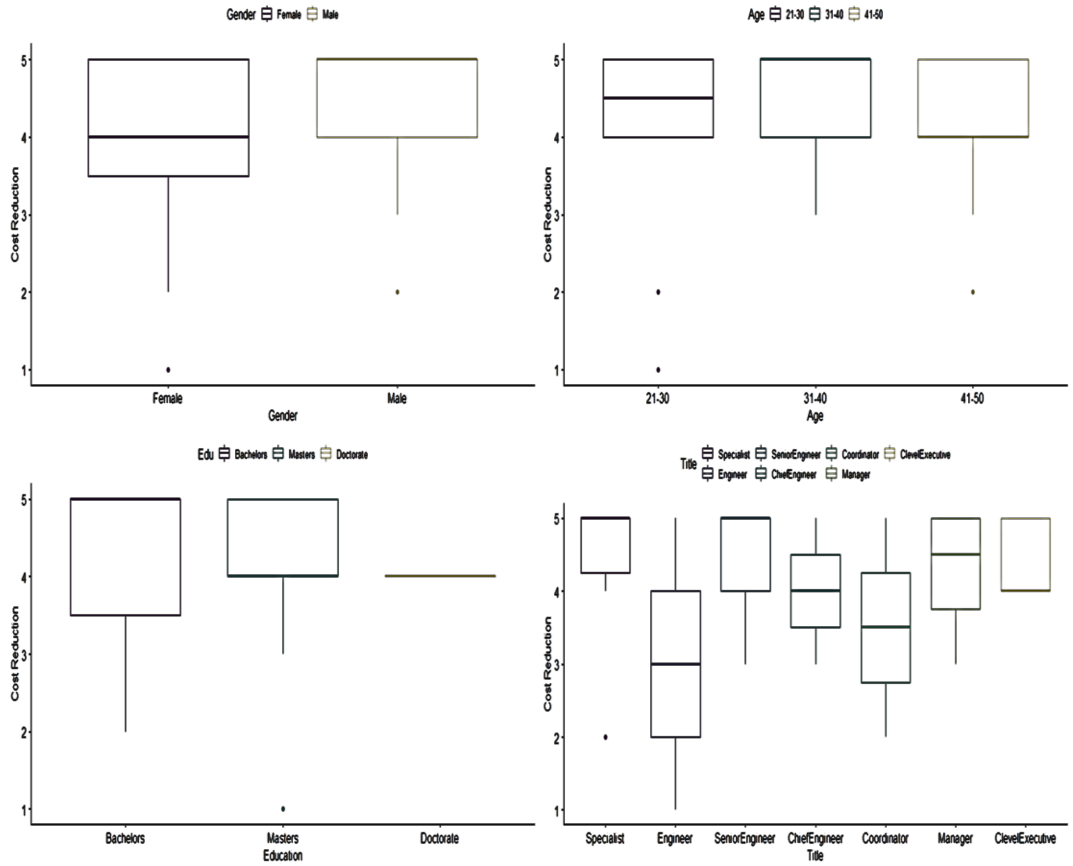

***Figure 22*. Representation of the scoring made by the respondents regarding the real-time data analytics' contribution to cost reduction based on the respondents' demographic characteristics**

When we look at Figure 22, it is observed that there are some differences among variables based on demographic characteristics. However, no difference was found in the results according to the one-way ANOVA test (see Appendix D, Table 15). The p.value for each variable was higher than the statistical significance level of 0.10. Based on this information, we can say that there is no statistically significant difference between the participants' opinions regarding the cost reduction based on their demographic characteristics.

4.1.6. Equipment Uptime Overview

Preventing equipment failures is one of the benefits offered by Big Data systems (Becker, 2016). By ensuring the long-lasting operation of the equipment, more production can be achieved in the oil and gas sector along with further cost reduction (Becker, 2016). When we look at Figure 23, it is observed that the majority of the participants gave 5 and 4 points to the question evaluating the contribution of real-time data analytics and Industry 4.0 applications to the life expectancy of the machinery and equipment in oil and gas industry. According to the results of the online questionnaire conducted on 36 people, 15 people gave 5 points. The number of people giving 4 points is 14 while 5 people gave 3 points and 2 people gave 2 points. Thus, we can deduce that real-time data analytics contributes to profitability by directly reducing the equipment costs.

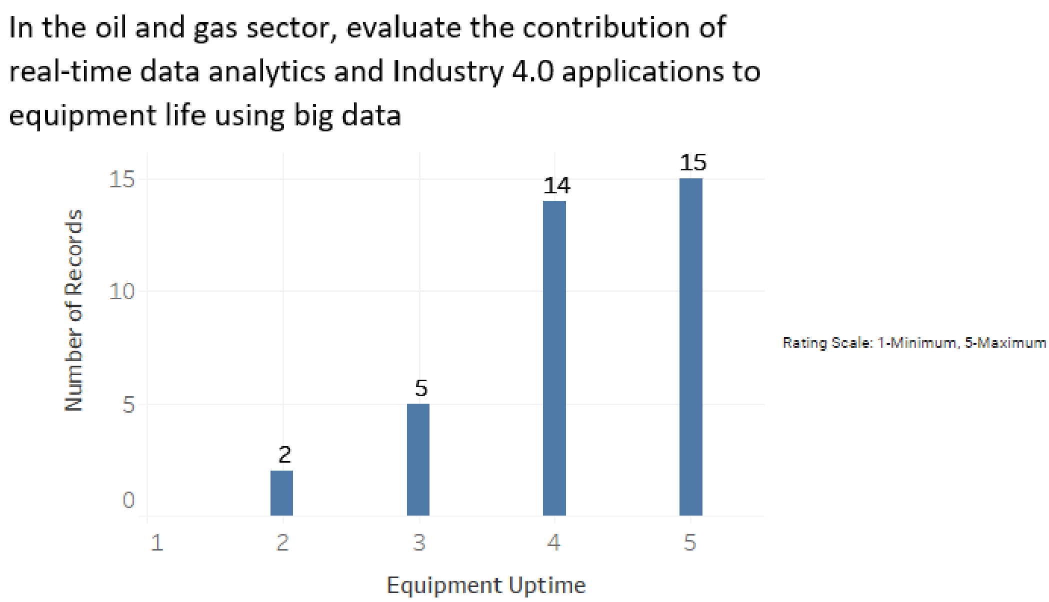

Figure 23. **Representation of the points given by the respondents to the question evaluating the contribution of real-time data analytics and Industry 4.0 to the oil and gas sector in terms of increasing the life expectancy of equipment**

Figure 23 indicates that real-time data analytics applications have competencies to help improve asset reliability and predict equipment performance. We see that the performance of the equipment can be improved by analyzing and interpreting Big Data. Thus, management of the equipment life is important for the new industrial revolution. Applying digital technologies used in the oil and gas industry to equipment can help production machines to do their job better. This can maximize the service life of the equipment (Matt el al., 2015).

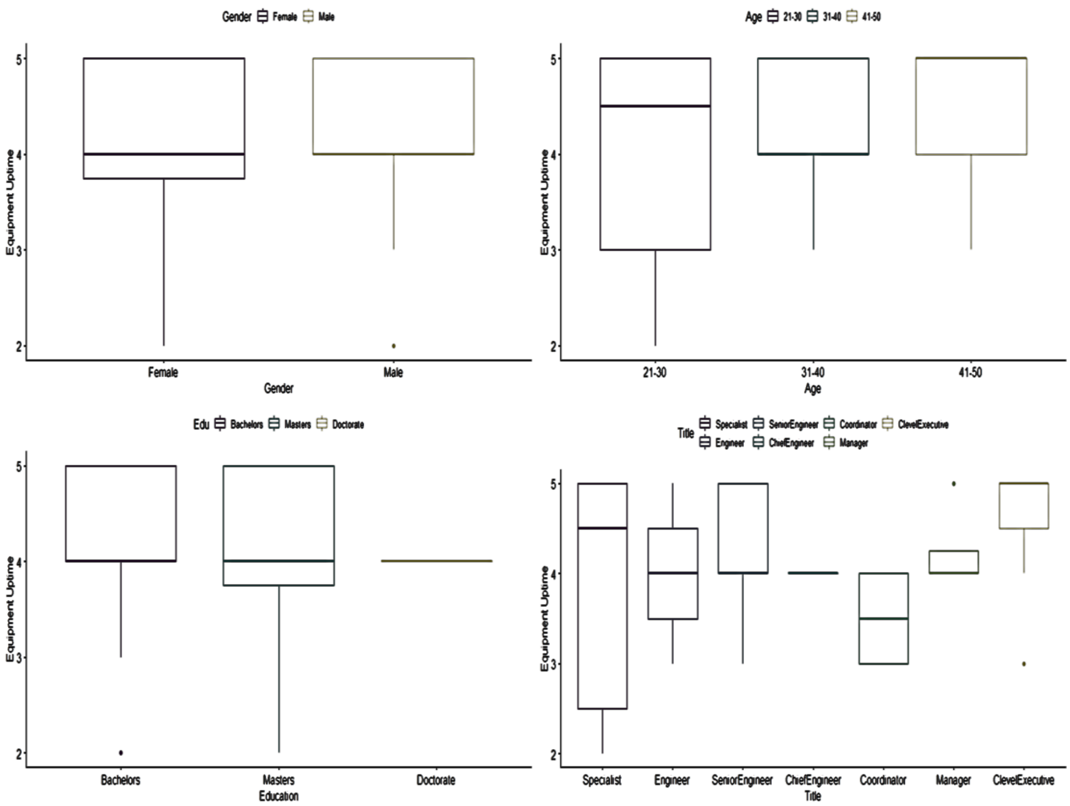

***Figure 24*. Representation of the points given by the respondents regarding the contribution of Big Data use to the life expectancy of the equipment according to respondents' demographic characteristics**

Figure 24 shows whether the demographic characteristics of the employees have an effect on their opinions about the extension of equipment life by the use of real-time data analytics. The biggest differences appear in consideration of titles. C-Level managers' faith in the contribution of Big Data use to equipment life was relatively high compared to other titles. When we look at the age groups, it is seen that the participants who are between the ages of 21-30 assess the contribution to the equipment life as lower than the other age groups. When the statistical results were analyzed, no significant difference was found at the level of 0.10 (see Appendix D, Table 16).

4.1.7. Operations Speed Overview

In the oil and gas sector, improving operational speed is expected to make a high contribution in terms of transaction volume (Perrons & Jensen, 2015). In this context, as can be seen in Figure 25, questionnaire participants evaluated the contribution of real-time data analytics and Industry 4.0 applications to the sector. As a conclusion that can be drawn from this evaluation, it was seen that a majority of 75% evaluated the contribution of the real-time data use between 4 and 5 points.

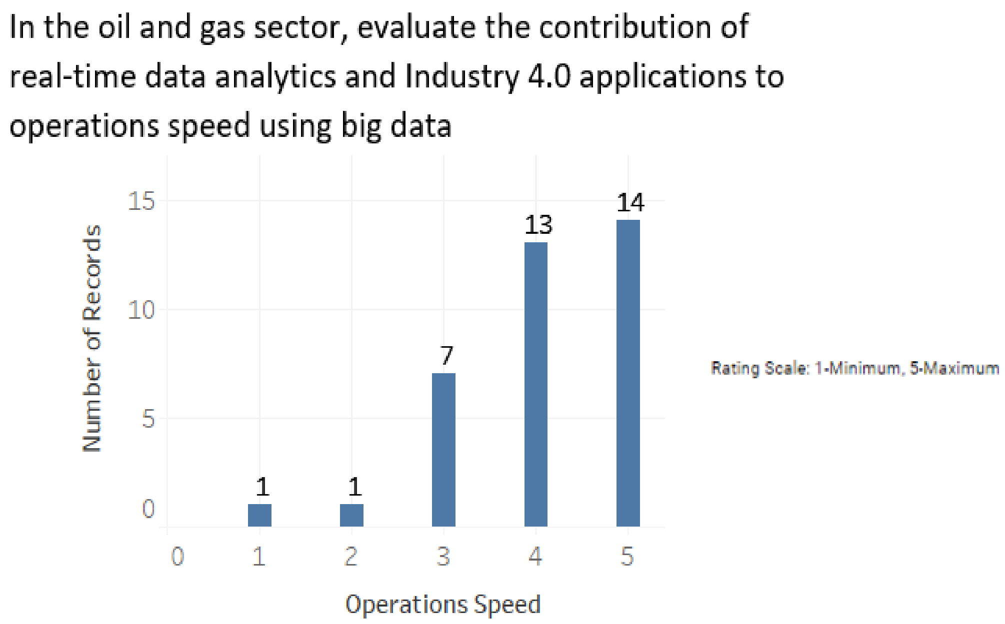

Figure 25. **Representation of the points given by the respondents to the question evaluating the contribution of real-time data analytics and Industry 4.0 to the oil and gas sector in terms of operation speed**

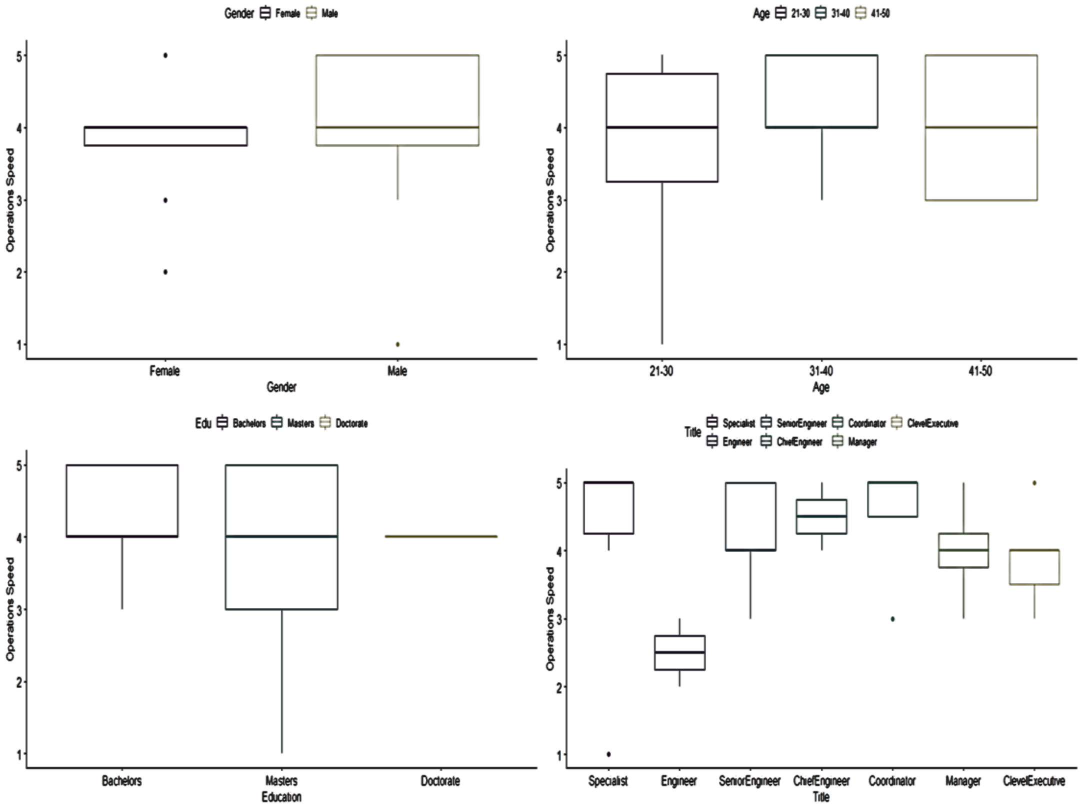

***Figure 26*. Representation of the points given by the respondents regarding the contribution of Big Data use to operation speed according to respondents' demographic characteristics**

We can see the scoring for the effect of real-time data analytics on operation speed based on demographic characteristics in Figure 26. As seen in the figure, the participants with the title of engineer evaluated the contribution to the operation speed below 3 points on average. As the expertise level increases and it comes close to the management level, scoring gets higher. When the differences were analyzed statistically by ANOVA method, no statistically significant difference was found at the level of 0,10 (see Appendix D, Table 17).

4.1.8. Product Quality Overview

Product quality is of great importance for the oil and gas sector in terms of profitability (Rüssmann et al., 2015). If the specs of petroleum products can be accurately predicted, it is easier to produce products with higher profitability and that are consistent with production planning (Rüssmann et al., 2015). Referring to Figure 27, we observe that the online questionnaire responses confirm this information regarding product quality. Approximately 86% of the respondents considered the contribution of real-time data use to product quality in the petroleum sector as high.

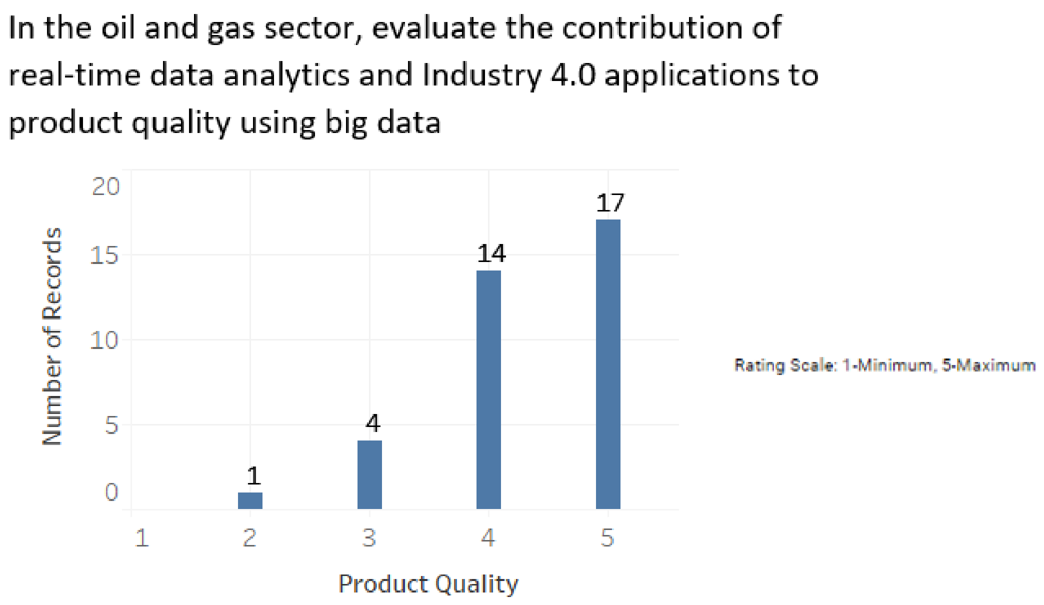

***Figure 27*. Representation of the points given by the respondents to the question evaluating the contribution of real-time data analytics and Industry 4.0 to the oil and gas sector in terms of product quality**

When we examine Figure 28 in detail, it is observed that there are several differences in the evaluation of the contribution of real-time data analytics use to product quality based on demographic characteristics. In particular, these differences appear as the age groups and titles change. In the 41-50 age group, the improvement of product quality with data analytics use was assessed as much lower. On the other hand, when we examine the answers in terms of titles, it is seen that the people at the level of engineers and coordinators give lower points compared to other title groups.

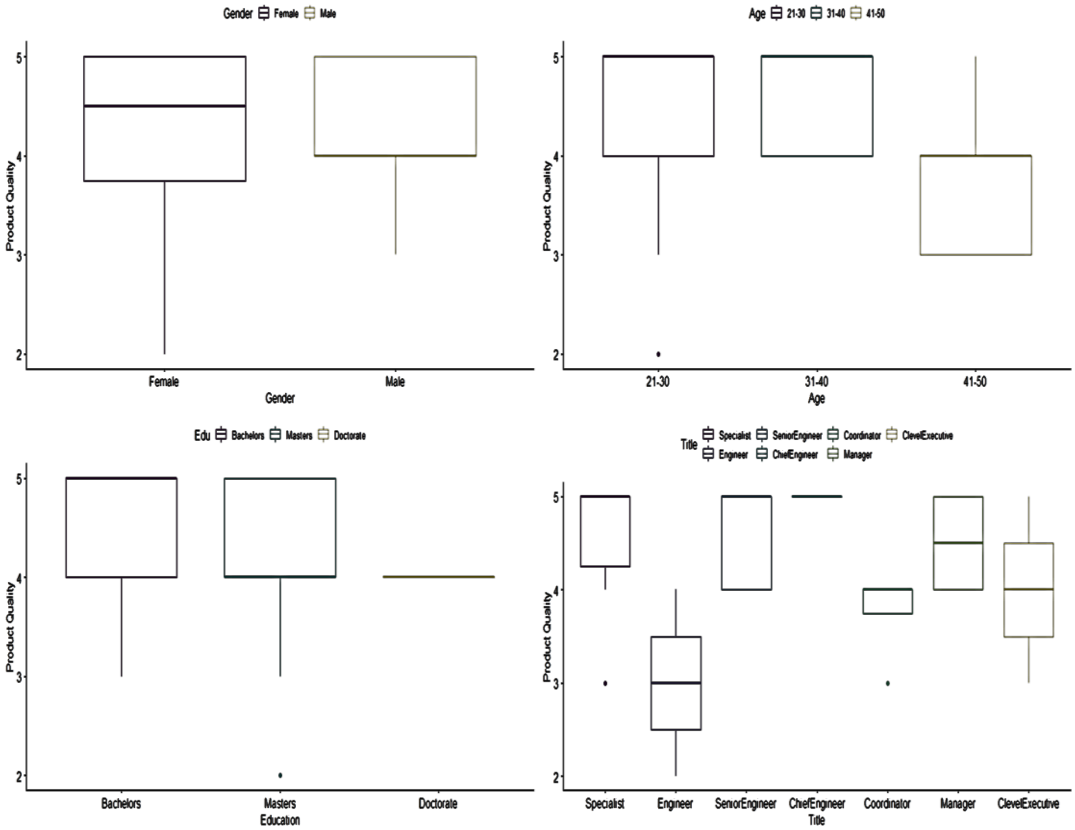

***Figure 28*. Representation of the points given by the respondents regarding the contribution of Big Data use to product quality according to respondents' demographic characteristics**

When the data were analyzed, statistically significant differences were determined for the age groups and title groups with a significance level of 0.05 (see Appendix D, Table 18). When we look at the differences between age groups, it is seen that the biggest difference is between 41-50 and 31-40 age groups (see Appendix D, Table 19). In order to test the accuracy of this inference, first of all, the assumption of normality was tested. However, according to the Shapiro-Wilk test, errors at the 0.01 significance level did not appear to be normally distributed. Therefore, it would not be right to use ANOVA analysis here. In the absence of ANOVA, the non-parametric statistical test is the Kruskal-Wallis rank test. In this case, the Kruskal-Wallis rank-sum test was used as an alternative. The resulting p.value is 0.02882 (see Appendix D, Table 20). At the 0.05 significance level, the hypothesis of equality between age groups was statistically rejected. When we examine the differences between the title groups statistically, it is seen that the biggest difference is between specialist and engineer roles (see Appendix D, Table 21). When we test the normality assumption for ANOVA, it is concluded that the normality assumption cannot be rejected at a significance level of 0.01 (see Appendix D, Table 22). When we test the homogeneity of the variances, p.value is calculated as 0.59. Based on this information, we can assume that the variances are not different between the groups and we can, therefore, rely on the results of the ANOVA statistical test (see Appendix D, Table 22).

These differences regarding the evaluation of the contribution to product quality will be examined in detail in the interview section of the thesis and the fields that need to be improved regarding the oil and gas sector will be investigated. Findings of the interviews will be combined with the results of the questionnaire analyzes and they will be evaluated in order to make policy recommendations.

4.1.9. Workplace Safety Overview

Workplace safety is very critical for the oil and gas sector (Aveva, 2018). If predictive measures can be identified to meet the needs of the oil and gas sector, safety gains are expected to be significant (Aveva, 2018). Therefore, using real-time data analytics to increase workplace safety is a potential gain for the oil and gas industry.

The scoring made by the respondents regarding the contribution of Big Data use and the production of analytical results in real-time to workplace safety is represented in Figure 29. Out of 36 participants, 16 people scored 4 points on a scale of 1-5. 9 people gave 5 points. It can be understood that, workplace security can be improved by real-time data analytics methods in the oil and gas industry. Therefore, we can state that statistical analyses and literature findings match each other.

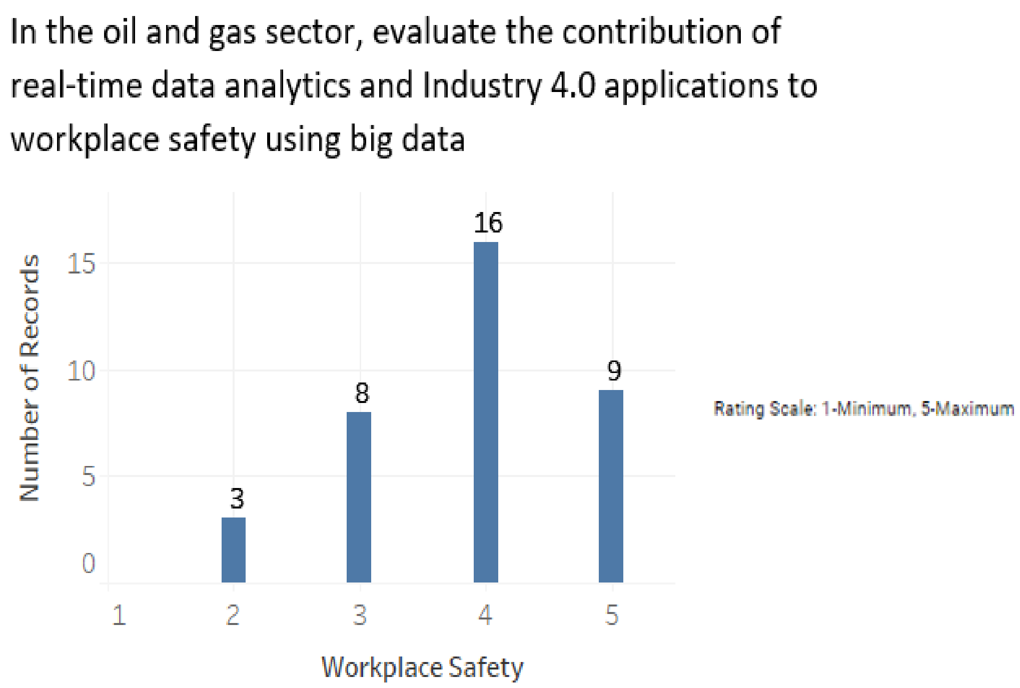

***Figure 29*. Representation of the points given by the respondents to the question evaluating the contribution of real-time data analytics and Industry 4.0 to the oil and gas sector in terms of workplace safety**

In terms of workplace safety, the difference between the opinions of the questionnaire participants can be examined in detail in Figure 30 based on their demographic characteristics. When we look at the gender variable, male participants voted higher on average. In addition, participants between the ages of 21-30 considered data analytics use as more important in terms of workplace safety than other age groups. When the differences were analyzed statistically by ANOVA method, no significant difference was found at the 0.10 significance level (see Appendix D, Table 23).

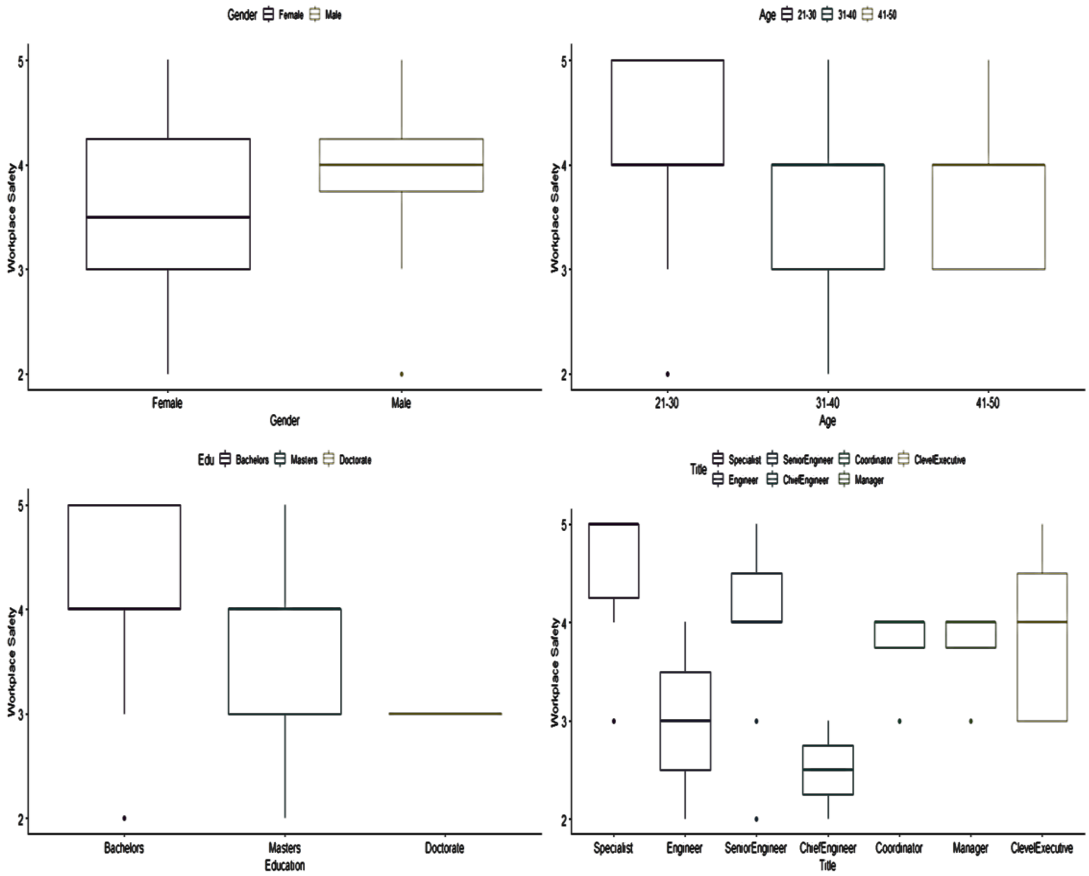

Figure 30. **Representation of the points given by the respondents regarding the contribution of Big Data use to workplace safety according to respondents' demographic characteristics**

4.1.10. Multivariate Association and Dimension Reduction Analysis

Correlation shows the direction and strength of the linear relationship between two or more random variables in statistics. We can say that there is a positive correlation between two variables if one of the variables increases when the other one increases. Correlation shows the linear relationship between two or more variables. By looking at the relations between the variables, we can determine the variables that are correlated with each other and we can design technology policies based on the information that would be derived from these correlations.

The Pearson correlation analysis of the variables used in the questionnaire can be seen in Figure 31. Dark colors represent a higher correlation. When we look at the overall figure, we do not see any inverse correlation among any of the variables. When we look at the correlations with a high value, it is seen that the variables coded as "RealTimeDataAnalytics" and "CostReduction" have the highest level of correlation between each other. Therefore, it is concluded that the employees indicated real-time data analytics use and cost reduction as highly correlated. In addition, real-time data analytics was found 70% correlated with both equipment uptime and operation speed. Correlation between real-time data analysis and other variables was found to be around 60%.

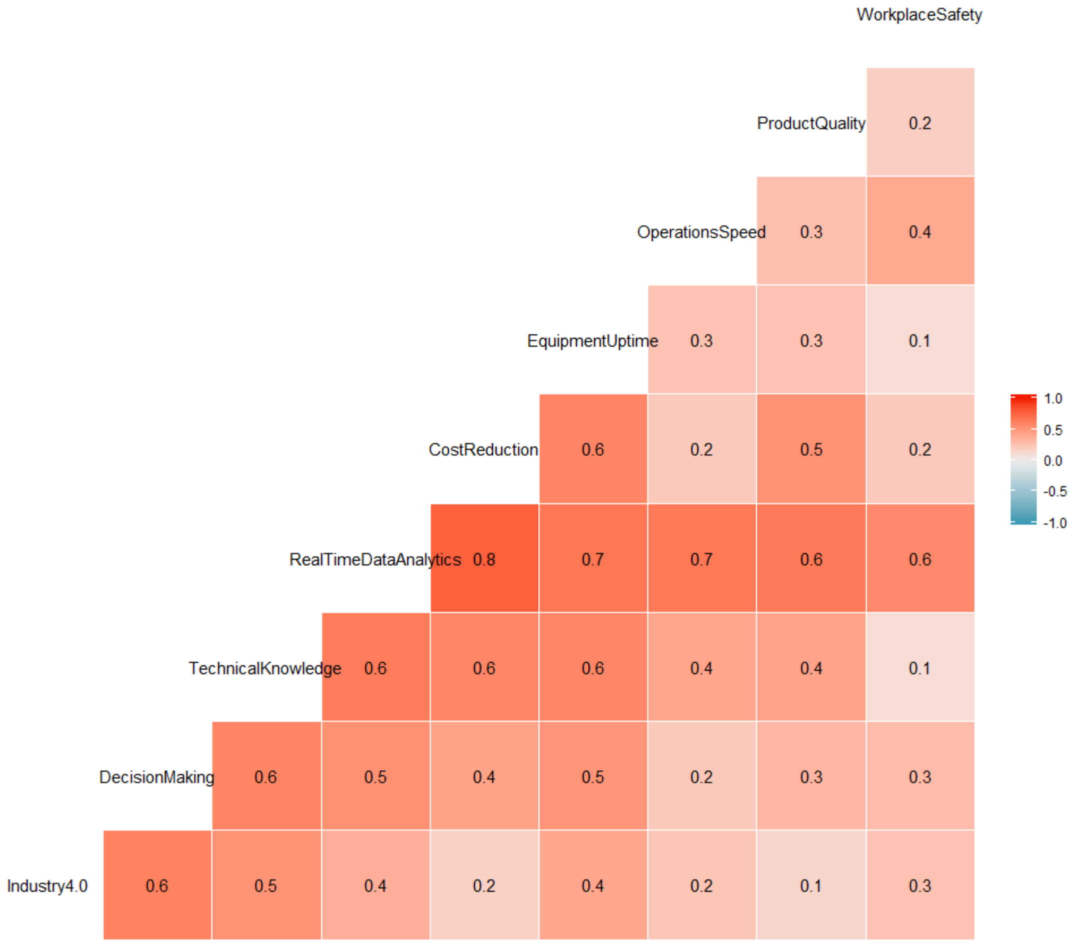

***Figure 31*. Correlation analysis of the variables assessed in the online questionnaire**

When we focus on the lowest values of correlation represented in Figure 31, we see a value of 10% correlation which represents the level of association between technical competence and workplace safety. At the same time, an association value around 0.10 was also observed between extending equipment life and improving workplace safety. Similarly, an association value close to 0.10 has been identified between Industry 4.0 and product quality. On the other hand, a low association value about 0.20 has been observed between reducing costs and increasing operational speed. In addition, a low correlation of 0.20 was found between workplace safety and cost reduction. When we test the hypotheses established for the thesis with correlation method, we can see that the hypotheses H1, H2, H3, H4 and H5 mentioned in Section 3.4 cannot be rejected (see Appendix D, Figure 38). Therefore, in the 95% confidence interval, we can state that real-time data analytics has a significant and positive effect with cost reduction, equipment uptime, operations speed, product quality and workplace safety.

The main purpose of the principal components analysis is to extract the maximum variance from the data set based on each component. The principal component analysis is a solution for the researcher who wants to briefly represent the result derived from a large number of variables by using a smaller number of components. PCA is a mathematical technique of explaining information that a multivariate dataset yields with fewer variables and minimum information loss. In another definition, PCA is a transformation technique that allows the size of the dataset containing a plurality of interrelated variables to be reduced to a smaller size while preserving the data in the dataset. PCA reduces dimensionality in large data datasets. The variables obtained after the transformation are called the basic components of the first variables. Statistical assumptions of PCA are checked and verified before starting PCA analyses.

Figure 32 shows how we can reduce the data set to less than nine variables according to the results of the principal component analysis. Moreover, we can see in the figure that 47.6% of the total variance is achieved through the reduction of only one component. It reaches a total value of 66.2% with two components and 77% with three components. One of the most important characteristics of the basic components is that the correlation between these components is zero. This prevents the loss of data and makes the maximization of the available information possible with the minimum variable.

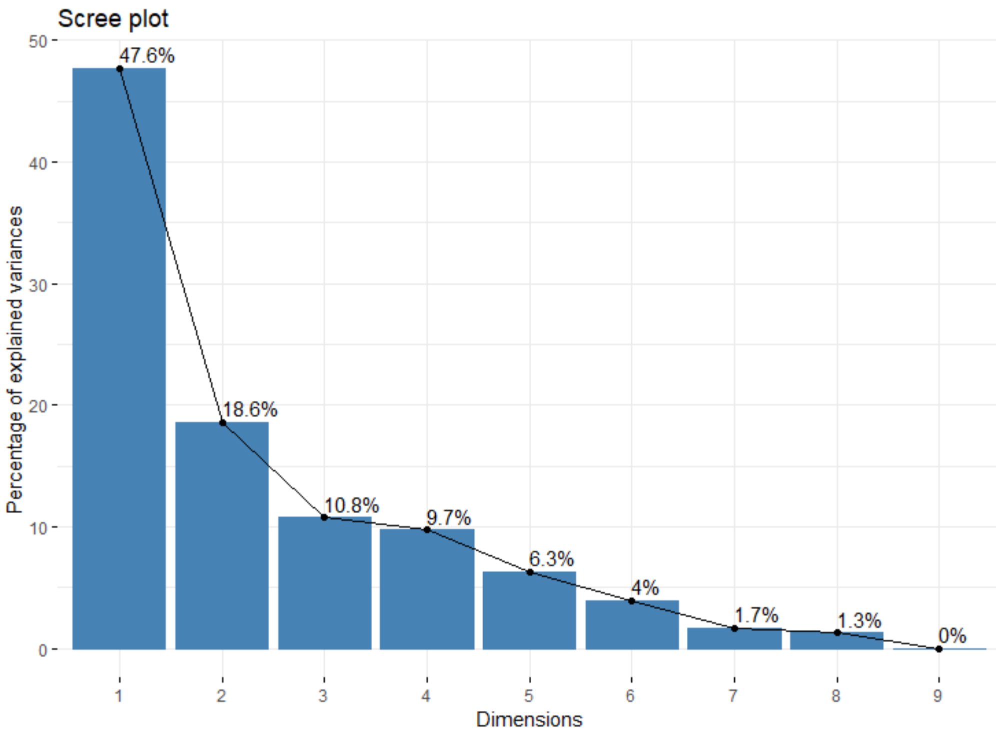

***Figure 32*. Reduction in the number of variables for the online questionnaire results after PCA is performed**

When we examine Figure 33, we can see which variables are used to collect the most information. Accordingly, the first component is most affected by the reduction of costs. Numerically, the first component is affected by the reduction of costs with a value of 28.31%, by extending equipment life with a value of 15.6%, by real-time data analytics with a value of 14.16% and by operating speed with a value of 13.91%. When we look at the second component numerically, we see that the rate corresponding to operation speed is 38.14% and to workplace safety is 31.09%. Therefore, the most intense data-related variables appear to be cost reduction, operational speed, equipment uptime, real-time data analytics, and workplace safety.

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5	Dim.6	Dim.7	Dim.8	Dim.9
Industry 4.0	1.604	0.07	1.57	7.22	19.631	8.97	32.159	28.75	0
Decision Making	4.218	0.3	0.05	5.95	18.73	14.94	55.61	0.17	0
Technical Knowledge	5.215	0.75	3.5	0	3.71	12.72	10.67	63.40	0
Real Time Data Analytics	14.16	0.46	0.215	0.1	0.11	1.52	0.01	0.07	83.3
Cost Reduction	28.31	18.28	8.06	1.28	24.483	12.54	0.15	3.53	3.33
Equipment Uptime	15.6	10.05	15.61	19.94	0.01	35.227	0.04	0.13	3.33
Operations Speed	13.91	38.14	28.01	9.75	3.80	0.788	0.802	1.451	3.33
Product Quality	9.497	0.812	7.802	37.335	29.459	11.661	0.05	0.048	3.33
Workplace Safety	7.471	31.09	35.17	18.40	0.045	1.556	0.492	2.420	3.33

***Figure 33*. PCA contribution analysis of the online questionnaire variables**

After identifying highly meaningful data among the components, we can review our PCA graph from Fig. 34, showing data that tends to coexist in the same direction. Accordingly, when we examine the relationship between the two most important components (66.2%), we observe that the equipment uptime has a strong relationship with the cost reduction. Similarly, operational speed and workplace safety seem to have a strong relationship in the same direction. The conclusion to be drawn from this information seems to be that the equipment uptime is directly related to cost reduction. In addition, the figure shows that providing a better operational speed will help to enhance workplace safety. Real-time data analytics and product quality also reflect a similar and strong relationship. Accordingly, we can state that the real-time data collection has a significant impact on the preservation of product quality.

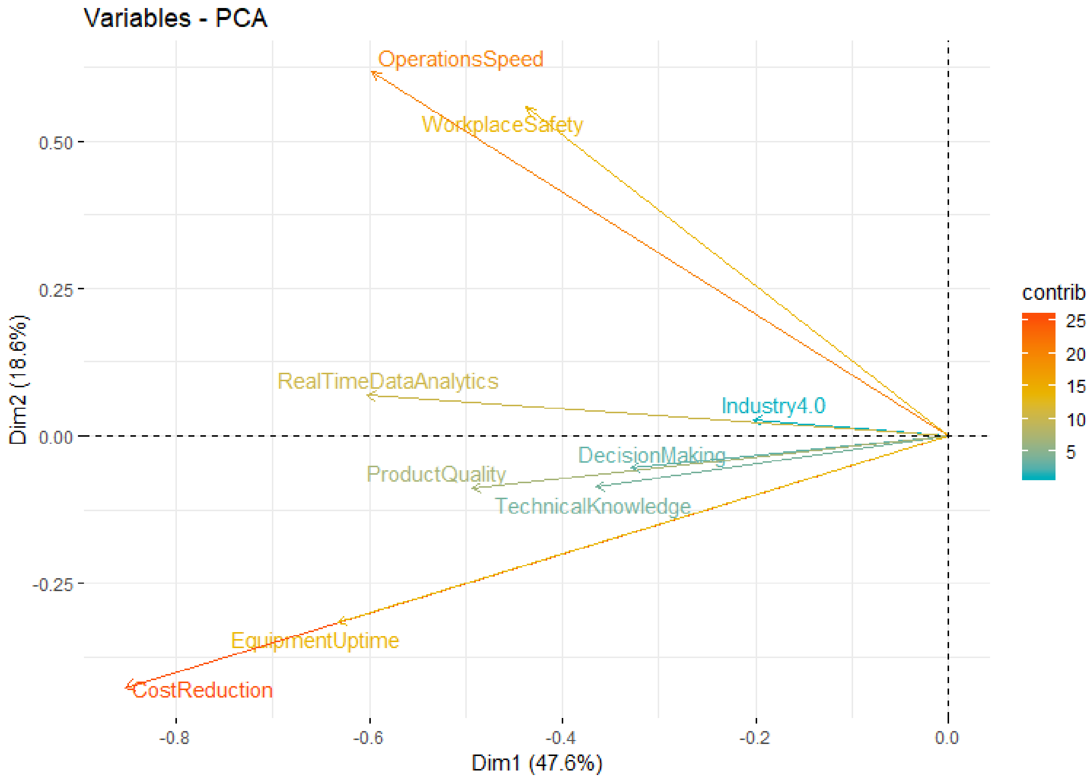

***Figure 34*. PCA association analysis of the online questionnaire variables**

It is possible to utilize certain techniques to determine the size of a scale developed to use in research. Factor analysis is one of these techniques. The main purpose of the factor analysis is to reduce the number of basic dimensions to facilitate the interpretation of the relationships between many variables considered to be related. Factor analysis is a technique used to derive fewer independent variables and new independent variables (factors) by using covariance or correlation matrix of data. Factor analysis differs from most other techniques. It is not designed to test hypotheses or to show that one group is significantly different from another. Factor analysis is used as a data reduction technique. It receives a large data set and looks for a way to reduce or summarize that data using a smaller set of factors or components. This is done by searching for stacks or groups between the correlations of a set of variables. Such a process is not possible to handle with the naked eye. Factor analysis can also be used to reduce a large number of related variables to a more manageable number before using them in other analyses, such as multiple regression or multivariate analysis of variance. Statistical assumptions of Factor analysis are checked and verified before starting Factor analyses.The results of the factor analysis applied to the online questionnaire variables can be seen in Table 24 (see Appendix D). In the principal component analysis, we found that approximately 66.2% of the data could be derived from two components. For this reason, the number of factors was considered as two and the analysis of these factors was performed. The hypothesis that two factors were sufficient to explain hidden factors behind the data obtained could not be rejected at the 0.05 significance level. Since the p.value is 0.0648, the hypothesis could not be rejected. Factor analysis is generally used to find hidden factors behind the variables. When we look at cumulative variance, it shows that two factors yield approximately 50% of the information. We see that real-time data analytics, operational speed, cost reduction, and product quality have a high impact on Factor1, which we can call profitability factor. These variables, which generally affect profitability, seem to be effective on the same hidden factor as they represent profitable transactions according to questionnaire participants. Therefore, it can be assumed that the employees take the profitability of the variables into consideration and fill in the answers in this direction. Factors such as Industry 4.0, decision support systems and technical competence are mostly influenced by Factor2. According to this information, we can call the second factor as the technical depth factor. While the employees are responding to the questions regarding decision-making systems, the implementation of Industry 4.0, and infrastructure adequacy, they mostly consider the technical depth, difficulty, and applicability of the process.

4.2. Analysis of the Findings from the Interviews

Some demographic characteristics of the 15 interviewees (EMPs: Employees interviewed for the thesis) are given in Table 6. Employees generally believe that Industry 4.0 applications and data analytics make it possible to access process data more easily, to obtain supply chain visibility, to monitor production and to make reasonable decisions in the company. Moreover, they think that these applications are beneficial for increasing operational speed, improving workplace safety and reducing costs.

Table 6

Demographic characteristics of the 15 EMPs who have been interviewed

EMP #	Gender	Education	Title	Age	Experience
EMP1	Male	Bachelor's	Specialist	21-30	1-5
EMP2	Male	Master's	Chief Engineer	31-40	10-15
EMP3	Female	Doctorate	Senior Engineer	31-40	5-10
EMP4	Male	Master's	C-Level Executive	41-50	20+
EMP5	Male	Bachelor's	Engineer	21-30	1-5
EMP6	Male	Bachelor's	Specialist	21-30	1-5
EMP7	Male	Master's	Senior Engineer	31-40	5-10
EMP8	Female	Doctorate	Coordinator	31-40	10-15
EMP9	Male	Bachelor's	Senior Engineer	31-40	10-15
EMP10	Male	Bachelor's	Specialist	21-30	1-5
EMP11	Male	Master's	Senior Engineer	31-40	5-10
EMP12	Male	Master's	C-Level Executive	41-50	20+
EMP13	Male	Master's	Manager	31-40	10-15
EMP14	Male	Bachelor's	Specialist	31-40	1-5
EMP15	Male	Bachelor's	Senior Engineer	31-40	5-10

Source: Based on the results obtained from the questionnaire.

4.2.1. Industry 4.0 Overview

Most participants stated that real-time data analytics applications had a positive effect on business processes and that they observed this positive effect more on the flexible production processes. Most of the participants stated that they have a significant amount of knowledge about Big Data, data analytics, and real-time data analysis and that the company gives strategic importance to this issue. On the other hand, it was also reported that there were some deficiencies in the adoption and dissemination of digital technologies within the organization. In this context, they stated that more training should be provided to employees on these issues.

The interviewees stated that senior management adopts a positive approach supporting the use of Big Data and data analytics. Except for EMP1 and EMP3, all participants stated that their managers attach importance to data analytics and digitalization. EMP8, EMP10, and EMP11 stated that they do not pay much regard to Industry 4.0 concepts while forming their business strategies since their departments are already functioning properly and they do not need new methods to employ. EMP7 and EMP2 stated that real-time data analytics have a great impact on the profitability of the company and they also attached great importance to it since it makes data-based transactions possible and affects the operations. They also stated that, while preparing their daily business plans, they make use of the results of real-time data analytics and make their decisions according to these results.

EMP4 and EMP11 indicated that the biggest contribution of Industry 4.0 applications is the continuous monitoring of production data. EMP15, on the other hand, stated that the data collected previously at certain times were processed faster with data analysis methods and mentioned that it accelerated the operation processes. He stated that the effect of operational speed on the oil and gas industry is very important and if the actions are taken quickly in the units, it can help to make a daily profit of millions of dollars. In addition, EMP6 stated that real-time data analytics are also used to estimate sales. He stated that they can plan the supply chain more details accurately thanks to a system that can predict the number of future sales using real-time data. In this way, they emphasized that they can reduce costs and increase operational efficiency.

According to EMP7 and EMP8, the oil and gas industry is a capital-intensive industry. However, the construction phase of the projects is long and requires big investments. On the other hand, digital technologies are developing rapidly and the opportunities they bring should not be missed. In addition, the oil and gas industry is in the midst of digital transformation, and the steps it will take at this point are crucial to keeping up with Industry 4.0 (EMP1, EMP2, EMP10, EMP11, and EMP14). In this respect, there are many who think that the oil and gas industry should be quick to take the required steps. Most of the participants stated that the acquisition of new digital equipment was requiring long-term senior management approval due to the high costs. Participants say that the importance of IT teams during the transition to Industry 4.0 applications is increasing for companies since the technological applications here are directly related to a well-designed IT infrastructure, talented workforce and decision-makers' vision. At this point, there are many who think that the roles of Chief Digital Officer on the IT side should stand out. They said that IT should represent the company at a higher level and accelerate the acquisition of digital technologies in this way. According to EMP10, the major advantage of the oil and gas industry was that there were sensors and an infrastructure already to collect data since it was always important for technicians to examine the status of operations. Based on this, EMP10 means that the oil and gas industry has already met the hardware requirements and has already established the necessary IT infrastructure in most fields. Therefore, the most important step is to adapt to automatic decision-making systems. Analytical studies are now proceeding in this direction (EMP10).

Oil and gas industry employees have also addressed some points that need to be improved for the sake of Industry 4.0 applications using Big Data systems. For example, the participants mentioned that the needs regarding the use of applications are constantly changing (EMP3, EMP4, EMP13, EMP14). Therefore, they stated that it would be more beneficial to analyze these continuously changing needs and solve the problems step by step. According to EMP13, the problems defined in terms of adapting to Industry 4.0 applications may change in time. Therefore, the applications should be developed step by step and transformed accordingly by the technical experts. It is stated that applications developed by processing real-time data will be able to respond to changing needs faster in this way. In addition, EMP12 stated that it is important for the manufacturing sector to obtain tax incentives for investments in goods and technologies that link physical and digital systems to make complex analysis in real time. He noted that the technology used in transition to Industry 4.0 applications is expensive. Thus, state support will make a significant contribution to companies (EMP12). According to EMP4, academy and industry cooperation plays an important role in the correct implementation of Industry 4.0 processes to companies. If secure data sharing environments can be provided between companies and universities, up-to-date information in the literature can be applied more easily in industrial companies. This will make the transition to Industry 4.0 easier (EMP4). He also stated that one of the most important factors in the spread of Industry 4.0 applications in the company is the negotiations with other technology companies. In this way, we have added the lessons learned by other companies to our knowledge and we have easily overcome the difficulties in the implementation phase (EMP4).

4.2.2. Decision Support Systems Overview

A positive approach to decision support systems that came with Industry 4.0 applications was also observed during the interviews. All participants stated that real-time data analytics results, which are monitored instantly from Big Data systems, help them in the decision-making process as they show the current state of business processes. According to EMP1, EMP2, and EMP9, with the real-time data collection, accident frequency rates and more detailed information about the accidents can be managed in refinery units. In this way, managers anticipate the occurrence of an accident and take preventive measures.

According to the results of the questionnaire, 33.3% of the participants strongly agreed, 50% of them agreed, and 16.7% of them neither agreed nor disagreed with the use of real-time data analytics in decision support systems to solve the problems experienced by the customers. 15 interviewees were asked to elaborate on this matter. In response, they stated that they use decision support systems in different works by making use of real-time data collected. For example, EMP9, EMP10 and EMP 12 stated that they could continuously monitor the petroleum products in the units during the production planning stages, thus they are able to make stock and supply chain plans accordingly. Similarly, EMP2 and EMP3 mentioned that the ability to monitor critical operations live (such as temperature, pressure, and oil flow values) in oil units helped them properly make the critical decisions that would greatly affect profitability. According to EMP8, due to the instant monitoring of production and oil processing stages, the actions are taken quickly which leads to great profitability considering the size of the oil and gas industry. For example, the instantaneous variables that can be predicted accurately such as the temperature and pressure values seriously change the quality of the oil production and thus it affects the profitability of the end product.

All of the participants stated that important product specifications of processed oil products such as temperature and pressure can be estimated by using artificial neural networks, machine learning, and statistical learning methods and these properties can be used in decision support system stage. They stated that complex processes in refineries were made more understandable by establishing dynamic simulation models, statistical modeling and mathematical equation systems thanks to Industry 4.0 applications using real-time data analytics methods (EMP2, EMP6, and EMP9).

4.2.3. Technical Competence Overview

We stated before that it is not easy to set up and implement Big Data analytics systems in companies and it is only possible with employees who can provide adequate technical support. We stated that real-time data acquisition with the help of sensors from the field, designing screens, running data analytics applications through these data requires high software knowledge and technical effort. Moreover, during the interviews, the participants stated that it is highly required to understand the real needs of the sector and Big Data applications. In this part of the thesis, the technical adequacy of real-time data analytics systems in the oil and gas industry is questioned.

52.8% of the employees stated that it was possible to analyze the products via real-time data analytics systems. During the interview, EMP1 and EMP4 stressed the importance of ensuring that the technical infrastructure needs to be robust and flawless. They said that the slightest data delay in these systems would change the way the operation proceeds, and that Big Data systems in the oil and gas industry and expert analytics software developers in the field must work to solve these challenges. According to EMP9, the fact that Big Data systems are working properly in the company is due to the fact that the company has employees with high technical competence. This is achieved through successful human resources practices and employment of the proper technologies (EMP9). According to EMP15, the performance of Big Data systems severely affects the way they do business. If the systems do not function properly, the possibility of making the wrong decision increases. Therefore, the correct selection of systems and having sufficient technological infrastructure affect the operational speed in the company.

4.2.4. Real-Time Data Analytics Overview

One of the areas where Industry 4.0 applications contribute to the manufacturing sector is to minimize the margin of error by combining digital decision-making methods such as machine learning and data analytics with real-time data, rather than identifying where deficiencies exist by looking at the reported past data. In this way, manufacturing companies can be one step ahead of their rivals in terms of making automatic decisions, reducing costs, extending equipment life, increasing operational speed, improving product quality and increasing workplace safety. In these complex systems, the importance of real-time data flow is undeniably high (Baaziz & Quoniam, 2014).

According to EMP5, the company was using previously recorded data to make analysis and proceed with strategic decisions in the past. Thanks to technology developing in parallel with the sector's needs, it is now possible to use instant data to make decisions simultaneously. Real-time data use helps to improve business and staff productivity within the company and optimize operational costs. It also allows the company to identify business opportunities, plan data-driven services, identify operational cost inefficiencies, and improve customer relationships. According to EMP11, rapidly improving performance thanks to real-time data analysis will contribute to the competitive position of the company through innovation and make the company flexible and able to quickly make strategic decisions. According to EMP6, the most important step in the transition to real-time data analytics use was to perform the strategic planning for the business. For this purpose, the human resources policies have been determined and employees that are capable of managing Big Data technologies have been selected. In addition, other technology companies were contacted to obtain information about the recruitment process. Open-source alternatives were considered and decisions were made based on previously applied examples.

4.2.5. Cost Reduction Overview

The respondents were asked to give examples of experience in reducing production costs and the applications of Industry 4.0 in production and also asked what these experiences meant for them. The employees gave their own business examples according to their departments. For example, employees working at the departments related to refinery said that they could reduce costs by anticipating the specs of valuable products such as gasoline and diesel with automatic quality estimators. By looking at the process data, they stated that they can achieve a high-quality end product and make the products more profitable without any extra expense thanks to the systems that can predict the specs for the end product beforehand. They stated that data analytics and machine learning applications make quality test automation possible by limiting the number of errors to generate. EMP4 and EMP8 stated that this leads to a reduction in scrapped products by ensuring better control over the production.

As another example, the participants explained that the planned maintenance of rotating equipment was carried out with real-time data analytics applications. They mentioned that rotating equipment is a critical part of the production in refineries. They predicted the probability of failure for this equipment and stated that they substantially reduced the production, sales and equipment costs (EMP2, EMP7, EMP8, EMP9, EMP10, and EMP11). In the oil and gas sector, the cost of equipment and machinery are quite high and possible breakdowns can lead to serious economic losses according to EMP2's opinion. Furthermore, not only the economic loss is important here, but also a breakdown in machinery can lead to loss of lives as EMP2 mentioned. EMP8, on the other hand, provides an example of how equipment can reduce costs by looking at it from a different aspect. According to EMP8, the equipment needs to run enduringly and properly so that the supply chain operations do not get interrupted. He said that real-time data analytics, which makes it possible to predict the condition of the equipment and machinery, can provide solutions. It can also help to make recommendations for maintenance planning and to reduce costs in this manner. According to EMP8, with the help of automated systems warning the employees about the maintenance and service requirements of the machinery, the best time to replace spare parts can be predicted, which would also help to cost reduction.

4.2.6. Equipment Uptime Overview

Employees stated that the equipment is a critical subject for refineries. It is underlined by each employee that each equipment is checked and operated with planned maintenance and that the oil and gas industry requires 24/7 maintenance. The participants, who thinks extending the life of the equipment through Industry 4.0 applications is possible, embraced a common opinion and stated the importance of predictive maintenance works. The equipment in each unit operates at high profitability rates. Since all the product is sold continuously, it is revealed that the systems that can learn from the data by estimating the state of the equipment and form an intelligent maintenance plan are very important according to participants.

Since machines can learn from past production cycles and make use of these data in the future, 24-hour production cycles that increase productivity are possible with less manual intervention. EMP11 and EMP12 mentioned that human errors can be eliminated by the complex process controls, thus it must be applied in product manufacturing. According to EMP1, the process generally proceeds as follows; data is continuously received from critical equipment and stored in Big Data systems. At the same time, data as about the past behavior of the equipment is collected, such as the behavior of malfunctioning or yielding abnormal values. Then, real-time data analytics applications using machine learning methods check for the equipment's temperature and pressure, recording meaningful relationships about past contradictions. Therefore, an action plan is formed suggesting the steps to take in order to bring back the equipment to its proper functioning condition. For example, the action can be in the purpose of optimizing the temperature and pressure values and prevent the equipment from malfunctioning. In this way, it provides the necessary information to engineers and technicians to extend the life of the equipment. Furthermore, it can make the necessary changes in the production lines by playing with the valve systems or other automated components where there is a need for instant decision-making.

4.2.7. Operations Speed Overview

While explaining how to improve the operational speed, EMP3, EMP11, EMP14, and EMP15 started with the supply chain examples. The production planning and sales departments said that by combining up-to-date data from production with market sales forecast data from analytical applications, the supply of the end product to the buyer can be handled in a much planned manner.

According to EMP4, which says that operational speed is directly related to non-stop and progressive production, the biggest advantage of real-time data analytics is the optimization of logistics operations. Considering that oil transportation is made with ships, real-time ship tracking data received from the satellite can be compared instantly with current refinery productions (EMP4, EMP5, EMP8, and EMP15).

According to EMP7, the company's production without interruption in the operational sense is very important for the profitability of the company. Because refineries work 24 hours a day, the slightest pause affects sales and can reduce the turnover rate. Therefore, improving operational speed through real-time data analytics was an important step for the company. For all these to be implemented correctly, the transition process had to be well managed. The company was able to keep up with the changes in the sector in terms of technology (EMP7). For this purpose, project management software has been designed to be more flexible and adaptable to changing needs. According to EMP1, the company has frequently reviewed project time plans and always made its employees feel the support of top management. According to EMP9, the company decided to invest in R & D and technology centers to maximize real-time data analytics applications. R & D and technology teams were formed to conduct research on real-time data analytics use. It was aimed to be close to universities by opening offices in different technopark campuses. In this way, it was aimed to get better academic support for the research studies.

4.2.8. Product Quality Overview

For nearly 15 years, manufacturers have significantly reduced errors using lean and six sigma programs. They also have been able to improve product quality by significantly reducing waste and deviations in the production process. But the process here was not automated. In industries where the consequences of the slightest changes in products, such as the pharmaceutical industry, are important, significant impacts can be achieved even through small improvements in product quality. For this reason, automatic analysis based on Big Data will contribute to the production sector in terms of product quality (McKinsey & Company, 2014).

In the previous chapters, we showed that in the oil and gas industry, data collected from production can be processed through intelligent software. According to EMP10, EMP11, EMP13, and EMP15, petroleum products are subjected to certain laboratory tests during production. Measurements were made on a daily or shift basis. According to the measurements here, chemicals that would affect the quality of the product in the production process were observed. However, due to the time lag, there were not enough precautions taken to make a positive impact on product quality. This is where Industry 4.0 applications that learn and decide together with Big Data come into play. According to EMP11, all data can be analyzed instantly and the effects of the past behaviors can be examined. Then the laboratory measurements can be made instantly according to the statistical correlations. Thus, product quality can be observed instantly. It makes taking precautions at the early stages of production possible and helps to increase the profitability of products. According to EMP4, the company has been working for many years to improve product quality. He pointed out that data security is the most important issue in the transition to real-time data analytics use to improve product quality. He stated that they are constructing data analytics systems with secure network infrastructure in order to produce accurate predictions. According to EMP12, the company organized awareness training in this respect. He stated that workshops are organized to raise awareness about real-time data analytics use in increasing product quality.

4.2.9. Workplace Safety Overview

Oil and gas sector is a key industry whose products have a wide area of usage and it operates under high volume manufacturing conditions. Using alarm systems is an indispensable part of security operations. Alarm systems are essential for the safety of the workplace and the smooth running of the production process (Srinivasan et al., 2004). Hence, alarms play an important role in the working life of operators and engineers. Alarm systems send alerts to give warnings about an unwanted event is about to occur or is occurring at the moment. Therefore, it has an important place in workplace safety. Moreover, workplace safety can be improved further thanks to systems that can combine past data and real-time data. For example, with the anomaly detection systems as a part of Industry 4.0 applications, we can learn why alarms occur and how to prevent them from occurring again in the future (Aveva, 2018).

According to EMP3 and EMP9, workplace safety is very important for the refinery sector, but it is implemented considering life safety in the first place rather than in consideration of profitability. For this purpose, alarms are set to give early warning signals as soon as critical process variables reach the predetermined extreme values so that technicians can take immediate action. According to statements of EMP13 and EMP14, the data collected from refinery operations are converted into reports at the end of the month and analyzed to ensure a trouble-free operation of the units. According to EMP10, the alarm reports help to predict the probability of errors to occur in the future operations and thus the continuity of the operations in the refineries is ensured and situations that may create weaknesses in terms of workplace safety are prevented. According to EMP11, they have always felt the support of the senior management in collecting the data from the production line in the purpose of increasing the workplace safety and its support provided them with the necessary motivation. He also stated that workplace safety is compatible with the company's digital strategy and it is decided that the problems related to the security of the units in the refinery can be solved analytically.

4.3. Policy Recommendations for Process Manufacturing Companies in Transition to Industry 4.0

During this study, real-time data analytics applications in the manufacturing sector are investigated. Based on the oil and gas sector, policy recommendations were made for the production sector. Policy-makers are becoming more worried about understanding the impact of policies that support production-based economic growth and technologies that affect the future of production (O'Sullivan et al., 2013). In this thesis, types of policies that should be adopted by production companies to get prepared for the digital world has been investigated through several methods. In light of research findings, policy recommendations will be made for manufacturing companies. Firstly, recommendations that would be beneficial to companies in the digital transformation process in terms of Industry 4.0 are considered.

- One of the primary findings is that companies need to have more skilled workforce to effectively manage systems that will be part of digital transformation. Given the time taken to train new recruits and retraining existing employees, strategic and long-term planning to create a proactive workforce will help to form comprehensive human resources policies.
- Manufacturing companies should direct their investments according to their production objectives, define their digital strategies and shape the digital transformation roadmap in the sector.
- Companies should invest in easily accessible technologies such as open-source ones that can be adapted quickly and have a significant impact on profit margin. The additional profit generated by the digital transformation should lead to a strong cycle of innovation within the company. With more automation and real-time data analysis, it would be possible to provide a better customer experience. Therefore, companies should invest in new technologies to enhance their internal processes. Since most of the industrial equipment that is currently in use is outdated and it may not have properties like product detection or digital product service capabilities. Companies which update their equipment and invest in future technologies can be one step ahead of their rivals by meeting the requirements of the digitalization process.

- We can conclude from the results of interviews and questionnaire that the needs of companies keep changing in time. Therefore, companies should embark on an active management style that keeps itself constantly updated according to always changing sectoral needs. The company's needs for digitalization must be identified and reviewed at regular intervals. These needs should be prioritized by the top management and project plans should be made in a shorter notice.
- Companies wishing to enhance their communication technologies and the collection of key information should consider making R&D investments that will enable the use of Big Data analytics, cloud technologies, high-performance computing, and applications of IoT, as well as technologies aiming to ensure security and privacy. They should establish technopark structures supporting R&D activities. Because they will be able to reach more technology and be closer to talented human resources. They should also take the power of the academy behind them by receiving support from the relevant departments of the universities. Investments in IoT applications, cloud computing, cybersecurity, and Big Data analytics should be supported by national policies. For this purpose, consultancy companies should be established with the support of the government, and product-oriented policies should be formed in order to meet the needs of production companies. In this way, dissemination of know-how within the company and throughout the other companies in the sector will be accomplished. One of the best examples of this method is the reciprocal visits of companies in order to realize their shortcomings and enhance their products and operations to meet the needs of the sector.

4.4. Policy Recommendations Mitigating the Effects of Challenges that Occur During the Process of Transition to Industry 4.0

It is often not easy for manufacturing companies to switch from classic systems to systems that make decisions automatically and perform automated transactions. In this part of the thesis, policy recommendations will be made for companies that make policies related to data analytics use and who are in the stage of benefiting from the financial advantages of Industry 4.0, or who have passed these stages and have difficulties in the process.

- Companies should start awareness-raising activities. This can be done through activities such as awareness-raising campaigns, training, and guidance studies. Companies should aim to increase their fund of knowledge with these activities and shape their organizational structure accordingly. Policies supporting industrial R&D investments related to industrial IT applications should be applied along with demand-side policies such as awareness-raising campaigns and training.
- Companies should develop a comprehensive innovation policy that promotes secure data sharing and encourages this approach throughout the related sectors. This policy should also include data sharing with the academics and their involvement in the projects. In this way, academicians can be more supportive regarding the sectoral studies.
- In a world where more and more companies are digitized, it is important to have a well-planned digital transformation strategy. Innovative business models that do not act quickly to develop a comprehensive IoT strategy fail companies and let them fall behind their competitors. Manufacturing companies should aim to provide their customers with the uninterrupted customer experience and neat solutions by using a strategy of digital transformation.
- The government should increase tax incentives related to Industry 4.0 applications for the private sector and public institutions. It should encourage the R&D activities of the companies that carry out studies on Big Data analytics, especially in the production sector.
- Mechanisms and programs to accelerate the transition process should be established in order to support the production companies on the digital transformation journey. To this end, the government should also encourage them to receive guidance and consultancy services that will be needed in the transformation.

4.5. A Brief Summary of the Research Findings

In this thesis, which explores the maturity of Industry 4.0 concept in the oil and gas sector, the concept of real-time data analytics and the contribution of Big Data applications to manufacturing companies in terms of costs, equipment, operations, products, and workplace safety are specifically emphasized. According to the findings of the study, the percentage of people involved in the data analytics applications and digitalization process in the oil and gas sector was 72.2%. Employees in the industry believe that real-time data analytics applications are beneficial to business processes. Employees also define the oil and gas sector as one of the most suited sectors for the adaptation of Industry 4.0 applications. It is concluded that real-time data analytics provide new opportunities for the manufacturing industry through the online questionnaire and interviews. The importance of having a vision in terms of increasing the added value through digitalization is demonstrated. It appears that these technologies should be used together with stakeholders in the sector to address the exact challenges. It is stated that the data obtained from the production equipment should be continuously processed together with a strong IT infrastructure and used in the decision-making process. In this way, the data obtained from the production processes can be used continuously to improve the operations. As a result of conducted interviews and the online questionnaire, it is found that the concept of data analytics is still not fully understood. Therefore, it can be concluded that companies should increase awareness training on data analytics. In addition, maintaining data quality and difficult user acceptance tests are among the biggest challenges for employees. By providing a secure data environment, it can be expected to increase the interaction between academia and industrial companies. Furthermore, according to the information obtained from the participants of the surveys and interviews, R&D investments in the field of data analytics should be made. With the support of top management, resources should be allocated to the studies in the field of data analytics. On the other hand, it is important for the continuity of Industry 4.0 applications that the data analytics algorithms running in live systems are reviewed regularly and made understandable to everyone in the company. The summary of technology policies can be found in Figure 35 and Figure 36.

	Recommendations for the manufacturing companies in terms of Industry 4.0 adaptation process
Skilled Workforce	• Establishment of a proactive workforce that is competent on big data analytics through comprehensive human resource policies
Roadmap	• Identifying the strategies that will increase production profitability through digitalization • Defining the exact role of Chief Digital Officer and proceed to gain the support of senior management
Technology	• Giving priority to make investments to easily accessible technologies such as open-source ones that can be implemented to production systems quickly and have a significant impact on profit • Updating the existing technologies in purpose of meeting the demand of digitalization in order to be one step ahead of the rivals
Management	• Embarking on an active management style designed to meet the always-changing sectoral requirements • Reviewing the requirements of digitalization regularly • Prioritization of the requirements of digitalization by the top management and making project plans applicable in a shorter time • Establishment of a team working on data analytics and provision of support by the senior management.
R&D Studies on Big Data and Data Analytics	• Supporting R&D investments in technologies enabling the use of Big Data analytics, high-performance cloud computing, and IoT applications • Establishing technopark structures to support R&D activities on real-time data analytics • Receiving academic support from the relevant departments of the universities • Establishment of consultancy companies that will work on real-time data analytics with the support of the government Focusing on the data analytics products that will cope with the problems in production

Figure 35. Reccomendations for the manufacturing companies in terms of Industry 4.0 adoption process

	Recommendations for manufacturing companies to mitigate the effects of challenges faced during the transition process to Industry 4.0
Awareness-raising	• Starting awareness-raising activities. This can be done through activities such as training and guidance studies in the company • Understanding the requirements of digitalization clearly • If data cannot be collected from the production lines where the problems need to be solved immediately, the company should invest in technologies that can collect data directly from the equipment and facilitate the process for collecting data from relevant points
Data security	• Developing a comprehensive innovation policy that will promote secure data sharing and encourages this approach throughout the related sectors • Increasing the use of data analytics within the company in the most secure way possible • Ensuring data security by applying reliable machine learning algorithms • Establishment of data management policy and mapping the locations of sensors transmitting data from the production area
Strategy for digitalization	• Since more and more analytical models are used in live systems as time passes by, the performance of past models should be continuously monitored with a well-planned digital transformation strategy • When data analytics models are applied to live systems, reports should be created in a format determined by the company, making them understandable by everyone, and making it possible for people to make corrections when required
Tax	• The government should increase tax incentives related to Industry 4.0 applications for the private sector and public institutions. It should encourage R&D activities of the companies that carry out studies on big data analytics, especially in the production sector
Process	• Production companies should establish mechanisms and programs to accelerate their transition process in their digital transformation journey • Tax relief should be provided in cooperation with Data Analytics consulting companies

Figure 36. Reccomendations for the manufacturing companies to mitigate the effects of challenges faced during the transition process to Industry 4.0

CHAPTER 5

CONCLUSION

5.1. Summary

According to the findings provided in the thesis, cost minimization requires the employment of sensor systems for process equipment and increasing the budget allocated to R&D studies conducted in the oil and gas industry. By performing real-time data analytics on Big Data, oil and gas production processes are expected to become more intelligent systems. With Industry 4.0 systems, data-driven software will be able to handle oil and gas processes by making predictions. Otherwise, handling the production in the oil and gas sector based on the previously collected data instead of real-time data will not be enough for companies to remain competitive in the sector. As the volume of the data generated by production systems increase, the use of real-time data analytics will become more widespread (Lee et al., 2014). With Big Data and real-time data analytics, manufacturing process data can be collected, analyzed and transformed into meaningful information, so that valuable insights will be gained about production processes. The findings of the thesis confirm that the most important components of Industry 4.0 are real-time data analytics and Big Data systems. It is found that data analytics technologies can solve the problems in the production stage. Moreover, these technologies can make many contributions to the manufacturing sector from cost reduction to product quality improvement. Interview and survey findings show that process manufacturing companies trying to remain competitive in the oil and gas sector should further increase their activities in data analytics and digitalization in order to catch up with the recent developments related to Industry 4.0. Companies that store their data in good quality and analyze them to solve production problems can take a step forward and get ahead of their rivals in the sector. Manufacturing companies that make an investment in technologies that will help them manage their operations better can take their business to the next level and make more accurate decisions (Evans and Anninziata, 2012).

In this thesis, it is explained that industrial revolutions have led to drastic changes in the production processes and profoundly influenced firms. However, the most important feature of the industrial revolution is its continuous development (Almada-Lobo, 2016). The factors that determined the second industrial revolution emerged after the first industrial revolution. In this period, the facilitation of transportation networks, especially railways, played an important role. On the one hand, raw materials and the end products reached new markets. In the third industrial revolution period, scientists were able to combine the inventions in physics and chemistry with technology and make mechanical equipment much more useful. In this period, the use of electricity became widespread (Yin et al., 2018). In addition, the concept of mass production was developed under the leadership of Ford Motor Company. The USA and Germany made the biggest breakthrough in this process and became the world leaders in the manufacturing industry. After the Second World War, the third technological revolution broke out and fields such as computer science, microelectronics, and genetics developed. The most prominent feature of the third industrial revolution was the rapid development of information technologies. Moreover, Industry 4.0 is a period in which huge profits are obtained with the proper use of data. Real-time data analytics, Big Data, automation, empowered sensors, and IoT are the exciting highlights of this era. Because of these recent developments, production patterns have changed and supply chains have gradually expanded (Almada-Lobo, 2016). With the development of computer programs, design activities have become diversified. Computer-aided design, production with advanced technology, the increase and spread of automation in production have led to a new era. This rapid development shows that the manufacturing sector has entered the fourth stage of industrialization (Almada-Lobo, 2016).

The reasons why Industry 4.0 is important for the process manufacturing industry are explained based on its benefits in this study. Industry 4.0 helps manufacturers to cope with the challenges faced by making production processes more traceable. By using real-time data analytics, process manufacturing companies can become more consumer-oriented. In section 4, it is demonstrated that manufacturing companies should use real-time data analytics to make more informed strategic decisions. To show a strong analytical approach is rapidly becoming crucial for manufacturing companies in terms of maintaining their competitiveness. According to the findings, however, showing an analytical approach is not enough for the manufacturing companies. For this reason, technology policy suggestions were made in order to ensure that the production companies do not experience any failures and make maximum use of data analytics. Policy recommendations are summarized in Section 4.5. Based on the results of the questionnaire and interviews conducted in the oil and gas sector, policy recommendations were made for the production sector in general. The technology policies produced within the scope of the thesis have been prepared to address two groups in the process manufacturing sector: those who are preparing to move towards industry 4.0 and those who are experiencing difficulties in transition.

5.2. Implications on Industry 4.0 and the Oil and Gas Industry

The main conclusion that can be drawn is that real-time data analytics and Big Data technologies need to be used to speed up the operations in the oil and gas industry (Khodabakhsh et al., 2017). Petrochemical industry yields a sufficient amount of data to perform real-time data analysis. Sensors are widely used in the processes in the oil and gas industry since these processes can be defined as mission-critical systems (Perrons and Jensen, 2015). In the oil and gas companies, raw data are continuously collected from the equipment such as drills, turbines, boilers, pumps, compressors, and injectors through computer systems, which measure important process parameters such as temperature, pressure, flow rate, vibration and depth (Khodabakhsh et al., 2017). More generally, the findings in this thesis are consistent with the literature showing that manufacturing companies should develop technology policies regarding Industry 4.0.

Oil is an important source of energy that affects both the world economy and international political relations. Since it is consumed at a higher rate compared to other nonrenewable resources, the contribution of oil to the economic development of the countries is enormous (Holdaway, 2014). The importance of real-time data analytics for the oil and gas sector is crucial as confirmed by survey results and face-to-face interviews. Overall, findings provided in the thesis demonstrate the strong effect of operation management based on the insights derived from real-time data analytics.

5.3. Concluding Remarks

Industry 4.0, real-time data analytics and technological transformation process of manufacturing sector present some challenges (Jagadish, 2015). The new era that comes with these developments has affected every aspect of daily life from production to trade and from health to entertainment. This period does not resemble any of mankind's previous experiences in terms of scope and complexity. The speed and the extent of this new revolution have not yet been fully grasped (Jeschke et al., 2017). The findings in this thesis confirm that there are opportunities and challenges in the transition to Industry 4.0. In the physical and digital worlds, new technological developments reinforce each other and lead to new leaps. This allows drawing the conclusion that developments in real-time data analytics can create new business models. Companies are undergoing change and their production, consumption, and logistics systems are being reshaped (Kagermann et al., 2013). Governments and institutions are also reshaping many systems, such as education, health, and transportation. These changes and transformations are of historical importance. We are heading towards a period in which traditional ways of doing business are rapidly transforming. This brings new opportunities and challenges for manufacturing companies. An intelligent manufacturing enterprise means a strong industrial enterprise with the highest level of data access. On this basis, we conclude that enterprises that use intelligent production systems are also flexible and efficient. It would appear that factories in which all production processes are controlled by smart systems will become important. Smart factories that increase productivity and enable flexible production can increase their profitability. In addition to these advantages, the findings in this thesis provide additional information about immediate access to the right information, effective planning of production and cost advantages. Industry 4.0 is a journey that has begun. Just like the transition in which information technologies are used in many areas, this process will likely to continue. The role of individuals, firms and even governments is to make the most of the opportunities of the new revolution, to take measures to minimize threats and risks and to act proactively.

On the whole, Industry 4.0 applications will process information at huge scales and increase the value of oil and gas production process by enabling the information infrastructure to be integrated into the means of production. The oil and gas sector, which has internalized the technology, is on the verge of creating a major transformation that will change its role in the global economy if this sector can understand the true value behind the Big Data and real-time data analytics.

5.4. Future Work

In this thesis, the research topic covers Big Data systems and real-time data analytics. However, concepts related to digital transformation, such as 3D printing, cloud computing, augmented reality and industrial robots, have not been emphasized in this study. The biggest shortcoming of this thesis is the limited number of interviewees and respondents to the online questionnaire. Findings of the study may remain limited and only apply to the oil and gas industry since the sample size was small. However, the results from both the questionnaire and interviews show consistency with each other and. When the sample size can be larger, we think the results will again converge to the findings in this thesis. Future research should consider the potential effects of real-time data analytics more carefully. For example, all production companies in the oil and gas sector can be taken into consideration. Thus, companies with differences between their production processes can have more specific solutions and policies. Our findings on Industry 4.0 applications reveal that real-time data analytics are crucial for the manufacturing sector. In making inferences for the oil and gas sector, we focus only on five main areas. These include reducing costs, extending equipment life, increasing operational speed, improving product quality and improving workplace safety. Therefore, this thesis may not include all the areas in the production sector. We can adapt this research to other sectors where it is often critical to producing meaningful results from the data collected through digital components. In addition to the five main areas included in the study listed above, we may identify different areas that the real-time data analytics can contribute to. In this thesis, an in-depth analysis that can help to solve all production problems is not discussed. Again, the relatively small sample size, which led to a lack of comprehensive statistical analysis that would yield statistically significant results, prevented us from constructing and testing comprehensive hypotheses. Thus, it will be important for future studies to conduct online questionnaires including more respondents and interviews with more participants.

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APPENDICES

APPENDIX A: ONLINE QUESTIONNAIRE CONTENT (TURKISH)

PETROL VE GAZ SEKTÖRÜNDE TAHMİNE DAYALI ÜRETİM İÇİN GERÇEK ZAMANLI VERİ ANALİTİĞİ YÖNTEMLERİNİN UYGULANMASI: ENDÜSTRİ 4.0 PERSPEKTİFİ

YİĞİT YELDAN - ODTÜ BİLİM VE TEKNOLOJİ POLİTİKASI ÇALIŞMALARI YÜKSEK LİSANS TEZ ANKETİ SORULARI

* Gerekli

1. soruya geçin.

Betimleyici Bilgiler

Tez analizi için betimleyici soruları içerir.

1. Cinsiyetiniz? *

Yalnızca bir şıkkı işaretleyin.

- Erkek
- Kadın

2. Yaşınız? *

Yalnızca bir şıkkı işaretleyin.

- 21-30
- 31-40
- 41-50
- 60 ve üzeri

3. Eğitim durumunuz nedir? *

Yalnızca bir şıkkı işaretleyin.

- İlkokul
- Lise
- Lisans
- Yüksek Lisans
- Doktora ve Üzeri

4. Toplam iş tecrübeniz hangi aralıktadır? *

Yalnızca bir şıkkı işaretleyin.

- 1-5 yıl
- 5-10 yıl
- 10-15 yıl
- 15-20 yıl
- 20 yıldan fazla

5. Ünvanınız Nedir? *

Yalnızca bir şıkkı işaretleyin.

- Bilgisayar Operatörü
- Uzman
- Mühendis
- Şef
- Koordinatör
- Başmühendis
- Müdür
- Üst Düzey Yönetici
- Diğer: ____________________

6. **Hangi departmanda çalışmaktasınız?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Bilgi Teknolojileri
- ◯ İşletme Güvenilirliği
- ◯ Arge
- ◯ Kalite Sistemleri
- ◯ Üretim Planlama
- ◯ Proses Otomasyon
- ◯ Bakım
- ◯ Üretim
- ◯ Teknik Emniyet
- ◯ İnsan Kaynakları
- ◯ Finans ve Mali İşler
- ◯ Genel Müdürlük Yönetim
- ◯ Rafineri Yönetim
- ◯ Diğer: ____________________

7. soruya geçin.

Endüstri 4.0'a Genel Bakış

Endüstri 4.0 kavramı hakkında sorular içerir.

7. **Şirketinizde bir veri analitiği veya dijitalleşme projesinde rol aldınız mı?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Evet
- ◯ Hayır

8. **Gerçek zamanlı veri analitiği uygulamalarının iş süreçlerinize olumlu bir etkisi olduğunu düşünüyor musunuz?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Evet
- ◯ Hayır

9. **Endüstri 4.0'ın ortaya çıkış amacı maliyeti düşürmek, daha verimli üretim süreçleri geliştirmek, daha hızlı ve esnek bir üretim sağlamaktır. Petrol ve Gaz endüstrisini Endüstri 4.0 sektörlerinden biri olarak tanımlar mısınız?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Evet
- ◯ Hayır

10. **Endüstri 4.0 ve gerçek zamanlı veri analitiği hizmetlerinin petrol ve gaz endüstrisine yeni olanaklar sağlayabileceğini düşünüyor musunuz?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Evet
- ◯ Hayır

11. **Endüstri 4.0 kapsamında kullanılan dijital teknolojilerin benimsenmesi ve kurum içinde yayınlaştırılması için bütçe ayrılması gerektiğini düşünüyor musunuz?** *
Yalnızca bir şıkkı işaretleyin.

- ◯ Evet
- ◯ Hayır

12. **Yöneticilerim veri analitiğine ve dijitalleşmeye önem verir.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

13. İş stratejimizi oluştururken Endüstri 4.0 konseptlerini göz önünde bulundururuz. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

14. Dijitalleşme projelerinden beklenen faydaları gerçekleştirecek şekilde bireyler/departmanlar için performans hedefleri belirliyoruz. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

15. Üretim süreçleri hakkında anlık izleme sağlayan ve birden fazla kullanıcı tarafından erişilebilen dijital teknolojilerin kullanımı petrol ve gaz sektörü için önemlidir. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

16. Petrol ve Gaz sektöründe rekabet gücü kazanmak için dijital bir vizyona sahip olunmalıdır. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

17. Gerçek zamanlı veri analitiğinin, petrol ve gaz sektörüne etkisinin önemli olduğunu düşünüyorum. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

18. soruya geçin.

Veri Analitiği Karar Destek Sistemi Ölçütleri

Petrol ve Gaz sektörü özelinde veri analitiği karar destek sistemleri hakkında sorular içerir.

18. Dijital teknolojiler, petrol ve gaz sektöründe iç ve dış müşterilerle iletişimde kalmak ve karşılaştıkları zorlukları çözmek için kullanılır. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

19. Üretim ekipmanlarından veri alacak sistemler kuruludur ve karar verme aşamasında kullanılabilecek gerçek zamanlı veriler mevcuttur. *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

20. **Petrol işleme süreçlerinden elde edilen gerçek zamanlı veriler sağlanan hizmetleri geliştirmek için devamlı olarak kullanılmalıdır.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

21. soruya geçin.

Veri Analitiği Teknik Yeterlilik Ölçütleri

Petrol ve Gaz sektörü özelinde veri analitiği gereksinimleri hakkında sorular içerir.

21. **Petrol ve gaz sektöründe, ürün bilgilerini gerçek zamanlı veri akışına dayanarak analiz etmek mümkündür.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

22. **Petrol ve gaz sektöründe geçmişe dayalı analizler yerine, Endüstri 4.0 ile gündeme gelen ve gerçek zamanlı veriler ile yapılan analitik çalışmaların etkilerini gözlemlemekteyim.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

23. **Petrol ve gaz sektöründe, gerçek zamanlı veri analitiğinin uygulanmasında en çok hangi zorlukla karşılaşıldığını düşünüyorsunuz?** *
Yalnızca bir şıkkı işaretleyin.

◯ Veri Kalitesinin Korunması
◯ Büyük Veri Performansının Sağlanması
◯ Veri Analitiği Kavramının Anlaşılması
◯ Kullanılan Teknolojilerin Kalitesi
◯ Maliyetlerin Yüksek Olması
◯ Kullanıcı Kabul Testlerinin Zor Olması
◯ Diğer: ____________________

24. **Petrol ve gaz sektöründe dijital dönüşümü sağlamak için veri analitiği alanında çalışan teknik uzmanlar görevlendirilmelidir.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

25. **Petrol ve gaz sektöründe, çalışanların veri analitiği alanında çalışma yapabilmeleri için gerekli yetkinlikte teknolojik araçlar kullanılmaktadır.** *
Yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5	
Kesinlikle Katılmıyorum	◯	◯	◯	◯	◯	Kesinlikle Katılıyorum

26. soruya geçin.

Gerçek Zamanlı Veri Analitiğinin Katkılarının Değerlendirilmesi
Değerlendirme Skalası: 1-En Az, 5-En Fazla

26. **Büyük veri kullanılarak yapılan gerçek zamanlı veri analitiği ve Endüstri 4.0 uygulamaları petrol ve gaz sektörüne katkılarını değerlendiriniz.** *

Her satırda yalnızca bir şıkkı işaretleyin.

	1	2	3	4	5
Maliyet azaltma					
Ekipman Kullanım Süresi					
Operasyon Hızı					
Ürün Kalitesi					
İşyeri Güvenliği					

27. **Büyük veri kullanılarak yapılan gerçek zamanlı veri analitiği ve Endüstri 4.0 uygulamalarının petrol ve gaz sektörüne en çok hangi alanda katkı sağladığını düşünüyorsunuz ?** *

Yalnızca bir şıkkı işaretleyin.

- Maliyet Azaltma
- Ekipman Kullanım Süresi
- Operasyon Hızı
- Ürün Kalitesi
- İşyeri Güvenliği
- Diğer: ____________________

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APPENDIX B: ONLINE QUESTIONNAIRE CONTENT (ENGLISH)

IMPLEMENTING REAL TIME DATA ANALYTICS METHODS FOR PREDICTIVE MANUFACTURING IN OIL AND GAS INDUSTRY: AN INDUSTRY 4.0 PERSPECTIVE

YİĞİT YELDAN - METU SCIENCE AND TECHNOLOGY POLICY STUDIES QUESTION THESIS SURVEY QUESTIONS

* Required

Descriptive Information

1. **What is your gender ?**
   Mark only one oval.
   - Male
   - Female

2. **What is your age ?**
   Mark only one oval.
   - 21-30
   - 31-40
   - 41-50
   - 60 and above

3. **What is your educational level ?**
   Mark only one oval.
   - Primary school
   - High school
   - Bachelor's Degree
   - Master's Degree
   - Doctorate degree

4. **What is your total work experience?**
   Mark only one oval.
   - 1-5 years
   - 5-10 years
   - 10-15 years
   - 15-20 years
   - More than 20 years

5. **What is your title ?**
   Mark only one oval.
   - Specialist
   - Engineer
   - Senior Engineer
   - Coordinator
   - Chief Engineer
   - Manager
   - C-Level Executive

6. **In which department do you work?**
Mark only one oval.

- ◯ Information Technologies
- ◯ Operational Reliability
- ◯ R&D
- ◯ Quality Systems
- ◯ Production Planning
- ◯ Process Automation
- ◯ Maintenance
- ◯ Production
- ◯ Technical Safety
- ◯ Human Resources
- ◯ Finance
- ◯ General Directorate
- ◯ Refinery Directorate
- ◯ Other: ____________________

Industry 4.0 Overview

Includes questions about the concept of Industry 4.0.

7. **Have you taken part in a data analytics or digitalization project in your company?**
Mark only one oval.

- ◯ Yes
- ◯ No

8. **Do you think that real-time data analytics applications have a positive effect compared to your previous business processes?**
Mark only one oval.

- ◯ Yes
- ◯ No

9. **The goal of Industry 4.0 is to reduce costs, develop more efficient production processes and provide a faster and more flexible production. Can you describe the oil and gas industry as an industry 4.0 sector?**
Mark only one oval.

- ◯ Yes
- ◯ No

10. **Do you think that Industry 4.0 and digital technology services can provide new opportunities for the oil and gas industry?**
Mark only one oval.

- ◯ Yes
- ◯ No

11. **Do you think it is necessary to allocate a budget for the adoption and dissemination of digital technologies used within Industry 4.0?**
Mark only one oval.

- Yes
- No

12. **My first manager is committed to real-time data analytics and digitalization.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

13. **We review the Industry 4.0 concepts when creating our business strategy.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

14. **We set performance targets for individuals / departments to realize the expected benefits of digitization projects.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

15. **The use of digital technologies that provide visibility into manufacturing processes and can be accessed by multiple users is important for the oil and gas industry.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

16. **The oil and gas sector must have a digital vision for transformation due to new market needs.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

17. **I think the impact of real-time data analytics on the oil and gas sector is important.**
Mark only one oval.

	1	2	3	4	5	
I strongly disagree						Absolutely I agree

Data Analytics Decision Support System Criteria

Includes questions about data analytics decision support systems specific to the Oil and Gas sector.

18. **Digital technologies are used to keep in touch with internal and external customers in the oil and gas sector and to solve the challenges they face.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

19. **Systems for obtaining data from production equipment are installed and there are real-time data to be used in the decision-making process.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

20. **Real-time data from oil processing processes should be used continuously to improve solutions, solutions and services.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

Data Analytics Technical Competency Criteria

Includes questions about data analytics requirements specific to the Oil and Gas sector.

21. **It is possible to analyze the produced product information based on real-time data flow.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

22. **In the oil and gas sector, I observe the effects of analytical studies with real-time data that have come up with Industry 4.0, rather than past-based analysis.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

23. **In the oil and gas sector, what challenges do you think are most likely to apply real-time data analytics?** *

Mark only one oval.

- ◯ Data Quality Protection
- ◯ Ensuring Big Data Performance
- ◯ Understanding the Concept of Data Analytics
- ◯ Quality of Technologies Used
- ◯ High Costs
- ◯ Difficult User Acceptance Tests
- ◯ Other: ______________________

24. **Digital experts working in the digital field should be employed to ensure digital transformation in the oil and gas sector.**

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

25. **In the oil and gas sector, technological tools are used in order to enable employees to work in the field of data analytics.** *

Mark only one oval.

	1	2	3	4	5	
I strongly disagree	◯	◯	◯	◯	◯	Absolutely I agree

Evaluating the Contribution of Real-Time Data Analytics

Rating Scale: 1-Minimum, 5-Maximum

26. **Evaluate the contribution of real-time data analytics and Industry 4.0 applications to the oil and gas sector using big data.** *

Mark only one oval per row.

	1	2	3	4	5
Cost Reduction	◯	◯	◯	◯	◯
Equipment Uptime	◯	◯	◯	◯	◯
Operations Speed	◯	◯	◯	◯	◯
Product Quality	◯	◯	◯	◯	◯
Workplace Safety	◯	◯	◯	◯	◯

27. **In which field do you think real-time data analytics using Big Data and Industry 4.0 applications contribute most to the oil and gas sector?** *

Mark only one oval.

- ◯ Cost Reduction
- ◯ Equipment Uptime
- ◯ Operations Speed
- ◯ Product Quality
- ◯ Workplace Safety
- ◯ Other: ______________________

APPENDIX C: APPLIED ETHICS RESEARCH CENTER APPROVAL

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

ORTA DOĞU TEKNİK ÜNİVERSİTESİ
MIDDLE EAST TECHNICAL UNIVERSITY

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Sayı: 28620816 / 258

10 Mayıs 2019

Konu: Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Prof.Dr. Teoman PAMUKÇU

Danışmanlığını yaptığınız **Yiğit YELDAN'ın "Petrol ve Gaz Sektöründe Tahmine Dayalı Üretim Politikalarının Oluşturulması İçin Gerçek Zamanlı Veri Analitiği Yöntemlerinin Uygulanmasına Yönelik Bir Analiz: Endüstri 4.0 Perspektifi"** başlıklı araştırması İnsan Araştırmaları Etik Kurulu tarafından uygun görülmüş ve **246-ODTÜ-2019** protokol numarası ile onaylanmıştır.

Saygılarımızla bilgilerinize sunarız.

Prof. Dr. Tülin GENÇÖZ

Başkan

Prof. Dr. Tolga CAN

Üye

Doç.Dr. Pınar KAYGAN

Üye

Dr. Öğr. Üyesi Ali Emre TURGUT

Üye

Dr. Öğr. Üyesi Şerife SEVİNÇ

Üye

Dr. Öğr. Üyesi Müge GÜNDÜZ

Üye

Dr. Öğr. Üyesi Süreyya Özcan KABASAKAL

Üye

APPENDIX D: STATISTICAL TABLES AND FIGURES

Table 7

ANOVA for Industry 4.0 related questions

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
Gender	1	0.047	0.04744	0.207	0.652	
Residuals	34	7.795	0.22927			
Age	2	0.091	0.04565	0.194	0.824	
Residuals	33	7.751	0.23489			
Edu	2	1.048	0.5239	2.544	0.0938	.
Residuals	33	6.795	0.2059			
Title	6	0.864	0.1440	0.598	0.729	
Residuals	29	6.979	0.2407			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Source: Based on the results obtained from the questionnaire.

Table 8

Tukey HSD Test for Industry 4.0 related questions

Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = Industry4.0 ~ Edu, data = data)

$Edu

	diff	lwr	upr	p adj
Masters-Bachelors	-0.2846382	-0.6624470	0.09317071	0.1698160
Doctorate-Bachelors	0.4647368	-0.6776498	1.60712347	0.5831557
Doctorate-Masters	0.7493750	-0.3983541	1.89710407	0.2589663

Source: Based on the results obtained from the questionnaire.

Table 9

Industry 4.0 Assumption Check for ANOVA

	Levene's Test for Homogeneity of Variance	Shapiro-Wilk Normality Test
p.value	0.3512	0.3316

Source: Based on the results obtained from the questionnaire.

Table 10

ANOVA for Decision Support

```
              Df Sum Sq Mean Sq F value Pr(>F)
Gender         1  1.074  1.0744   4.041 0.0524 .
Residuals     34  9.041  0.2659

Age            2  0.098 0.04901   0.161  0.852
Residuals     33 10.017 0.30355

Edu            2  0.973  0.4864   1.756  0.189
Residuals     33  9.142  0.2770

Title          6  1.203  0.2005   0.652  0.688
Residuals     29  8.912  0.3073

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Source: Based on the results obtained from the questionnaire.

Table 11.

Decision Support Assumption Check for ANOVA

	Levene's Test for Homogeneity of Variance	Shapiro-Wilk Normality Test
p.value	0.9917	0.05092

Source: Based on the results obtained from the questionnaire.

Table 12

ANOVA for Technical Competence

```
              Df  Sum Sq  Mean Sq  F value  Pr(>F)
Gender         1   0.814   0.8136    3.405  0.0737 .
Residuals     34   8.124   0.2389

Age            2   0.139   0.0693     0.26   0.773
Residuals     33   8.799   0.2666

Edu            2   0.118  0.05921    0.222   0.802
Residuals     33   8.819  0.26724

Title          6   1.332   0.2220    0.846   0.545
Residuals     29   7.606   0.2623

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Source: Based on the results obtained from the questionnaire.

Table 13

Technical Competency assumption check for ANOVA

	Levene's Test for Homogeneity of Variance	**Shapiro-Wilk Normality Test**
p.value	0.1275	0.0186

Source: Based on the results obtained from the questionnaire.

Table 14

ANOVA for Real-Time Data Analytics

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	0.731	0.7314	2.016	0.165
Residuals	34	12.339	0.3629		
Age	2	0.548	0.2738	0.722	0.493
Residuals	33	12.522	0.3795		
Edu	2	0.569	0.2845	0.751	0.48
Residuals	33	12.501	0.3788		
Title	6	3.128	0.5213	1.52	0.207
Residuals	29	9.942	0.3428		

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Source: Based on the results obtained from the questionnaire.

Table 15

ANOVA for Cost Reduction

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	2.03	2.032	1.94	0.173
Residuals	34	35.61	1.047		
Age	2	1.52	0.7606	0.695	0.506
Residuals	33	36.12	1.0945		
Edu	2	0.04	0.0217	0.019	0.981
Residuals	33	37.60	1.1393		
Title	6	6.114	1.019	0.937	0.484
Residuals	29	31.525	1.087		

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Source: Based on the results obtained from the questionnaire.

Table 16

ANOVA for Equipment Uptime

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	0.286	0.2857	0.364	0.55
Residuals	34	26.714	0.7857		
Age	2	1.041	0.5206	0.662	0.523
Residuals	33	25.959	0.7866		
Edu	2	0.092	0.0461	0.056	0.945
Residuals	33	26.908	0.8154		
Title	6	4.157	0.6928	0.88	0.522
Residuals	29	22.843	0.7877		

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Source: Based on the results obtained from the questionnaire.

Table 17

ANOVA for Operations Speed

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Gender	1	0.96	0.9603	0.992	0.326
Residuals	34	32.93	0.9685		
Age	2	2.26	1.1297	1.179	0.32
Residuals	33	31.63	0.9585		
Edu	2	1.77	0.8836	0.908	0.413
Residuals	33	32.12	0.9734		
Title	6	6.562	1.0937	1.161	0.354
Residuals	29	27.327	0.9423		

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Source: Based on the results obtained from the questionnaire.

Table 18

ANOVA for Product Quality

```
             Df Sum Sq Mean Sq F value Pr(>F)
Gender        1  0.335  0.3353   0.535  0.469
Residuals    34 21.304  0.6266

Age           2  3.866  1.9328   3.589 0.0389 *
Residuals    33 17.773  0.5386

Edu           2  0.218  0.1089   0.168  0.846
Residuals    33 21.421  0.6491

Title         6  7.843  1.3072   2.748 0.0308 *
Residuals    29 13.795  0.4757

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Source: Based on the results obtained from the questionnaire.

Table 19

Tukey HSD test on Product Quality in terms of age variable

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = ProductQuality ~ Age, data = data)

$Age
                  diff        lwr         upr     p adj
31-40-21-30  0.2882353 -0.4294292  1.00589984 0.5910294
41-50-21-30 -0.5222222 -1.3496300  0.30518558 0.2819117
41-50-31-40 -0.8104575 -1.5528012 -0.06811382 0.0299390
```

Source: Based on the results obtained from the questionnaire.

Table 20

Product Quality assumption check for ANOVA in terms of age variable

	Kruskal-Wallis rank sum test	Shapiro-Wilk Normality Test
p.value	0.02882	0.001374

Source: Based on the results obtained from the questionnaire.

Table 21

Tukey HSD test on Product Quality in terms of title variable

Tukey multiple comparisons of means
95% family-wise confidence level

Fit: aov(formula = ProductQuality ~ Title, data = data)

$Title

	diff	lwr	upr	p adj
Engineer-Specialist	-1.500000e+00	-3.28186721	0.2818672	0.1441760
SeniorEngineer-Specialist	1.363636e-01	-0.97121217	1.2439394	0.9996771
ChiefEngineer-Specialist	5.000000e-01	-1.28186721	2.2818672	0.9715853
Coordinator-Specialist	-7.500000e-01	-2.15868972	0.6586897	0.6310615
Manager-Specialist	1.776357e-15	-1.40868972	1.4086897	1.0000000
ClevelExecutive-Specialist	-5.000000e-01	-1.71413785	0.7141378	0.8449937
SeniorEngineer-Engineer	1.636364e+00	-0.04120888	3.3139361	0.0595183
ChiefEngineer-Engineer	2.000000e+00	-0.18233273	4.1823327	0.0891976
Coordinator-Engineer	7.500000e-01	-1.13995558	2.6399556	0.8659622
Manager-Engineer	1.500000e+00	-0.38995558	3.3899556	0.1923434
ClevelExecutive-Engineer	1.000000e+00	-0.74975887	2.7497589	0.5533120
ChiefEngineer-SeniorEngineer	3.636364e-01	-1.31393615	2.0412089	0.9924178
Coordinator-SeniorEngineer	-8.863636e-01	-2.16057143	0.3878442	0.3256435
Manager-SeniorEngineer	-1.363636e-01	-1.41057143	1.1378442	0.9998568
ClevelExecutive-SeniorEngineer	-6.363636e-01	-1.69150793	0.4187807	0.4911801
Coordinator-ChiefEngineer	-1.250000e+00	-3.13995558	0.6399556	0.3830894
Manager-ChiefEngineer	-5.000000e-01	-2.38995558	1.3899556	0.9787701
ClevelExecutive-ChiefEngineer	-1.000000e+00	-2.74975887	0.7497589	0.5533120
Manager-Coordinator	7.500000e-01	-0.79314227	2.2931423	0.7205566
ClevelExecutive-Coordinator	2.500000e-01	-1.11784943	1.6178494	0.9969883
ClevelExecutive-Manager	-5.000000e-01	-1.86784943	0.8678494	0.9044095

Source: Based on the results obtained from the questionnaire.

Table 22

Product Quality assumption check for ANOVA in terms of title variable

	Levene's Test for Homogeneity of Variance	Shapiro-Wilk Normality Test
p.value	0.59	0.01939

Source: Based on the results obtained from the questionnaire.

Table 23

ANOVA for Workplace Safety

```
              Df Sum Sq Mean Sq F value Pr(>F)
Gender         1  0.573  0.5734   0.703  0.408
Residuals     34 27.732  0.8157

Age            2  0.987  0.4936   0.596  0.557
Residuals     33 27.318  0.8278

Edu            2  2.766  1.3830   1.787  0.183
Residuals     33 25.539  0.7739

Title          6  7.948   1.325   1.887  0.117
Residuals     29 20.357   0.702

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Source: Based on the results obtained from the questionnaire.

Table 24

Factor Analysis Test Results

```
Uniquenesses:
         Industry4.0        DecisionMaking    TechnicalKnowledge RealTimeDataAnalytics
               0.617                 0.439                 0.543                 0.005
       CostReduction       EquipmentUptime       OperationsSpeed        ProductQuality
               0.458                 0.455                 0.608                 0.629
     WorkplaceSafety
               0.758
Loadings:
```

Table 24 (cont'd)

```
                      Factor1 Factor2
DecisionMaking                0.744
TechnicalKnowledge    0.350   0.578
RealTimeDataAnalytics 0.894   0.442
CostReduction         0.602   0.425
EquipmentUptime       0.353   0.649
OperationsSpeed       0.621
ProductQuality        0.584   0.174
WorkplaceSafety       0.487

               Factor1 Factor2
SS loadings      2.386   2.103
Proportion Var   0.265   0.234
Cumulative Var   0.265   0.499

Test of the hypothesis that 2 factors are sufficient.
The chi square statistic is 29.08 on 19 degrees of freedom.
The p-value is 0.0648
```

Source: Based on the results obtained from the questionnaire.

```
Reliability analysis
Call: alpha(x = datareltest)

raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd median_r
     0.81      0.83    0.88      0.35 4.8 0.046  4.2 0.5     0.39

lower alpha upper     95% confidence boundaries
0.72 0.81 0.9

Reliability if an item is dropped:
                      raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
Industry4.0                0.81      0.83    0.87      0.38 4.9    0.047 0.032  0.40
DecisionMaking             0.80      0.81    0.87      0.35 4.3    0.050 0.039  0.37
TechnicalKnowledge         0.79      0.80    0.87      0.34 4.1    0.052 0.037  0.31
RealTimeDataAnalytics      0.75      0.77    0.81      0.30 3.4    0.060 0.027  0.27
CostReduction              0.78      0.80    0.85      0.34 4.1    0.055 0.031  0.37
EquipmentUptime            0.78      0.80    0.87      0.34 4.1    0.054 0.036  0.37
OperationsSpeed            0.81      0.82    0.87      0.37 4.6    0.047 0.037  0.39
ProductQuality             0.80      0.82    0.88      0.36 4.5    0.050 0.035  0.39
WorkplaceSafety            0.82      0.83    0.88      0.39 5.0    0.044 0.033  0.39
```

***Figure 37*. Cronbach's alpha test for the online questionnaire**

Independent Variable	Dependent Variables	Correlation	P.value
RealTimeDataAnalytics	CostReduction	0.7747315	2.933e-08
RealTimeDataAnalytics	EquipmentUptime	0.6654116	9.514e-06
RealTimeDataAnalytics	OperationsSpeed	0.6541274	1.512e-05
RealTimeDataAnalytics	ProductQuality	0.6491346	1.846e-05
RealTimeDataAnalytics	WorkplaceSafety	0.5710321	0.0002757

***Figure 38*. Correlation test for hypotheses**

APPENDIX E: INTERVIEW QUESTIONS (TURKISH)

1. Endüstri 4.0 uygulamalarının getirdiği kazançlar nelerdir? Hangi alanda Büyük Veri ve Endüstri 4.0 uygulamalarını kullanan gerçek zamanlı veri analizinin petrol ve gaz sektörüne daha fazla katkı sağladığını düşünüyorsunuz?

2. Gerçek zamanlı veri analizi uygulamalarının iş süreçleriniz üzerindeki etkisi nedir?

3. Endüstri 4.0 ve gerçek zamanlı veri analizi uygulamalarının petrol ve gaz endüstrisine sağlayabileceği yeni olasılıklar nelerdir?

4. Petrol ve gaz sektöründe, gerçek zamanlı veri analitiği açısından en muhtemel zorlukların neler olduğunu düşünüyorsunuz?

5. Gerçek zamanlı veri analizi sürecinde karşılaştığınız zorluklar nelerdir? Bunları kategorize etmek istiyorsanız hangi kategoriler oluşturulabilir?

6. Endüstri 4.0 uygulamalarını istenen düzeyde gerçekleştirmek için daha fazla ne geliştirilmelidir?

7. Şimdi büyük bir veri projesine başlıyor olsanız, projenin hangi süreçlerini değiştirmek istersiniz? Öğrendiğiniz dersler neler?

8. Maliyetleri azaltmak için Endüstri 4.0 uygulamaları açısından daha iyi yapılması gerekenler nelerdir?

9. Ekipman çalışma süresini artırmak için Endüstri 4.0 uygulamaları açısından daha iyi yapılması gerekenler nelerdir?

10. İşletim hızını artırmak için Endüstri 4.0 uygulamaları açısından daha iyi yapılması gerekenler nelerdir?

11. Ürün kalitesini artırmak için Endüstri 4.0 uygulamaları açısından daha iyi yapılması gerekenler nelerdir?

12. İşyeri güvenliğini arttırmak için Endüstri 4.0 uygulamaları açısından daha iyi yapılması gerekenler nelerdir?

APPENDIX F: INTERVIEW QUESTIONS (ENGLISH)

1. What are the gains brought by the Industry 4.0 applications? In which field do you think real-time data analytics using Big Data and Industry 4.0 applications contribute most to the oil and gas sector?
2. What impact do real-time data analytics applications have on your business processes?
3. What new possibilities do you think Industry 4.0 and real-time data analytics applications can provide to the oil and gas industry?
4. In the oil and gas sector, what challenges do you think are most likely to occur in terms of real-time data analytics?
5. What are the challenges you face during the real-time data analytics process? What categories can be created if you want to categorize them?
6. What needs to be developed further to perform Industry 4.0 applications at the desired level?
7. If you want to start a big data project now, which processes of the project would you like to change? What are your learned lessons?
8. What needs to be done better in terms of Industry 4.0 applications to reduce costs?
9. What needs to be done better in terms of Industry 4.0 applications to increase equipment uptime?
10. What needs to be done better in terms of Industry 4.0 applications to increase operational speed?
11. What needs to be done better in terms of Industry 4.0 applications to increase product quality?
12. What needs to be done better in terms of Industry 4.0 applications to increase workplace safety?

APPENDIX G: TURKISH SUMMARY / TÜRKÇE ÖZET

PETROL VE GAZ SEKTÖRÜNDE TAHMİNE DAYALI ÜRETİM İÇİN GERÇEK ZAMANLI VERİ ANALİTİĞİ YÖNTEMLERİNİN UYGULANMASI: ENDÜSTRİ 4.0 PERSPEKTİFİ

Şirketler, geçmiş sanayi devrimlerinin getirdiği gelişmeler ışığında sanayinin dönüşümünü gerçekleştirememeleri nedeniyle önemli fırsatları kaçırdılar (Stock ve Seliger, 2016). Bu tezde, üretim sektöründe gerçek zamanlı veri analitiğinin ve büyük veri sistemlerinin etkileri araştırılmaktadır. Endüstri 4.0 kavramı için gerekli yatırımlar ve teknoloji politikaları ile firmaların performansları üzerindeki etkileri, Türkiye'deki petrol ve gaz endüstrisi örneğine dayalı olarak incelenecektir.

Dijitalleşme, üretim yöntemlerinden müşteri beklentilerine ve dağıtım kanallarına kadar şirketlerin iş süreçlerini büyük ölçüde değiştirmektedir (Almada-Lobo, 2016). Dijitalleşme sayesinde şirketler, bilginin üretimi ve işlenmesinden karar alma süreçlerine ve yeni pazarlara erişime kadar birçok alanda önemli kazanımlar elde etme potansiyeline sahipler (Gilchrist, 2016). Bu avantajlar, şirket performansının arttırılmasında ve şirket hedeflerine ulaşılmasında ve en önemlisi rekabet edebilirliğin arttırılmasında kritik bir rol oynamaktadır. Tüm bu gelişmeler sanayiyi yeni bir aşamaya getirmektedir ve ülkelerin dijital dönüşüm yarışına girmesine yol açmaktadır (Kagermann et al., 2013). Dijitalleşme, itici güç görevini üstlenerek sektördeki dönüşümün merkezindedir. Dijital teknolojiler şirketler tarafından değişen müşteri taleplerinin yanı sıra operasyonel gelişmelere cevap vermek için de kullanılabilmektedir. Büyük Veri analizi, şirketlerin müşteri taleplerini daha kapsamlı bir şekilde anlamalarını sağlar ve ilave üretim gibi teknolojiler şirketlerin toplu olarak özelleştirilmiş ürünler üretmesini sağlamaktadır (Lee et al., 2014). Üretim şirketleri, verimliliği artırmak için hızlı karar verme sürecindeki yüksek hacimli verilerle mücadele ederken zorluklarla karşı karşıya kalmaktadır. Bu sürecin iyi yönetilmesi üretim şirketleri açısından kritik önem taşımaktadır. Endüstri 4.0 ve

Büyük Veri terimleri, geleneksel veri tabanı sistemleri için çok büyük olan veri kümelerinin toplanması, yönetimi ve analizini yönetebilen sistemler için kullanılmaktadır (Tambe, 2014). Endüstri 4.0 teknolojileri sadece gerçek zamanlı olarak üretim verilerini gösteren ekranlar değil aynı zamanda trendleri bulmak, analiz etmek, üretimin geleceğini öngörebilmek ve bilgi temelli karar vermek için kurgulanan yapılardır. Üretim süreçlerinin geleceğini öngörebilmek ve bu doğrultuda aksiyon alabilmek için depolanan verilerin analiz edilebildiği bir raporlama ve yönetim modülüdür (Snatkin ve arkadaşları, 2013).

İlk sanayi devrimi mekanik yeniliklerle su ve buhar gücüne dayanırken, bunu ikinci sanayi devrimi, fabrikaların elektrifikasyonu ve seri üretim izlemiştir. Endüstri 2.0'da Frederick Taylor, bilimsel yönetim prensibini yayınlamıştır. Endüstri 2.0'da talep iki boyutta gerçekleşmiştir: hacim ve değişim. Bu talep ortamına istikrarlı bir pazar denilebilir. Taylor Teorisi, iki yenilikçi kişi, Henry Ford ve Taiichi Ohno tarafından takip edildi. Ford, ürün miktarlarında seri üretim montaj hatları kullanarak tedarik kıtlığını giderdi. Ardından, üçüncü sanayi devrimi olan dijital devrim, bilgisayarlaştırmayı getirdi (Dalenogare ve diğerleri, 2018). Otomasyon, bilgisayar ve elektronik bu aşamada tanıtıldı. Üçüncü sanayi devrimi, Ford'un daha yüksek üretkenliğe geçişi ile Endüstri 4.0 aşamasındaki akıllı prosedürler arasındaki geçiş noktasıdır. Ford'da olduğu gibi işlemler basitleştirilmekle kalmadı, aynı zamanda otomasyon üretim süreci için gerekli bileşenlerin verimliliğini arttırdı (Yin ve diğerleri, 2018). Son olarak, Endüstri 4.0, Almanya'nın üretimle ilgili araştırma ve geliştirme yatırımlarını tanımlamayı amaçladı (Almada-Lobo, 2016). Endüstri 4.0'daki geliştirme ve üretim süreçleri giderek daha esnek, etkili ve kişisel bir hal almıştır. Endüstri 4.0, Büyük Veri ve Nesnelerin İnterneti'nin (IoT) gücünü kullanarak hatalı üretim, stok atık ve ekipman arızası gibi endüstrilerin sorunlu kısımlarını çözmeyi amaçlamaktadır (Gilchrist, 2016). Endüstri 4.0 uygulmalarında, akıllı öğeler gömülü donanım ve yazılımla birbirine bağlanır. Örneğin, düşük maliyetle üretim, minimum enerji kullanımı, zaman tasarrufu, yüksek hızda çalışma, daha yüksek verim ve daha kaliteli ürünler Endüstri 4.0'ın hedefleri arasındadır (Stock ve Seliger, 2016).

Büyük veri ve gerçek zamanlı veri analitiği kavramları, Endüstri 4.0'daki ana başlıklar arasındadır. Büyük Veri tanımı genellikle analiz edilecek çok büyük miktarda veri ile ilişkilidir. Büyük Veri, işlemek için yenilikçi çözümler gerektiren yüksek hacimli, yüksek hızlı ve yüksek değişkenlikli veriler olarak tanımlanır (Jagadish, 2015). Verilerin ilişkilendirilip bilgiye dönüştürülebilmesi için, toplanan verilerin belirli bir düzen ve sistematik içerisinde kaydedilmesi gerekmektedir. Veri ambarları, özellikle Büyük Veri kavramı ile önem kazanmıştır. Verilerin değerinin anlaşılmasının bir sonucu olarak, verilerin toplanması, işlenmesi, sunulması, saklanması ve analiz edilmesi gibi birçok farklı teknik ön plana çıkmıştır (Tan ve diğerleri, 2015). Büyük Veri, verilerin elde edilmesiyle başlar, daha sonra verilerin analizini, verilerin doğrulanmasını, verilerin depolanmasını ve nihayetinde verilerin kullanılmasını gerektirir (Tambe, 2014).

Endüstri 4.0 uygulamalarından örnek vermek gerekirse, önemli bir uçak üreticisi olan Airbus, ürün test süreçlerini hızlandırmak için Büyük Veri analizi kullanmıştır (Oracle, 2016). Aslında, her test uçuşu uçağın performansını gösteren terabaytlarca veri üretmektedir. Büyük Veri analizi, Airbus analistleri için veri toplama ve analiz işlemlerini hızlandırarak test süresini yüzde 30 azaltmıştır. Artık şirket her zamankinden daha hızlı uçak teslim edebilir hale gelmiştir (Oracle, 2016). Öte yandan, Nesnelerin İnterneti, cihazlara dijital sensörler ve ağ teknolojileri eklemeyi de içermektedir. Bilgisayarlar veya akıllı telefonlar tarafından izlenebilecek sistemlerin kontrolü ile ilgilenir. Üretim firmalarının kompleks operasyon süreçlerini düşündüğümüzde, sensörler tarafından izlenen üretim hatlarından gelen verileri sürekli izlemenin ve analiz etmenin önemini anlayabiliriz (Hazen ve diğerleri, 2014). Endüstri 4.0, endüstriyel devrimi bilgi sistemleri yardımı ile işletmelere getirmeyi amaçlamaktadır. Bu nedenle, şirketler için dijitalleştirme, verilerin anlık olarak kullanılmasına ve hızlı kararlar almak için gerçek zamanlı veri analitiğinin kullanımına karşılık gelir (Gilchrist, 2016). Gerçek zamanlı toplanan verilerin, büyük veri sistemlerinde depolanması ve ileri veri analitiği yöntemleri ile analiz edilmesi sayesinde üretim şirketleri maliyetlerin azaltılmasında, operasyon hızlarının artmasında ve ürün kalitelerinde iyi yönlü iyileşmeler sağlayabilir (Tambe, 2014). Bu tezin ana araştırma konusu da Endüstri 4.0 teknolojilerinin petrol ve gaz sektöründeki gerçek zamanlı üretim sistemlerine uygulanması maliyet azaltma, ekipman çalışma süresi, işlem hızı, ürün kalitesi ve işyeri güvenliğini nasıl etkilediğini saptamaktır.

Operasyon süreçlerine dair doğru kararlar vermek için, imalatçı firmaların üretim sistemlerinden verilere ihtiyacı vardır. Bant genişliği, depolama ve sensör maliyetlerinin düşmesiyle birlikte BT sistemleri endüstriyel makinelerin izlenmesini daha kolay desteklemektedir (Beckwith, 2011). Bu, Büyük Veri ve Nesnelerin İnterneti sayesinde endüstriyel makinelerin işletme ölçeğinde izlenebileceği anlamına gelir. Bununla birlikte, makinelerin sorunsuz izlenmesi, gelen verilerin kalitesiyle doğrudan ilgilidir (Tan ve diğerleri, 2015). Bu nedenle, değerli bilgilerin yaratılması için verilerin kalitesi çok önemlidir. Kurumsal veri depolama ve kaliteli veri işleme, şirketlerin dijitalleşmesinde ve Endüstri 4.0 uygulamalarına geçişlerinde kritik rol oynamaktadır. Eksik veya yanlış veri, zaman kaybına ve karar alma fırsatlarının kaybına neden olur (Tan ve diğerleri, 2015). Tezin içerisindeki ana bulgular da veri kalitesinin üretim şirketleri için önemini destekler niteliktedir. Son yıllarda, hemen hemen tüm endüstrilerdeki şirketler, yeni dijital teknolojileri keşfetmek ve bunlardan yararlanmak için birçok girişimde bulundu. Dijital teknolojiler ürünleri, süreçleri, ayrıca organizasyonel yapıları ve yönetim kavramlarını etkilemektedir. İmalat şirketleri için bu yeni teknolojiler, Büyük Veri ve gerçek zamanlı veri analitiğidir (Cecchinel ve diğerleri, 2014). Üretimde verimliliği artırmanın yolu, üretim ve üretim sonrası aşamalar gibi süreçler üzerinde tam kontrol sahibi olmaktır (Dalenogare ve diğerleri, 2018). Ürettim hattındaki problemler verimlilik kaybına yol açabilir. Bu kaybı önlemek için sürecin her aşamasını kontrol etmek akıllıca olacaktır (Jagadish, 2015). Verimlilik, üretimin her aşamasında Büyük Veriden elde edilen bilgilerle artırılabilmektedir. Dijital devrimin geleceğini tam olarak tahmin etmek mümkün olmamakla birlikte, bu çalışmada büyük veri ve gerçek zamanlı veri analitiğinin üretim sektörüne nasıl katkı sağladığı araştırılmıştır. Büyük veri ve gerçek zamanlı veri analitiği yöntemleriyle dijital dönüşümün, daha ucuz, daha sürdürülebilir ve daha verimli üretime olanak tanıyan endüstri işlemlerinin gerçek zamanlı incelenmesine olanak sağladığı görülmektedir (Matt el al., 2015). Örneğin, 93 ülkeden ve 25 girişimin 4.000'den fazla bilgi teknolojisi uzmanı ile yaptığı araştırmaların ışığında, IBM Tech Trends Report

(2011), Büyük Veri analizini 2010'larda göze çarpan dört yenilikten biri olarak ayırmıştır.

Petrol ve gaz sektöründe, sensörler aracılığıyla elde edilen veriler operasyonları iyileştirmek, verimliliği artırmak ve arıza mekanizmalarını önlemek için kullanılabilir (Perrons ve Jensen, 2015). Büyük veri sistemleri işletme hızını arttırdıkça, daha iyi koşullarda tedarikçilerle çalışmak ve maliyetli üretim parçalarını optimize etmek için kullanılabilirler (OECD, 2017). İmalat endüstrisinde dijital dönüşümün beklentisi, üretim süreçlerini, dijital teknolojilerin getirdiği hız, verimlilik, esneklik ve kaliteyi artıran uygulamalarından azami şekilde yararlanabilecekleri şekilde geliştirerek katma değeri artırmaktır. Geleneksel olarak, çoğu uygulayıcının Endüstri 4.0'dan ne gibi büyük avantajlar istediği sorulduğunda, şirketler karı artırmak, operasyon süreçlerini iyileştirmek ve işletme maliyetlerini düşürmek istediklerini söylemektedirler (Lee ve diğerleri, 2013). Tezdeki bulgulara göre, Büyük Veri'den analitik yaklaşımlar ile operasyonel süreçleri geliştirmek için avantajlar elde edilmesinin ulaşılabilir bir hedef olduğu gözükmektedir. Örneğin, kestirimci bakım ekipman arızasının ne zaman ortaya çıkabileceğini tahmin etmeyi ve üretim sistemlerinden gelen Büyük Verileri analiz ederek sorun oluşmadan önce arızayı önlemeyi amaçlar (Mozdianfard ve Behranvand 2015). Genel olarak, analitikteki yöntemler girdi ve çıktı arasındaki ilişkiyi en iyi açıklayan parametreleri bulmaktan oluşur. Bilgisayar Mühendisliği ve İstatistik analitik çalışmalarda kullanılan en önemli iki araştırma alanıdır. Sanayi şirketlerinin çoğu, yatırım ve sonuçların en hızlı geri dönüşünü sağladığı için Büyük Veri'yi kullanarak doğrudan öngörücü bakımı hedefler (Gilchrist, 2016). Bu tezdeki bulgular da göstermektedir ki, gerçek zamanlı veri analitiğini kullanarak üretim şirketleri operasyonlarını daha iyi kontrol edebilmekte ve karlılıklarını arttırabilmektedir.

Üretim endüstrisinde dijitalleşme, değer zincirinin her aşamasında verimlilik artışlarıyla değer yaratma potansiyeline sahiptir (McKinsey, 2014). Dijitalleşme, bu konuda ilerleme kaydeden ülkeler ve işletmeler için önemli fırsatlar sunarken, bu alanda adım atmamış ülkeler ve işletmeler için büyük bir tehdit oluşturmaktadır (Gilchrist, 2016). Tezdeki bulguların da desteklediği gibi, imalat sanayinin dijital dönüşüm sürecinde, rekabetçi bir pozisyonda olabilmesi için dijital teknolojileri verimli ve etkin bir şekilde kullanması gerekmektedir. Endüstri 4.0'a ulaşmak için imalat firmalarının büyük miktarda veriye sahip olması ve üretimi sürekli izlemesi gerektiği ortaya çıkmıştır. Ayrıca şirketlerin yüksek işlemcili bilgisayarlarla verilerini gerçek zamanlı olarak işleyebilmeleri ve depolayabilmeleri gerektiği vurgulanmıştır. Literatür ve tezdeki bulgular ışığında görülmüştür ki, birbirleriyle iletişim halinde olan sensörler tarafından üretilen verilerden elde edilen anlam, üretim şirketleri için değerli bilgilerdir. Bu görüşler, istatistik ve bilgisayar mühendisliği ile kesişen veri analizi ve makine öğrenmesi ile ulaşılabilir olduğu tezdeki bulgular dahilinde de gözlemlenebilmiştir. Veri analitiği, yüksek hacimli verilerden iş değeri oluşturmak için istatistiksel bilimi ve modern sayısal hesaplama yöntemlerini birleştirerek bilgi potansiyelini ortaya çıkarmayı amaçlayan bir çalışma alanıdır (Simeone, 2018). Gerçek zamanlı veri analizi, istatistiki teknikler yoluyla veri yığınları arasından gözle görülemeyen bilgileri ortaya çıkartabilir. Veri analizinde yaklaşık yüzlerce algoritma ve saha metodu vardır (Provost ve Fawcett, 2013). Makine öğrenmesi, geçmiş ve devamlı olarak gelen verileri kullanarak bir durumu modellemeyi amaçlamaktadır, böylece yeni veriler geldiğinde, öğrenilen sistem ile üretim için önemli olan bilgiler tahmin edilebilmektedir. Tezdeki bulgularında gösterdiği gibi, makine öğrenmesi, şirketin daha yüksek düzeyde bilgi edinmesine yardımcı olacak bilgileri kullanmak için yaratıcı yöntemler bulmak amacıyla kullanılabilir gelmiştir. Makine öğrenim modelleri sürekli veri eklendikçe güncellenmektedir. Buradaki değer, firmaların gerçek zamanlı verileri bağlamında makine öğrenmesiyle en iyi ve sürekli değişen veri kaynaklarını kullandıkları için geleceği tahmin etme fırsatına sahip olmalarıdır (Simeone, 2018). Tezdeki bulguların da desteklediği gibi, üretim şirketleri bu sayede maliyetlerini azaltma, ekipman ömürlerini uzatma, operasyon hızlarını artırma, ürün kalitesini iyileştirme ve işyeri güvenliğini artırma konularında kendilerine ve ekonomiye fayda sağlamaktadır.

Verilerden anlam çıkarmak şirketler için her zaman önemliydi (Regalado, 2014). Ancak, Büyük Veri önceki veri yönetim sistemlerine göre farklıdır. İnternet kullanımının artması ve depolama maliyetinin düşmesi Büyük veriyi hacmi, hızı ve çeşitliliği açısından farklı kılmıştır (McAfee ve Brynjolfsson, 2012). Hacim, kurumsal sistemler tarafından üretilen veri miktarını temsil eder. Hız, verilerin üretildiği hız ile ilgilidir. Çeşitlilik, şirket sistemleri tarafından üretilebilecek tüm yapılandırılmış ve yapılandırılmamış verileri temsil eder (Zikopoulos ve diğerleri, 2012). Dijital dönüşümün gerekliliği tüm endüstrilerde inovasyon oranında çarpıcı bir artışa yol açmıştır (Matt ve diğerleri, 2015). Bir dizi yeni çalışma, verilerin büyüme hızının iki yılda bir iki kat artmasının beklendiğini göstermiştir (Regalado, 2014). Bu eğilim imalat alanında da geçerlidir. Endüstri 4.0'ın vizyonu, üretim süreçlerinin, kurumsal bilgi teknolojilerinin mimarisiyle uyumlu bir ağ üzerinden bilgi alışverişinde bulunabileceği ve bunun sonucunda üretim süreçleri için önemli etkileri bulmanın daha kolay olacağı bir endüstriyel altyapı oluşturmayı amaçlamaktadır (Nagorny ve diğerleri, 2016). Dolayısıyla, Endüstri 4.0, şirketlerin gelişmiş analitik metotların yardımıyla anında fikir sahibi olmalarına yardımcı olur ve üretim süreçlerini, ürün kalitesini ve tedarik zinciri optimizasyonunun performansını doğru bir şekilde anlayabilmelerini sağlar. Bu sayede üretimdeki verimsizlikleri tespit etmelerine ve bu analizler sonucunda düzeltici veya önleyici faaliyetlerde bulunmalarına yardımcı olmaktadır (Almada-Lobo, 2016). Ayrıca, Büyük Veri kullanımından elde edilecek potansiyel faydaların ve ortaya koyacağı zorlukların doğal olarak sektörden sektöre farklılık göstereceği tahmin edilmektedir. İmalat sanayilerinin, bilgi teknolojisi sektörlerinin, devlet kuruluşlarının yanı sıra finans ve sigorta sektörlerinin de Büyük Veri kullanımından büyük ölçüde fayda sağlaması beklenmektedir (Yin ve Kaynak, 2015). Analizler, büyük veri ve gerçek zamanlı veri analitiğinin önümüzdeki yirmi yılda küresel gayri safi yurtiçi hasıladan 15 trilyon dolara kadar fayda sağlayabileceğini göstermektedir (Evans ve Anninziata, 2012).

Mevcut endüstriyel devrim, üretim sektörünü Büyük Veri ortamında birbirine bağlı sistemlerden fayda üretmeye doğru yönlendirmektedir. Kültürlerinde yeni metodolojiler ortaya koyan daha fütüristik vizyona sahip üretim şirketleri, yakın gelecekte önemli ölçüde başarılı ve karlı olma fırsatına sahip olacaklardır (Bagheri ve ark., 2014). Büyük Veri analizinin olası faydalarını daha net bir şekilde göstermek için, çeşitli sektörler için entegre mühendislik, tasarım, proje yönetimi, tedarik ve imalat hizmeti sağlayıcısı olan SPEC adlı şirket için bir durum araştırması yapılmıştır. Makalelerinde, Tan ve arkadaşları (2015), ilgili şirketin yöneticilerinin rekabet avantajı elde etmek için mevcut Büyük Veriyi kullanmalarında analitik altyapının gerekli olduğunu belirtmiştir. Makalede, yöneticilerin ihtiyaç duydukları, problemleri çözecek analitik yaklaşımların tutarlı bir resmini oluşturmak için çeşitli veri akışlarını yapılandırmak ve birbirine bağlamak olduğu belirtilmektedir. Şirketin CEO'su, Büyük Veri ve Nesnelerin İnterneti ile SPEC şirketinin, sistemlerindeki faydalı bilgiler sayesinde maksimum kapasite üretim şartlarına ulaşabildiklerini belirtmiştir (Tan ve diğerleri, 2015, s.230).

Son zamanlarda, IoT, sensörlerin verilerini toplayan üretim şirketlerinin ürünlerinin durumunu daha iyi izlemelerini ve böylece gerçek zamanlı işlem verilerini kullanarak daha iyi kararlar almalarını sağlamaktadır (OECD, 2017). Örneğin Rolls-Royce, 1980'lerde tek başına jet motorları satmayı bıraktı ve bir süre boyunca sabit maliyetli bir hizmet paketi olan saat başına güç satmaya başladığında bu yaklaşımın öncüsü oldu (OECD, 2017, s.75). Dünyanın en büyük kamyon karoseri üreticilerinden biri, römorklarının bakımını denetlemek için Büyük Veri ve Nesnelerin İnterneti'ni kullanmaktadır (OECD, 2017). Dahası, veri analitiği işlemleri güç üretimi ekipmanları üreticileri tarafından karmaşık işlemlerinde beklenmeyen durumları öngörmek için kullanılmaktadır (Chick, Netessine ve Huchzermeier, 2014). Japonya'dan yapılan tahminler, şirketlerdeki gerçek zamanlı veri analizlerinin kullanılmasının bakım maliyetlerini 5 trilyon JPY kadar karşılayabileceğini göstermektedir (OECD, 2017). Ek olarak, elektrikle ilgili maliyet tasarrufuyla 45 milyar JPY'den fazla kazanılabileceği öngörülmektedir (MIC, 2013). Almanya için yapılan tahminler üretimde IoT sayesinde veri analitiği kullanımının artmasının, verimliliği %5 ila %8 artırabildiğini göstermektedir (OECD, 2017). Mekanik ve endüstriyel parça üreticilerinin ve otomotiv şirketlerinin ise en yüksek verimlilik artışlarını elde etmeleri beklenmektedir (Rüssmann vd., 2015). Almanya'da Endüstri 4.0 ile, 2025 yılına kadar, özellikle mekanik, otomotiv, kimya ve bilişim sektörlerinde potansiyel katkılar olarak, 2025 yılına kadar 78 milyar avroya ulaşılabileceği tahmin ediliyor (OECD, 2017).

Bu tezde, Bölüm 2 içerisinde geniş bir literatür taraması kapsamında, Endüstri 4.0'ın tanımı, dijital süreçlerin kilit bileşenleri olarak veri analitiği ve makine öğrenmesi, Büyük Veri sistemlerinin endüstrideki kullanımları, Endüstri 4.0'a olan geçişin öngörülen faydaları, petrol ve gaz endüstrisinin temel işleyiş yapısı, dijital teknolojilerin petrol ve gaz endüstrisindeki kullanımı ve üretim sektörünün Endüstri

4.0’a olan ihtiyacını incelemiş olan yayınların bir derlemesi yapılmıştır. Bu bölümde sunulan bilgilerin, sadece bu tezde elde edilen bulgular ve bu bağlamda sunulan kritik değerlendirmeler arasındaki bağlantıyı kurması değil, aynı zamanda tezde elde edilen bulguların, daha geniş kapsamda dünyada yapılan araştırmalarla nasıl örtüştüğünü ortaya koyması beklenmektedir. Bölüm 3, tez kapsamındaki araştırmalarım sırasında kullanmış olduğum yöntemleri açıklamaktadır. Bölüm 4’te gerçek zamanlı veri analitiği yöntemlerinin uygulanmasının petrol ve gaz sektöründe maliyetler, ekipman ömrü, ürün kalitesi, operasyon hızı ve işyeri güvenliği yönünden nasıl katkı sağladığı konularında elde edilen araştırma sonuçları incelenmiştir ve hangilerinin petrol ve gaz sektörü için daha önemli olduğu ortaya konulmaktadır. Son olarak sonuç bölümünü oluşturan Bölüm 5’te, elde edilen bulguları gözden geçirilmekte, devlet, üretim sektörü ve rafineri sektörü aktörlerine dönük bir dizi politika önerisinde bulunulmakta, çalışmanın kısıtları üzerinde durulmakta ve gelecekte bu konuda yapılabilecek çalışmalara yönelik temel oluşturulmaktadır.

Dünyada petrol ve gaz sektörü üzerine yapılan çalışmalar az sayıdadır. Bu az sayıdaki çalışmalar da, bu tezde incelenen konulardan birçok yönden ayrılmaktadır. Bildiğim kadarıyla, bu tezin ana araştırma konusunu oluşturan husus hakkında, yani petrol ve gaz endüstrisinde dijital dönüşüm ve veri analitiği uygulamalarının nasıl katkı sağladığına dair yapılmış bir diğer çalışma mevcut değildir. Ayrıca, anket sırasında sorulan sorular ve sorulara verilen cevaplar daha önce Türkiye’de benzer bir çalışmada kullanılmamıştır. Petrol ve gaz sektörü ile ilgili olarak oluşturulmuş olan politika önerileri daha önceki çalışmalarda oluşturulan öneri veya hipotezlerden farklıdır. Tüm bu özellikler, benim fikrime göre, tezin özgünlük gereksinimini karşılayabilecek niteliktedir. Bu tez, yukarıda bahsedilen konu hakkında literatüre katkı yapmayı amaçlamakta ve politika belirlemeden sorumlu otoritelere uygun politika çözümleri oluşturmada yardımcı olmayı hedeflemektedir.

Anket ve mülakatlar sonucunda edinilen bilgiler, bu tezin öne sürdüğü teknoloji politikalarına özgünlük katmıştır. Hem nitel hem de nicel biçimde edinilen bilgiler sayesinde, gerçek zamanlı veri analitiğine geçiş sürecinde yer almış ve şu an bu sistemleri aktif kullanan firma örneği özellikle seçilmiştir. Bu sayede, hem Endüstri 4.0 uygulamalarına geçiş aşamasında yaşanılan zorluklar öğrenilmiş hem de bu sürece yeni başlamak isteyen şirketlerin neleri başarması gerektiği konusunda somut veriler elde edilmiştir. Toplanan verilerden elde edilen bulgular, üretim şirketlerinin bu alanda yapacakları çalışmalara yol göstermesi beklenmektedir. Anket ve mülakat aşamalarında özellikle Endüstri 4.0 uygulamalarına geçiş aşamalarında yaşanan zorluklara ve daha iyi yapılması gereken süreçlere dikkat çekilmiştir. Ayrıca, gerçek zamanlı veri analitiği ile yönetilen uygulamalar ile eski sistemlerin arasındaki farklılıklar incelenmiş ve potansiyel katkıların neler olduğu araştırılmıştır.

Bu tez, petrol ve gaz sektöründeki bulgulardan yola çıkıp üretim sektörü için gerçek zamanlı veri analitiği ve büyük veri sistemlerinin nasıl katkılar yaptığını araştırmakta ve bu doğrultuda politika önerileri sunmaktadır. Politika yapıcılar arasında, üretime dayalı ekonomik büyümeyi destekleyen politikaların ve bu politikaların üretimin geleceğini etkileyen teknolojiler üzerindeki etkisini daha iyi anlama ihtiyacı konusunda artan bir eğilim olduğu gözükmektedir (O'Sullivan ve diğerleri, 2013). Bu tezde, üretim şirketlerinin kendilerini dijital dünyaya hazırlayabilmek için ne tür politikalar benimsemeleri gerektiği araştırılmış ve karma yöntemlerle çeşitli bulgulara ulaşılmıştır. Bu bulgular ışığında imalatçı firmalar için politika önerileri yapılacaktır. İlk olarak, Endüstri 4.0 yolculuğunun başlangıcındaki şirketler için dijital dönüşüm ve politika tasarımı göz önünde bulundurulmuştur.

- Başlıca bulgulardan biri, şirketlerin dijital dönüşümü gerçekleştirecek sistemleri etkin bir şekilde yönetmek için daha yetenekli bir işgücüne sahip olmaları gerektiğidir. Büyük veri yönetimi ve veri analitiği alanında çalışanlar yetiştirmek ve mevcut çalışanları yeniden eğitmek için harcanan zaman göz önüne alındığında, proaktif bir işgücünün stratejik ve uzun vadeli planlanması kapsamlı insan kaynakları politikaları oluşturulmasına yardımcı olacaktır.
- İmalat şirketleri yatırımlarını üretim hedeflerine göre yönlendirmeli, dijital stratejilerini tanımlamalı ve sektördeki dijital dönüşüm yol haritasını şekillendirmelidir. Ayrıca, BT birimi üst düzey yönetimden desteklenecek şekilde konumlandırılmalı ve buna uygun organizasyon yapısı oluşturulmalıdır.

- Uygulanılabilirliği sektörde kanıtlanmış ve kar üzerinde en yüksek etkiye sahip olan açık kaynaklı teknolojilerin kullanımına öncelik verilmelidir. Dijital dönüşümün yarattığı ek kar, şirket içinde güçlü bir inovasyon döngüsünü beslemeleli ve şirketler bu yazılımların kullanımını yaymalıdır. Ayrıca, eski yapıya sahip teknolojik sensörler, veri alınmaya uygun hale gelecek şekilde güncellenmeli ve yeni ekipmanlar bu doğrultuda temin edilmelidir.
- Şirketlerin ihtiyaçlarının zaman içinde değiştiğini mülakat ve anket sonuçlarından gözlemledik. Bundan dolayı, imalatçı firmaların çevik proje yönetimi tasarımına geçmeleri gerekmektedir. Şirketin dijital ihtiyaçları düzenli aralıklarla belirlenmeli ve gözden geçirilmelidir. Bu ihtiyaçlar üst yönetim tarafından önceliklendirilmeli ve bu önceliklendirmeye göre proje planları yinelemeli olarak yapılmalıdır.
- Üretim şirketleri, Büyük Veri analitiği, bulut ve yüksek performanslı bilgi işlem ve IoT gibi teknolojilerini sağlayan Ar-Ge yatırımlarını desteklemeyi düşünmelidir. Ar-Ge faaliyetlerini destekleyen teknopark yapıları kurmalıdırlar. Çünkü bu sayede daha fazla teknolojiye ulaşabilecekler ve yetenekli insan kaynaklarına daha yakın olacaklardır. Ayrıca üniversitelerin ilgili bölümlerinden destek alarak akademinin gücünü de almaları gerekmektedir. Bu amaç ile kurulan şirketlere devlet destek vermeli ve ürün odaklı çalışmalar ile üretim şirketlerinin ihtiyaçlarını karşılayacak ürünlere odaklanmalıdır. Bu şekilde, şirketler arası bilgi birikimi doğrusal olmayan bir şekilde yayılacak ve ekosisteme katkıda bulunacaktır. Bunun en iyi örneklerinden biri, şirketlerin eksikliklerini anlamak ve bu ihtiyaçları karşılamak için teknoloji şirketleri ile ürünler geliştirmek için birbirlerini ziyaret etmeleridir.

Üretim şirketlerinin verilerden karar veren ve otomatik işlem yapan sistemlerden veriye geçmeleri genellikle kolay değildir. Petrol ve gaz endüstrisinde bile, gerekli donanım yetkinliklerine rağmen, teknik zorluklar yaşandığı gözlemlenmiştir. Tezin bulgular bölümünde veriye dayalı karar veren ve otomasyonun finansal avantajlarından yararlanma aşamasında olan veya bu aşamaları geçen ve bu süreçte zorluk çeken şirketler için politika önerileri yapılacaktır.

- Şirketler kendi içlerinde bilinçlendirme faaliyetlerine başlamalıdır. Bu, bilinçlendirme, eğitim ve rehberlik gibi faaliyetlerle yapılabilir. Bu destekler, özellikle örgütsel değişim olmak üzere, tamamlayıcı bilgi tabanlı sermaye biçimlerindeki yatırımları teşvik etmeyi amaçlamalıdır.
- Şirketler, güvenli veri paylaşımını teşvik eden ve sektörlere olumlu yayılmaya destek veren bir inovasyon politikaları karışımı geliştirmelidir. Bu, sektörel bilgi birikiminin yayılması için önemlidir. Araştırmacılar, akademik makalelerin alıntılarına benzer şekilde veri setlerine erişebilmelidir. Bu şekilde, akademik destek üretim sektörüne daha fazla yayılabilir.
- Giderek daha fazla şirketin dijitalleştirildiği bir zamanda, iyi planlanmış bir dijital dönüşüm stratejisine sahip olmak önemlidir. Kapsamlı bir IoT stratejisi geliştirmek için hızlı hareket etmeyen yenilikçi iş modelleri ve şirketlerin rakiplerinin gerisinde kaldığı görülmektedir. Bağlı üreticilerden kesintisiz müşteri deneyimi sunan katma değerli servislere ve perakendecilere kadar, üretim şirketlerinin her müşteriye olağanüstü deneyimler sunmaya odaklanması gerekir.
- Her şeyden önce, üretim şirketlerini dijital dönüşüm yolculuğunda desteklemek ve ilerlemelerini sağlam bir temelde oluşturmak için geçiş sürecini hızlandıracak mekanizmalar ve programlar oluşturulmalıdır. Öncelikle bu konularda çalışan şirketler için vergi indirimleri sağlanmalıdır.
- Hükümet, üretim sektöründe dijital dönüşümü hızlandıran programlarla dönüşüm yolculuğunda ihtiyaç duyulacak rehberlik ve danışmanlık hizmetleri almalarını teşvik etmelidir.

Bu tezde, Petrol ve gaz sektörü için çıkarımlar yaparken yalnızca beş ana alana odaklanılmıştır. Bunlar, maliyetlerin azaltılması, ekipman ömrünün uzatılması, operasyonel hızın artırılması, ürün kalitesinin iyileştirilmesi ve işyeri güvenliğinin geliştirilmesi konularıdır. Gerçek zamanlı veri analitiği ve büyük veri sistemlerinin, beş ana alan için de olumlu yönde katkı sağladığı tespit edilmiştir. Fakat analiz edilen veriler, üretim sektöründen petrol ve gaz endüstrisini göz önüne alarak elde edilmiştir. Bu nedenle, bu tez tüm üretim sektörüne genellenemeyebilir. Bu tezdeki araştırmayı sensör verilerinden anlamlı sonuçlar üretmenin çoğunlukla kritik olduğu üretim sektörlerine uyarlayabiliriz. Yukarıda sıralanan beş ana çalışma alanına ek olarak, farklı katkılar da belirlenebilir. Bu tez çalışmasında, tüm üretim problemlerini çözebilecek derinlemesine bir analiz tartışılmamıştır. Yine, istatistiksel olarak anlamlı sonuçlar verecek kapsamlı bir istatistiksel analizin olmamasına neden olan nispeten küçük örneklem büyüklüğü, kapsamlı hipotezler inşa etmemi ve test etmemi engellemiş bulunmaktadır.

Genel olarak, Endüstri 4.0 sistemleri bilgiyi büyük ölçeklerde işleyecek ve bilgi altyapısının üretim araçlarına entegre edilmesini sağlayarak petrol ve gaz sektörünün değerini artıracaktır. Teknolojiyi içselleştiren üretim sektörleri, eğer Büyük Veri'nin ve gerçek zamanlı veri analizinin arkasındaki gerçek değeri anlayabiliyorsa, küresel ekonomideki rolünü değiştirecek büyük bir dönüşüm yaratmanın eşiğindedir.

APPENDIX H: TEZ İZİN FORMU

TEZ İZİN FORMU / THESIS PERMISSION FORM

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TEZİN ADI / TITLE OF THE THESIS (**İngilizce** / English) : IMPLEMENTING REAL-TIME DATA ANALYTICS METHODS FOR PREDICTIVE MANUFACTURING IN OIL AND GAS INDUSTRY: FROM THE PERSPECTIVE OF INDUSTRY 4.0

TEZİN TÜRÜ / DEGREE: **Yüksek Lisans** / Master ■ **Doktora** / PhD ☐

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A copy of the decision of the Institute Administrative Committee will be delivered to the library together with the printed thesis.

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