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ANALYZING THE FINANCIAL PERFORMANCE OF AUTOMOTIVE COMPANIES BEFORE AND AFTER INDUSTRY 4.0: AN APPLICATION IN THE BIST SUSTAINABILITY INDEX

OTOMOTİV FİRMALARININ ENDÜSTRİ 4.0 ÖNCESİ VE SONRASI FİNANSAL PERFORMANSLARININ ANALİZİ: BİST SÜRDÜRÜLEBİLİRLİK ENDEKSİ'NDE BİR UYGULAMA*

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Abstract

Today, the "Industry 4.0 revolution", which offers opportunities such as a substantial competitive advantage, increase in production capacity, and cost reduction, is preparing to move institutions to a rapidly changing information age. Therefore, the importance of keeping up with innovations and providing sustainable performance is increasing for businesses in this age. On the other hand, it draws the attention of researchers to whether there is a difference between the financial performances of companies before-after industry 4.0. The study compares the financial performances of automotive companies that have adopted Industry 4.0 methods in the BIST Sustainability Index, before and after Industry 4.0. For this purpose, the companies' financial performances were analyzed and compared between 2013-2015 and 2016-2018 with the Gray Relational Analysis method, one of the multi-criteria decision-making techniques. The entropy which is an objective method, was preferred for weighting the criteria. Ten financial ratios were used as criteria in the performance evaluation. As a result, almost all companies increase their financial performance, but a decrease occurs only in one company's financial performance with the transition to Industry 4.0. So it can be stated that the increase in the share of R&D expenditures and Industry 4.0 investments will positively affect the financial performance of companies.

Keywords: Bu alanda Automative, Borsa Istanbul, Corporate Sustainability, Gray Relational Analysis, Financial Analysis, Industry 4.0, Multi-Criteria Decision Making Techniques, Performance.

Öz

Günümüzde çok büyük bir rekabet avantajı, üretim kapasitesi artışı ve maliyet azaltma imkânı sunan "Endüstri 4.0 devrimi", kurumları çok hızlı değişen bir bilgi çağına taşımaya hazırlanmaktadır. Dolayısıyla işletmeler için, ortaya çıkan yeniliklere ayak uydurmanın ve sürdürülebilir performans sağlamanın önemi giderek artmaktadır. Diğer yandan firmaların finansal performanslarında endüstri 4.0 öncesi ile sonrası arasında bir fark olup olmadığı araştırmacıların dikkatini çekmektedir. Çalışmada, BİST Sürdürülebilirlik Endeksi'ndeki Endüstri 4.0 metotlarını benimsemiş otomotiv şirketlerinin, Endüstri 4.0' dan önceki ve sonraki finansal performansları karşılaştırılmaktadır. Bu amaçla, bu şirketlerin çok kriterli karar verme tekniklerinden Gri İlişkisel Analiz yöntemi ile 2013-2015 ve 2016-2018 yılları arasındaki finansal performansları analiz edilmiş ve yıllara göre sıralanmıştır. Kriterlerin ağırlıklandırılmasında, objektif bir yöntem olan Entropi yöntemi tercih edilmiştir. Performans değerlendirmesinde kriter olarak on adet finansal oran kullanılmıştır. Sonuç olarak, Endüstri 4.0'a geçişle birlikte şirketlerin çoğunda finansal performans artışı görülmüş, sadece bir firmanın finansal performansında düşüş ortaya çıkmıştır. Böylece, Endüstri 4.0 yatırımlarının ve Ar-ge harcamalarının payının artmasının şirketlerin finansal performansını olumlu yönde etkileyeceği ifade edilebilir.

Anahtar Kelimeler: Borsa İstanbul, Çok Kriterli Karar Verme Teknikleri, Endüstri 4.0, Finansal Performans, Gri İlişkisel Analiz, Kurumsal Sürdürülebilirlik, Otomotiv, Performans.

GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Dünya da olduğu gibi, Türkiye'de de endüstri 4.0 uygulamalarını gündemine alan sektörlerin başında otomotiv sektörü gelmektedir. Bu çalışmanın amacı, sürdürülebilirlik endeksinde yer alan otomotiv şirketlerinin endüstri 4.0 kapsamındaki faaliyetlerinin, bu şirketlerin finansal performanslarına nasıl bir etkide bulunduğunu araştırmaktır.

Araştırma Soruları

Araştırmanın temel sorusu "Endüstri 4.0 uygulamalarını benimsemiş şirketlerin bu uygulamalara geçmeden önceki finansal performansları ile, geçtikten sonraki finansal performansları arasında bir fark var mıdır?" şeklinde ifade edilebilir.

Literatür Araştırması

Kung ve Wen (2007), Tayvan'daki girişim sermayesi işletmelerinin finansal performansını etkileyen önemli mali oran değişkenleri ve diğer finansal göstergeleri bulmayı amaçladıkları çalışmada gri ilişkisel analiz ve gri karar verme yöntemlerini kullanmışlar ve işletmelerin nitelikleri ile finansal performansları arasında anlamlı bir ilişki olduğu ve gri sistem teorisinin, ilişkiyi test etmede uygun bir yöntem olduğu sonuçlarına ulaşmışlardır. Lin ve Wu (2011), bankacılık sektörü için 111 örnekli gerçek veri seti ile bir finansal kriz uyarı sistemi geliştirmeyi amaçlayan çalışmalarında gri ilişkisel analiz yöntemini kullanmışlar ve önerilen modelin geleneksel modellerden daha iyi tahmin doğruluğu gösterdiği sonucuna ulaşmışlardır. Peker ve Baki (2011), sigorta sektöründeki üç şirketin finansal performanslarını gri ilişkisel analiz yöntemiyle ölçmüşler ve likidite oranları ile finansal performansın başarısı arasında doğru orantı olduğu sonucuna ulaşmışlardır. Doğan (2013), gri ilişkisel analiz yöntemini kullanarak 2005-2011 döneminde İMKB' de işlem gören 10 bankanın finansal performansının ölçümünü yapmışlardır. Sonuç olarak bankaların varlıklarının karlılığı ile finansal performansları arasında doğru orantı olabileceği sonucuna ulaşmışlardır. Stanujkic ve diğerleri (2013), farklı yöntemlerin kullanılmasının, farklı alternatif sıralama düzenleri üretip üretmeyeceğinin belirlenmesi amacıyla gri ilişkisel analiz, Aras, Copras, Moora, Cp, Vikor ve Topsis yöntemlerini uygulamışlar ve farklı sonuçlara yol açan bazı nedenler bulunduğu ve kullanılan her yöntemin kendine özgü özelliklerinin olduğu sonuçlarına ulaşmışlardır. Altan ve Candoğan (2014), Türkiye'deki katılım bankalarının geleneksel performans ölçüm sonuçları ile gri ilişkisel analiz ölçüm sonuçlarının karşılaştırılması amacıyla gri ilişkisel analiz ve oran analizi yöntemlerini kullanmışlar ve sonuçta her iki analiz türünün sonuçlarının birbirinden farklı olduğu görülmüştür. Ecer ve Günay (2014), BIST' teki 9 turizm şirketinin 2008-2012 dönemine ilişkin finansal performansını değerlendirmek için gri ilişkisel analiz metodunu uygulamışlar ve finansal performans ölçümünde en önemli göstergenin kaldıraç oranı olduğu sonucuna varmışlardır. Wang ve diğerleri (2015), Gri ilişkisel analiz yöntemini kullanarak Tayvan otelcilik sektörünün 2008-2012 yıllarındaki finansal performansının saptanması amacıyla yaptıkları çalışmanın sonucunda varlık getirisinde, hisse başına kazanç oranının en yüksek etkiye sahip olduğu ve bunu borç oranı, aktif devir hızı ve kâr marjının izlediğini saptamışlardır. Özdağoğlu ve diğerleri (2017), BIST' teki 98 imalat şirketinin 2015 yılına ait finansal performansını değerlendirmek üzere gri ilişkisel analiz metodunu uygulamışlar ve en yüksek performansa sahip firmanın bir kırtasiye firması olduğu sonucu ortaya çıkmıştır. Güleç ve Özkan (2018), çalışmalarında 2005 – 2016 döneminde BIST' teki 16 çimento şirketinin finansal performansları ile "satın al ve elde tut getiri yöntemi" ile işletmelerin hisse senedi getirilerinin hesaplanması ve gri ilişkisel analiz değerleriyle karşılaştırılmasını amaçlamışlardır. Sonuç olarak çimento şirketlerinin dönemler itibariyle kârlı, etkin ve yüksek hisse senedi getirisine sahip olduğunu ve gri ilişkisel analiz yöntemiyle bulunan değerler ile hisse senedi getirileri yöntemiyle elde edilen değerler arasında farklılık olduğunu bulmuşlardır. Sarraf ve Nejad (2020), İran'da 35 adet belediye su ve atık su şirketinin performanslarının dengeli puan kartı kriterlerine dayanarak gri ilişkisel analiz ve veri zarflama analizi yöntemleriyle değerlendirişler ve gri ilişkisel analizin performans ölçmede veri zarflama analizine göre daha doğru bir yöntem olduğu sonucuna varmışlardır. Akgün ve Akgün (2019), Türkiye'deki bilişim teknolojisi şirketlerinin Endüstri 4.0 ortamındaki performanslarının TOPSIS yöntemi kullanarak 9 finansal oran ile analizini gerçekleştirdikleri çalışmalarının sonucunda, 2017 yılında BIST bilişim teknoloji endeksindeki en yüksek performansa sahip şirketin LOGO firması olduğu belirlenmiştir.

Yöntem

Araştırmada Borsa İstanbul' da işlem gören, sürdürülebilirlik raporu yayınlayıp, Endüstri 4.0 faaliyetlerinde de bulunan otomotiv üretim firması şirketlerin, 2013 ve 2018 yılları arasındaki mali verilerinden yararlanarak finansal oranları hesaplanmıştır. Bu oranların ağırlıkları Entropi Yöntemi ile objektif olarak hesaplandıktan sonra, çok kriterli karar verme tekniklerinden biri olan Gri İlişkisel Analiz Yöntemi ile değerlendirilmiştir. Araştırmanın kısıtı ise, analize konu olan firmaların ve yıl sayısının az olmasıdır. Endüstri 4.0 kavramının sürdürülebilirlik raporlarında 2016 yılından itibaren görüldüğü için, çalışmada bu tarihten önceki ve sonraki üç yıl ele alınmıştır. Bu firmaların Endüstri 4.0'a geçişlerinin finansal performanslarında meydana getireceği olası değişikliği görebilmek için literatürde bulunan dört temel finansal oran göstergesi (likidite, finansal yapı, devir hızı, karlılık) içinde yer alan 9 finansal oran ile buna ek olarak işletmelerin ar-ge giderleri / toplam varlıklar oranı analizlerde kullanılmıştır.

Sonuç ve Değerlendirme

Çalışmada hemen hemen tüm firmaların, analizi gerçekleştirilen dönemin ilk yarısını oluşturan yıllara göre ikinci yarısını oluşturan yıllarda, finansal performanslarında daha fazla gelişme gösterdiği ve bunun da Ar-ge yatırımlarıyla ilişkili olduğu söylenebilir. Bu sonuca göre, Endüstri 4.0 faaliyetlerinin şirket performansındaki sonuçları pozitif olarak etkilediği söylenebilir. Bir firma için ise, incelenen dönemde Ar-ge harcamaları payının çok değişmediği, bu nedenle ilgili dönemin ikinci yarısında finansal performansında da bir iyileşme görülemediği söylenebilir.

1. INTRODUCTION

As in all areas of life, sustainability has become an essential issue for institutions, one of whose purposes is to maintain their existence. Thus, while keeping up with changes in industry, they should also aim to be sustainable.

The foundations of the fourth industrial revolution, officially introduced at the Hannover Fair in Germany in 2011, were laid at the end of the 20th century (Özsoylu, 2017). Industry 4.0 allows the creation of an intelligent network of machines, products, components, features, individuals, and ICT systems across the entire value chain in order to create a smart factory (Mrugalska and Wyrwicka, 2017). In brief, this revolution is explained as a technological development process based on advanced digitalization in smart factories, the combination of "smart" objects between the internet and later technologies, and a new, fundamental paradigm shift in industrial production (Lasi et al., 2014).

This study examines automotive companies that have switched to these technologies by focusing on companies that use industry 4.0 technologies in the BIST Sustainability Index. The basis of the study is to reveal the effects of industry 4.0-related changes on the financial performance of companies in the Turkish automotive sector. The first part of the study presents the conceptual framework and industry 4.0 concept and gives samples of technologies. The second part discusses similar previous research. The third part presents the findings obtained through Grey Relational Analysis, and the last part offers an overall evaluation of the research and its conclusion.

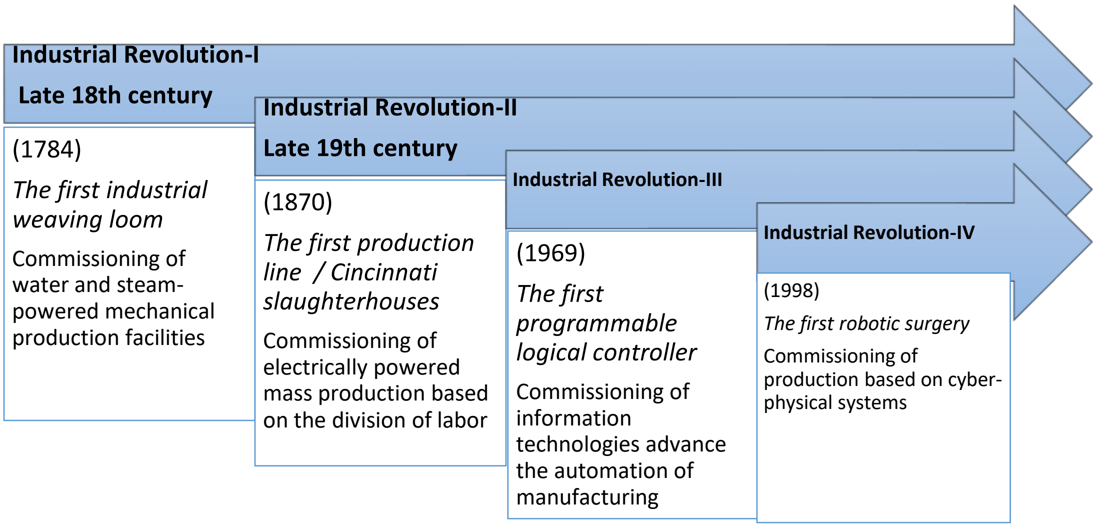
2. WHAT IS THE INDUSTRY 4.0 REVOLUTION?

The original meaning of the word “industry” in French was hard work, or to reveal by working. The meaning of the word “industry”, which is used synonymously in Turkish, is "the whole of the methods and tools used to process raw materials and create energy resources." (Türk Dil Kurumu Sözlükleri, 2019).

Before the Industrial Revolution, people made their living by hunting and gathering. Accordingly, they led a nomadic and scattered lifestyle (Özsoylu, 2017). After the agricultural revolution (8000 BC), professions such as animal husbandry and craft-based work such as weaving, carpentry, and blacksmithing emerged alongside a settled form of life (Özdemir, 2013). After the transition of people to settled life, there emerged problems like an increase in urbanization and the consequent inability of supply to meet demand (Özsoylu, 2017). These problems initiated the first industrial revolution.

Each revolution lays the foundations for the next and paves the way for it to emerge. The industry 4.0 revolution has emerged due to the previous revolutions and will form the basis for the following revolutions. Figure 1 shows the industrial revolutions in chronological order.

Figure 1. The Historical Development of Industrial Revolutions



Resource: (Drath, R. and Horch, A., 2014).

Industry 4.0 is considered the fourth stage of industrialization, the "internet of machines, computers, people and things." For this reason, some studies also call it the industrial internet (Özsoylu, 2017). Industry 4.0 uses the latest technological inventions and innovations to combine operational information and communication technologies and transform them into production (Gilchrist, 2016).

- The targets of industry 4.0 are as follows:
- Advanced digitalization in factories
- Combination of future technologies and internet technologies into "smart" objects (machines and products)
- Creation of a new basic model of industrial production
- Realization of technology in which products control their production processes
- •Production of personalized products while maintaining the economic conditions of existing mass production (Lasi et al., 2014)

Industry 4.0 enables transparency and improved communication between units in production, easy access to information, and efficient production due to lower costs and energy use. In addition, it strengthens cyber security to ensure confidentiality when data is stored in the cloud, and, overall, creates reliable, efficient production of a high standard (Tanrıverdi, 2017). In previous development process, a need arose (for example, in industry 1.0, the supply became unable to meet the demand) and then inventions were realized. Industry 4.0, however, has emerged not due to necessity like other revolutions but due to technological and scientific developments.

While all the benefits of previous industrial revolutions come from actions, the fourth revolution has a chance to proactively guide the way it transforms the world (Gilchrist, 2016). The core vision of industry 4.0 is to create global supply chains so that industrial enterprises can create cyber-physical systems that will intelligently connect and control their machines, factories, and storage facilities in the future (PWC, 2019).

In contrast to the traditional production process, this represents a new model, a change from "centralized" to "decentralized" production, that has emerged with technological advances. It refers to the technology revolution, where industrial production machines no longer only produce a product but can also communicate with other machines to inform them how to make it. Some of the principles that distinguish industry 4.0 businesses from others include the following:

Meeting the personal needs of the customer, flexibility, optimized decision making, resource efficiency and effectiveness, the creation of value opportunities through new services, and responses to demographic changes in the workplace.

3. NEW TECHNOLOGIES EMERGED WITH INDUSTRY 4.0

The primary idea that triggered the industry 4.0 revolution was the creation of factories that can manage themselves and have smart production processes. Different technologies are required to build smart factories (EBSO, 2015). The most common technologies are described below.

3.1. Three-Dimensional (3D) Printers

First invented by Chuck Hull in 1984 (EBSO, 2015), 3D printers melt and superimpose thin layers of material (metals, polymers, organic materials) to create a physical object from a digital design. In short, 3D printers are next-generation technology that transforms computer virtuality into tangible reality (Banger, 2017).

Thanks to 3D printers, any model can turn into a tangible object based on its design. Even complex things that were once impossible to manufacture can become actual products, as long as they can be designed. The resulting outcome can be produced in chosen dimensions and sizes, and can use more than 100 different materials (solid, liquid, or powder) for printing (Ekici, 2012). In addition, after producing a prototype, it generates less environmental waste than other production methods (Kabaklarlı, 2016).

3.2. Internet of Things (IOT)

The Internet of Things can be defined as a smart connection of smart devices that can detect and communicate with each other (Albert, 2015) or as a network structure in which devices and machines transmit data among themselves and make decisions based on the information they generate.

This technology results from a system of various devices that create a smart network by communicating through mutual data sharing (Akkuş, 2016). It was first employed in 1991 when 15 academics at Cambridge University working on different floors of their building shared a coffee machine. They developed a system to instantly monitor the amount of coffee in the machine from their computers (Kutup, 2011). The concept was first used in an official context in a presentation describing the benefits of radio frequency identification (RFID) technology in 1999 (Ashton, 2009).

The Internet of Things applies to every aspect of daily life. Other products developed with Internet of Things technology include smart wearable devices, smart cities and smart homes. Smart lighting, smart thermostats, smoke and gas sensing security systems, smart traffic control, unmanned autonomous navigation, cloud-based air monitoring, noise and air pollution monitoring systems, earthquake and tsunami early warning systems, wearable Mimo monitors (that measure data such as breathing and body temperature in babies), polotech shirts, smart refrigerators (that uses a memory system to remind you when you have finished products, or that can order products for you), and smart gadgets (Oral and Çakır, 2017).

3.3. Smart Factory

Smart factories are flexible systems that can function through a network, adapt to all prospects, and independently learn and manage the production process. These factories have different characteristics from traditional ones, with their main distinguishing features being Internet-based, technology-oriented, and stock-free work; system integration among machines that have sensors to recognize errors; and a comprehensive connection structure among all business stakeholders (Şekkeli and Bakan, 2018). In other words, they incorporate all the technological developments of industry 4.0, like autonomous robots, cyber-physical systems, the industrial Internet, cloud computing, 3D printers, and system integration (Banger, 2017). The first factory equipped with information and communication technologies was established in Kaiserslautern, Germany, in 2005 to produce soap (Öztuna, 2017). Unlike in traditional factories, the human factor exists almost entirely outside the system in smart factories, except in extraordinary situations (Görçün, 2016).

3.4. Cyber-Physical Systems

Cyber-physical systems bring the physical and virtual worlds together through invisible connections. The cyber-physical system is an industrial automation system that integrates innovative functions established over the network to enable actual processes connected with computing and communication infrastructures (Lu, 2017). These systems provide businesses with transparency, a new control and surveillance method, and efficiency in the production process (Hofman and Rüsch, 2017). These systems open the way for technology and innovation by removing the boundaries between the real and virtual worlds thanks to a broad communication network through the Internet of Things (Özsoylu, 2017).

3.5. Cloud Computing Systems

Cloud Computing Systems are informatics services that facilitate data sharing between computing devices and the conversion of this data into information (Çetin et al., 2013). A cloud computing system provides services over the internet via computers, tablets, or smart mobile devices without any software or storage units (Kavzaoğlu and Şahin, 2012). Everything except a computer and network—for example, computation, the storage and security of data, and the development and execution of applications—is performed by an IT company. This provides convenience in many areas by reducing the responsibilities of users (Ege, 2012).

Since payments in cloud computing depend on the infrastructure, service usage time, and amount, it reduces investments in hardware and software. The system also provides unlimited calculation and information processing opportunities and allows more than one user to utilize the system (Banger, 2017).

3.6. Autonomous Robots

Robots are more capable of sensing, analyzing, and storing data than most humans. They can operate smoothly in environments with less light, heat, and decoration. In many cases, robotic systems have quickly become economic alternatives to human labor (Strange and Zucchella, 2017).

Unlike conventional robots, autonomous robots have been developed to not need the human factor at all. An autonomous robot is a new generation of robot technology that uses artificial intelligence, senses its surroundings like a human, can make decisions based on what it perceives, and can take action according to these decisions (Prowmes Blog, 2018).

SHAKEY, built in 1966, is considered the first autonomous robot. It was the first example of robot technology that sensed its surroundings and acted by making decisions based on its perceptions (Yazıcı, 2016). Autonomous robots are used in many areas, such as health, industry, transportation, aviation, and space technology.

3.7. Artificial Intelligence

Artificial intelligence is the machine learning technology developed to transfer human intelligence to machines and to enable these machines to think and behave like humans without input from any living organism (Aydın and Değirmenci, 2019).

The foundations of today's developments were laid in an article written by Alan Turing in 1950 about producing thinking machines. The first actual work in this field was carried out in 1951 by Christopher Strachey and Dietrich Prinz, who wrote computer programs to play checkers and chess, respectively. John McCarthy used the term "artificial intelligence" at a conference in 1956 and announced the concept to the world for the first time.

3.8. Big Data

Big data is an evaluated and activated form of data that emerges by analyzing information obtained from many sources, such as web servers, internet statistics, climate sensors, GSM, and GPS. When interpreted well, it allows strategic decisions to be taken correctly and existing risks to be managed in the best way (Gabaçlı and Uzunöz, 2017).

3.9. Simulation

Simulation is a method of imitating the operation of a process or system in the physical world by developing a set of mathematical, logical, and symbolic relationship assumptions between it and related entities. The purpose of simulation is to forecast a system's performance measures with generated data (Banks et al., 2010). A simulation is a virtual reality created using computer technology, imitating the three-dimensional world and human activities within it (Tuma et al., 2014).

Simulation can be used in many fields, such as education, health, and architecture; it ensures that necessary precautions are taken against various possible risky situations (Çelen, 2017). Thanks to simulations, business managers do not have to produce expensive and untested prototypes.

3.10. Augmented Reality Applications

Augmented reality is a technology that enables people to interact with computer-generated data, such as audio, video, graphics, or GPS information, by transferring it into a real-world environment (Demirer and Erbaş, 2015). Augmented reality complements physical reality by using virtualities rather than completely changing it (Azuma, 1997).

Augmented reality is sometimes confused with virtual reality or considered as an extension of it. However, these two technologies are entirely different. While virtual reality transfers reality to a completely virtual environment, augmented reality is the enrichment of something belonging to the real world by means of artificial inputs (Köroğlu, 2012).

Recently, companies have been trying to use industry 4.0 technologies to compete in the global market and increase their market share. In Turkey, as is the case globally, the automotive sector is a leader in putting industry 4.0 on its agenda. Industry 4.0 technologies can quickly adapt and respond to this industry’s needs, making it easier for it to adapt to them. For this reason, the automotive sector in Turkey provides the basis for this study. The study investigates the possible effects of industry 4.0 activities on the financial performance of automotive companies in the BIST sustainability index.

4. CONCEPTUAL FRAMEWORK

4.1. Entropy Weight Method

This study used entropy, an objective method, to weight the data in the study. According to Rudolf Clausius's 1865 definition, in thermodynamics, entropy is the absence of energy in a system for the purpose of doing work; it has also been explained as a measure of disorder (Zhang et al., 2011) and as the measurement of the uncertainty of information (Wu et al., 2011).

Weighting criteria is essential to calculating their comparable importance level. There are two methods for determining weights. The first is the type of weight determined by the knowledge and experience of experts, which is the subjective method, and the second is the objective method of weight measurement based on statistical data. According to information entropy, the amount or quality of information is one of the determinants of the significance and reliability of the decision-making problem. So, entropy is a good scale when applied to decision-making processes in different cases. Entropy can also measure the amount of useful information that data provides (Wu et al., 2011).

The entropy method consists of 4 steps, as follows: (Karami and Johansson, 2014).

Step 1: The p_{ij} value is calculated by normalizing the decision matrix to eliminate the outliers of the criteria.

$$p_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \tag{1}$$

i=Alternative Value, j= Criterion, X_{ij} = The utility value of alternative i for criterion j

Step 2: The entropy value e_{ij} is calculated for each criterion.

$$e_{ij} = \left\{\frac{-1}{ln(m)}\right\} \sum_{i=1}^{m} P_{ij}\, ln\, P_{ij} \tag{2}$$

Step 3: The uncertainty equation d_j is calculated.

$$d_j = 1 - e_j \tag{3}$$

Step 4: The weight value w_j of each criterion is calculated.

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j} \tag{4}$$

4.2. Grey Relational Analysis Method

This method is a grading, classification, and decision-making technique based on grey relational degrees developed using grey system theory (Yıldırım, 2014). The grey system was first described in the early 1980s in terms of the known and the unknown (Long, 1982).

Grey relational analysis is a method of analyzing the uncertainties of multi-criteria decision-making problems. It measures the relationships among variables over time in a particular system. Grey relationship analysis measures the relationships between parts according to the similarity or dissimilarity of development trends (Feng and Wang, 2000). In other words, it offers a more straightforward solution than mathematical methods in cases of uncertainty (Yıldırım, 2014). Grey relationship analysis provides critical information on the factors that constitute a system, consisting of a small amount of incomplete information. The advantages of the method include the production of effective results with uncertain data, the easy calculation of grey correlation coefficients, and the lack of any requirement for data set distribution (Erden and Ceviz, 2015).

Grey relationship analysis can measure the relationship between two series numerically and logically. It can numerically calculate the relationship between the series to be compared. The calculated degree of the relationship is called the grey relationship degree and takes values between “0” and “1” (Feng and Wang, 2000). The colors used in the method serve to define the information within a system. A grey system means some of the information is known, a white system means the information is wholly known, and a black system means the information is wholly unknown. The goal of grey theory is to transform black information into grey information in the system (Peker and Baki, 2011).

Grey relational analysis is a set of processes consisting of 6 steps: (Wu, 2002; Yıldırım, 2014)

Step 1: Generating the data set and the decision matrix,

In the matrix, m factor series and reference series to be compared about the decision problem are determined. M decision matrix is formed as (x × y). Here, “x” represents the criteria, and “y” represents the alternatives.

$$x = \left\{ \begin{matrix} x_1(1) & x_1(2) \; ... \; x_1(n) \\ x_2(1) & x_2(2) \; \dots \; x_2(n) \\ \vdots & \vdots \qquad \vdots \\ x_m(1) & x_m(2) \; \dots \; x_m(n) \end{matrix} \right\}$$

Step 2: Generating the reference series and the comparison matrix,

x0 (j); (j) shows the optimal value of the criterion j within the normalized values. The comparison matrix is obtained by adding the reference series to the first row of the decision matrix.

$x_0 = (x_{0(j)})$; $j = 1,2,\ldots\ldots,n$

$x_0 = x_{0(1)}, x_{0(2)}, \ldots\ldots\ldots, x_{0(n)}$

Step 3: Normalization of the decision matrix,

Since different criteria are used among the indicators when calculating the Grey relation coefficients, the data must be standardized by the transformation process to make the indicators comparable. A series is normalized in three ways according to its benefit, cost, or optimum oriented.

- In case the criteria are benefit-oriented;

$$x_{ij} = \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)} \tag{5}$$

- In case the criteria are cost-oriented;

$$x_i = \frac{x_i(j) - \min x_i(j)}{\max x_i(j) - \min x_i(j)} \tag{6}$$

- In case the criteria are optimum-oriented;

$$x_i^* = \frac{x_i(j) - x_{ob}(j)}{\max x_i(j) - x_{ob}(j)} \tag{7}$$

$x_{0b}(j)$ = Target (Ideal) Value, $\max_j x_i(j) \geq x_{0b}(j) \geq \min_j x_i(j)$

$$x^* = \begin{Bmatrix} x_1^*(1) & x_1^*(2) & \ldots & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & \ldots & x_2^*(n) \\ \vdots & \vdots & & \vdots \\ x_m^*(1) & x_m^*(2) & & x_m^*(n) \end{Bmatrix}$$

Step 4: Generating the absolute value table,

$\Delta_{0i} = | x_0(j) - x_i(j) |$ $\quad i = 1,2,\ldots,m$ $\quad j = 1,2,..,n$

$$\Delta_{0i} = \begin{Bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \ldots & \Delta_{01}(n) \\ \Delta_{02}(1) & \Delta_{02}(1) & \ldots & \Delta_{02}(n) \\ \vdots & \vdots & & \vdots \\ \Delta_{0m}(1) & \Delta_{0m}(2) & & \Delta_{0m}(n) \end{Bmatrix}$$

Step 5: Generating the Grey relational coefficient matrix,

$$\gamma 0i\,(j) = \frac{\Delta\min + \zeta\,\Delta\max}{\Delta 0i\,(j) + \zeta\,\Delta\max} \tag{8}$$

$\Delta_{max} = \max_i \max_j \Delta_{0i}(j)$ $\quad \Delta_{min} = \min_i \min_j \Delta_{0i}(j)$

ζ = value of coefficient matrix (It is a value between 0 and 1 and is usually taken as 0.5)

Step 6: After the Grey relationship degrees are calculated, they are ordered from largest to smallest, and at the end of the ranking, the first option is determined as the most suitable alternative option.

$\Gamma_{0i} = \sum_{j=1}^{n}$ (wi (j). ɣ0i (j)) $\quad A = \pi r^2$i =1,2,…,m

4.3. Literature Review

Reviewing the literature shows that many studies have been conducted using grey relational analysis. Information about studies that measure financial performance using the grey relational analysis, as well as the combined use of industry 4.0 and multi-criteria decision-making (MCDM), is presented in Table 1.

Table 1. Literature Review

Research	Purpose	Method	Results
Kung and Wen (2007)	Finding important financial ratio variables and other financial indicators that affect the financial performance of venture capital firms in Taiwan	Grey Relational Analysis and Grey Decision-Making	There is a significant relationship between the qualifications of the enterprises and their financial performance, and the Grey System Theory is an appropriate method to test the relationship
Lin and Wu (2011)	Developing a financial crisis warning system with a dataset of 111 examples for the banking industry	Grey Relational Analysis	The proposed GRA model showed better prediction accuracy than conventional ones
Peker and Baki (2011)	Comparing the financial performances of three companies in the insurance sector	Grey Relational Analysis	There is a positive correlation between the liquidity ratios and the financial performance.
Doğan (2013)	Measuring the financial performance of 10 banks traded in the ISE in the period 2005-2011	Grey Relational Analysis	There is a positive correlation between the return on assets (ROA) and financial performance.
Stanujkic et al. (2013)	Determining if choosing different Multi Criteria Decision Making Methods will create different performance ranking alternatives	Grey Relational Analysis, ARAS, COPRAS, MOORA, CP, VIKOR, TOPSIS	Different sorting outcomes resulted from different methods.
Altan and Candoğan (2014)	Comparison of participation bank's financial performance measured with traditional method and Grey Relationship Analysis method in Turkey.	Grey Relational Analysis, Ratio Analysis	The results of both analyzes are different from each other
Ecer and Günay (2014)	Evaluating the financial performance of 9 tourism companies in BIST for the period 2008-2012	Grey Relational Analysis	The most important indicator in measuring their financial performance is the leverage ratio
Wang et al. (2015)	Determining the financial performance of the hotel industry in Taiwan for the period 2008-2012	Grey Relational Analysis	Return on assets has the highest impact on earnings per share, followed by financal leverage, asset turnover, and profit margin.
Özdağoğlu et al. (2017)	Determining the financial performance of 98 manufacturing companies in BIST for 2015	Grey Relational Analysis	The company with the highest performance is a stationery company.
Güleç and Özkan (2018)	Comparison of the financial performances of 16 cement production companies in BIST and the stock returns obtained with the "buy and hold" model in the period 2005 - 2016	Grey Relational Analysis	These companies have high stock returns, and there is a remarkable difference between Grey Relational Analysis scores and stock returns.

Akgün and Akgün (2019)	Analysis of industry 4.0 performance of information technology companies in Turkey using nine financial ratios in the TOPSIS method	TOPSIS	In 2017, the company with the highest performance in the BIST Information Technology Index was LOGO.
Sarraf and Nejad (2020)	Evaluation of the performance based on balanced scorecard criteria of 35 municipal companies in Iran	Grey relational analysis and Data envelopment analysis	Grey relational analysis is a more accurate method for measuring performance than data envelopment analysis.

5. APPLICATION

5.1. Research Subject

Corporate sustainability provides companies with a competitive advantage in the international arena in the globalizing economy. It allows entrance into global markets and increases transparency. All business activities within the framework of corporate sustainability and published corporate sustainability reports are essential to work done by businesses to fulfill their responsibilities to humanity and leave a better world for future generations.

The critical factor of economic sustainability is keeping up with ever-evolving technology. Therefore, the industry 4.0 tools that appeared in the twenty-first century have become a necessity for businesses. This process, which continues with new inventions, aims to minimize inefficiency in production, the need for human labor, and the consumption of many energy sources; it will thus radically change the management styles of businesses. Companies must catch up with this revolution and pioneer in this field.

The automotive sector has been the first to be included in the Borsa Istanbul Sustainability Index and to engage in industry 4.0-related activities since 2016. Therefore, the research subject of this paper is whether there has been a change in the financial performance of automotive companies between the periods that before industry 4.0 and after. The companies in the sustainability index have been chosen for analysis because information about their transition to industry 4.0 appears in published sustainability reports.

5.2. Purpose and Importance of the Research

The primary purpose of this study is to compare the financial performances of automotive companies that are on the BIST Sustainability Index and use industry 4.0 tools in their activities. Grey relational analysis, a multi-criteria decision-making technique, was used for the three-year periods before and after the adoption of the fourth industrial revolution's tools. Financial performance was calculated for the three years before these companies started to publish corporate sustainability reports (2013, 2014, 2015) and for the next three years (2016, 2017, 2018). These periods were chosen because industry 4.0 tools were first mentioned in the companies' sustainability reports in 2016. There are five automotive companies in the BIST Sustainability Index, but this study examines only four because of the lack of information about industry 4.0 in the reports from Doğuş Otomotiv for the years covered by the study. This study will make it possible to measure the impact on financial performance of technology investments among companies in the automotive sector, who are pioneers in industry 4.0 in Turkey.

The sub-objectives of this research are a comparative evaluation of companies' financial performances over the years thanks to analysis results and contributions to the literature on corporate sustainability, industry 4.0, and grey relational analysis.

5.3. Research Method and Limitations

The financial ratios of four automotive manufacturing companies traded in Borsa Istanbul were calculated according to their published sustainability reports, using financial data for the period 2013–2018. Raw data were obtained from the information's of the companies on the public disclosure platform (PDP) and converted into financial ratios. After weighting these ratios objectively with the entropy method, they were evaluated using grey relational analysis, a multi-criteria decision-making (MCDM) technique. The financial ratios of the companies were calculated based on the annual reports available on the (PDP). The limitations of this research are that the number of companies and years subject to analysis is small. Table 2 shows the Borsa Istanbul stock codes and trade names of the companies examined.

Table 2. The Borsa Istanbul Codes and Trade Names of The Companies

Stock Codes	Trade Names
TOASO	Tofaş Türk Otomobil Fabrikası A.Ş.
OTKAR	Otokar Otomotiv ve Savunma Sanayi A.Ş
FROTO	Ford Otomotiv Sanayi A.Ş.
TTRAK	Türk Traktör ve Ziraat Makineleri A.Ş.

Resource: PDP, 2019 https://www.kap.org.tr/tr/Sektorler

This study investigates the automotive sector because the innovations related to industry 4.0 primarily began in this sector. The reason for a 6-year research period framework is that industry 4.0 activities were first reported in 2016. Thus, this research used data from the three years before and after 2016, as the application part of the study was performed in 2019.

In order to see the possible changes in the financial performance of these four companies with the transition to industry 4.0, the R&D expenditure ratio and most used nine financial ratios, included in the four fundamental financial ratio indicators (liquidity, capital structure, turnover rate, profitability) were used in the analysis (Akgün and Akgün, 2019: 717). Table 3 shows financial ratios (valuation factors), formulations and codes measuring financial performance of the companies in the application.

Table 3. The Financial Valuation Factors

Financial Ratios	Formulations	Ratio Codes
Current Ratio	Current Assets / Short Term Liabilities	CR
Quick Ratio	(Current Assets - Inventory) / Short Term Liabilities	QR
Financial Leverage	Total Liabilities / Total Assets	FL
Inventory Turnover	Cost of Goods Sold / Average Inventory	IT
Asset Turnover	Net Sales / Total Assets	AT
R&D Intensity	Research & Development Expenditures / Total Assets	RD

Profit Margin	Net Income /Net Sales	PM
Return on Assets	Net Income / Total Assets	ROA
Return on Equity	Net Income / Common Equity	ROE
Operating Profit Margin	Operating Profit / Net Sales	OP

5.4. Results

These steps were applied to all four companies. However, to save space, only the tables for the company Tofaş are presented here.

Step 1:

The data set (decision matrix) of the decision problem consisting of the financial ratios of four companies between 2013-2018 is given in Table 4. The matrix rows show the years covered in the study, and the columns show the criteria.

Table 4. Decision Matrix Table of Tofas Company

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	1.32	1.15	0.68	14.28	1.17	0.22	6.17	7.25	2.19	6.92
2014	1.14	0.99	0.69	14.00	1.14	0.21	7.72	8.80	2.77	7.17
2015	1.15	1.02	0.74	14.12	1.17	0.10	8.37	9.78	3.45	7.15
2016	1.10	0.90	0.75	14.62	1.31	0.19	6.82	8.94	3.50	5.93
2017	1.13	0.94	0.74	14.82	1.36	0.40	7.34	9.97	3.92	7.47
2018	1.16	0.96	0.71	12.17	1.38	0.51	7.15	9.90	3.65	9.45

Then, criterion weights are determined by the entropy method. It consists of the following four stage as mentioned in the method section.

Stage a: First, the data must be standardized to compare values, as can be seen in Table 5.

Table 5. Normalizing the Decision Matrix of Tofas Company $P_{İJ}$ Values

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	0.1886	0.193	0.1577	0.17	0.1554	0.1318	0.1416	0.1327	0.1125	0.157
2014	0.1629	0.1661	0.159	0.1666	0.1514	0.1305	0.1772	0.1611	0.1423	0.1626
2015	0.1643	0.1711	0.1713	0.1681	0.1554	0.0614	0.1921	0.179	0.1768	0.1622
2016	0.1571	0.151	0.1741	0.174	0.174	0.1179	0.1565	0.1636	0.1798	0.1345
2017	0.1614	0.1577	0.172	0.1764	0.1806	0.2455	0.1685	0.1825	0.2013	0.1694
2018	0.1657	0.1611	0.1658	0.1449	0.1833	0.313	0.1641	0.1812	0.1873	0.2143

Stage b: The entropy values of the standardized data are presented in Table 6.

Table 6. Entropy Values of Tofas, Otokar, Ford, Türk Traktor Companies E_J Values

TOFAS	0.9990	0.9983	0.9996	0.9989	0.9983	0.9290	0.9975	0.9969	0.9904	0.9944
OTOKAR	0.9864	0.9805	0.9998	0.9870	0.9962	0.9987	0.9805	0.9858	0.9894	0.9949
FORD	0.9995	0.9975	0.9993	0.9939	0.9960	0.9890	0.9989	0.9940	0.9859	0.9946
TURK TRAKTOR	0.9903	0.9884	0.9948	0.9891	0.9987	0.9993	0.9843	0.9806	0.9926	0.9945

Stage c: Entropy values subtracted from 1 to calculate the degree of diversity in Table 7.

Table 7. D_J Values of Tofas, Otokar, Ford, Türk Traktor Companies

TOFAS	0.0010	0.0017	0.0004	0.0011	0.0017	0.0710	0.0025	0.0031	0.0096	0.0056
OTOKAR	0.0136	0.0195	0.0002	0.0130	0.0038	0.0013	0.0195	0.0142	0.0106	0.0051
FORD	0.0005	0.0025	0.0007	0.0061	0.0040	0.0110	0.0011	0.0060	0.0141	0.0054
TURK TRAKTOR	0.0097	0.0116	0.0052	0.0109	0.0013	0.0007	0.0157	0.0194	0.0074	0.0055

Stage d: Table 8 shows the calculated criteria weights using D_J values.

Table 8. W_J Values of Tofas, Otokar, Ford, Turk Traktor Companies

TOFAS	0.0103	0.0179	0.0042	0.0112	0.0173	0.7260	0.0257	0.0322	0.0982	0.0570
OTOKAR	0.1354	0.1934	0.0025	0.1289	0.0375	0.0125	0.1934	0.1406	0.1052	0.0507
FORD	0.0100	0.0486	0.0131	0.1193	0.0771	0.2148	0.0213	0.1158	0.2744	0.1055
TURK TRAKTOR	0.1113	0.1324	0.0591	0.1249	0.0150	0.0075	0.1796	0.2220	0.0846	0.0636

Step 2:

The reference series can be created with the resulting best value of each criterion in the decision matrix or the ideal value of each criterion. Since the current ratio, quick ratio, and financial leverage have an ideal value, the ideal value of these criteria was used to create the reference series. The reference value of the other criteria was selected from the best values in the alternatives (Table 9).

Table 9. Data Set Containing Reference Series of Tofas Company

TOFAS	**CR**	**QR**	**FL**	**IT**	**AT**	**RD**	**PM**	**ROA**	**ROE**	**OP**
Referance	*2(ideal)*	*1(ideal)*	*0.5(ideal)*	*14.8200*	*13.8000*	*0.5110*	*8.3700*	*9.9700*	*39.2300*	*9.4500*
2013	1.3200	1.1500	0.6790	14.2800	11.7000	0.2151	6.1700	7.2500	21.9300	6.9200
2014	1.1400	0.9900	0.6850	14.0000	11.4000	0.2131	7.7200	8.8000	27.7400	7.1700
2015	1.1500	1.0200	0.7380	14.1200	11.7000	0.1002	8.3700	9.7800	34.4500	7.1500
2016	1.1000	0.9000	0.7500	14.6200	13.1000	0.1925	6.8200	8.9400	35.0300	5.9300
2017	1.1300	0.9400	0.7410	14.8200	13.6000	0.4008	7.3400	9.9700	39.2300	7.4700
2018	1.1600	0.9600	0.7140	12.1700	13.8000	0.5110	7.1500	9.9000	36.5000	9.4500

Optimal values of current ratio, quick ratio and financial leverage that can be seen in Table 10 were found by calculating their distance from the reference value.

Table 10. Optimal Values of Current Ratio, Quick Ratio and Financial Leverage of Tofas Company

TOFAS	**CR**	**QR**	**FL**
2013	0.6800	0.1500	0.1790
2014	0.8600	0.0100	0.1850
2015	0.8500	0.0200	0.2380
2016	0.9000	0.1000	0.2500
2017	0.8700	0.0600	0.2410
2018	0.8400	0.0400	0.2140

Step 3:

Data needs to be standardized in order to compare different criteria. Therefore, the normalization process is performed.

Table 11. Normalization of Decision Matrix of Tofas Company

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	1.0000	0.0000	1.0000	0.7962	0.1250	0.2798	0.0000	0.0000	0.0000	0.2813
2014	0.1818	1.0000	0.9155	0.6906	0.0000	0.2748	0.7045	0.5699	0.3358	0.3523
2015	0.2273	0.9286	0.1690	0.7358	0.1250	0.0000	1.0000	0.9301	0.7237	0.3466
2016	0.0000	0.3571	0.0000	0.9245	0.7083	0.2248	0.2955	0.6213	0.7572	0.0000
2017	0.1364	0.6429	0.1268	1.0000	0.9167	0.7316	0.5318	1.0000	1.0000	0.4375
2018	0.2727	0.7857	0.5070	0.0000	1.0000	1.0000	0.4455	0.9743	0.8422	1.0000

Step 4:

The absolute values are calculated by taking the absolute difference between the normalized reference series and the criterion values in Table 12.

Table 12. Absolute Values Table of Tofas Company

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	0.0000	1.0000	0.0000	0.2038	0.8750	0.7202	1.0000	1.0000	1.0000	0.7188
2014	0.8182	0.0000	0.0845	0.3094	1.0000	0.7252	0.2955	0.4301	0.6642	0.6477
2015	0.7727	0.0714	0.8310	0.2642	0.8750	1.0000	0.0000	0.0699	0.2763	0.6534
2016	1.0000	0.6429	1.0000	0.0755	0.2917	0.7752	0.7045	0.3787	0.2428	1.0000
2017	0.8636	0.3571	0.8732	0.0000	0.0833	0.2684	0.4682	0.0000	0.0000	0.5625
2018	0.7273	0.2143	0.4930	1.0000	0.0000	0.0000	0.5545	0.0257	0.1578	0.0000

Step 5:

While creating the Grey correlation coefficient matrix, the value of the discriminant coefficient matrix is determined as 0.5 in Table 13.

Table 13. Grey Correlation Coefficient Matrix of Tofas Company

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	1.0000	0.3333	1.0000	0.7105	0.3636	0.4098	0.3333	0.3333	0.3333	0.4103
2014	0.3793	1.0000	0.8554	0.6177	0.3333	0.4081	0.6286	0.5375	0.4295	0.4356
2015	0.3929	0.8750	0.3757	0.6543	0.3636	0.3333	1.0000	0.8774	0.6441	0.4335
2016	0.3333	0.4375	0.3333	0.8689	0.6316	0.3921	0.4151	0.5690	0.6732	0.3333
2017	0.3667	0.5833	0.3641	1.0000	0.8571	0.6507	0.5164	1.0000	1.0000	0.4706
2018	0.4074	0.7000	0.5035	0.3333	1.0000	1.0000	0.4741	0.9510	0.7601	1.0000

Then, the Grey correlation coefficient matrix is multiplied by the entropy criterion weight (Table 14).

Table 14. Results of Multiplication of Tofas's Coefficient Matrix and Criterion Weights

TOFAS	CR	QR	FL	IT	AT	RD	PM	ROA	ROE	OP
2013	0.0103	0.0060	0.0042	0.0080	0.0063	0.2975	0.0086	0.0107	0.0327	0.0234
2014	0.0039	0.0179	0.0036	0.0069	0.0058	0.2963	0.0162	0.0173	0.0422	0.0248
2015	0.0040	0.0157	0.0016	0.0073	0.0063	0.2420	0.0257	0.0283	0.0632	0.0247
2016	0.0034	0.0078	0.0014	0.0097	0.0109	0.2847	0.0107	0.0183	0.0661	0.0190
2017	0.0038	0.0104	0.0015	0.0112	0.0148	0.4724	0.0133	0.0322	0.0982	0.0268
2018	0.0042	0.0125	0.0021	0.0037	0.0173	0.7260	0.0122	0.0306	0.0746	0.0570

Step 6:

Finally, after calculating Grey relational degrees considering the criterion importance, success is ranked by years (Table 15).

Table 15. Grey Relational Degrees of the Companies

	TOFAS		OTOKAR		FORD		TURK TRAKTOR	
YILLAR	**Degree**	**Rankings**	**Degree**	**Rankings**	**Degree**	**Rankings**	**Degree**	**Rankings**
2013	0.0408	6	0.0657	2	0.0419	5	0.0716	1
2014	0.0435	3	0.0434	5	0.0365	6	0.0588	3
2015	0.0419	5	0.0465	4	0.0445	4	0.0485	5
2016	0.0432	4	0.0372	6	0.0560	3	0.0675	2
2017	0.0685	2	0.0561	3	0.0762	1	0.0554	4
2018	0.0940	1	0.0832	1	0.0716	2	0.0440	6

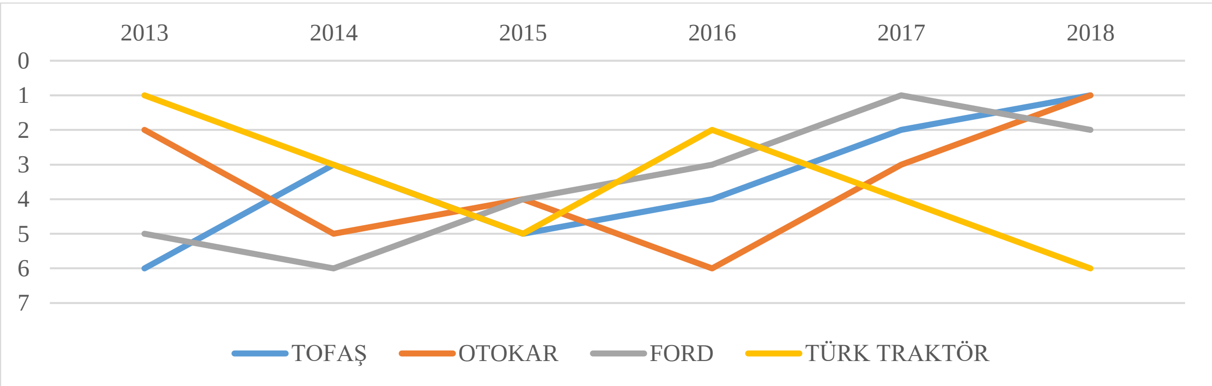
The comparative performance rankings of the companies included in the study for the three-year periods before and after they started industry 4.0 activities are shown, divided into two sections in Table 16.

Table 16. The Comparative Performance Rankings of the Companies

	Previous Three Years			Following Three Years		
COMPANIES	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
TOFAS	6	3	5	4	2	1
OTOKAR	2	5	4	6	3	1
FORD	5	6	4	3	1	2
TURK TRAKTOR	1	3	5	2	4	6

Figure 2 compares the financial performance rankings of the companies for six years, covering the first and second three-year periods.

Figure 2. Graph of the Financial Performance Rankings of The Companies



Of the analyzed years, 2018 was the most successful year for the company Tofaş in financial terms, and 2013 was the least successful. Ford's most successful financial performance year was 2017, and the least successful was 2014. Otokar's most successful year in terms of financial performance was again 2018, and 2016 was the least successful. In other words, the years in which these companies were most successful occurred during the industry 4.0 period in almost all cases, and the least successful years were in the period before industry 4.0.

On the other hand, Turk Traktor's most successful year in financial terms was 2013—before the industry 4.0 period, unlike for the other companies. While 2016 was the company's second-best year, 2014 was its third-best. Meanwhile, the year with the least successful financial performance for this company is 2018, during the industry 4.0 period.

6. CONCLUSION AND RECOMMENDATION

The sustainability of businesses is an issue that has been studied frequently in recent years. It is important not only for businesses but also for stakeholders. Real efficiency will be achieved if businesses consider all economic, environmental, and social sustainability elements together. Ensuring economic sustainability requires a strict follow-up and the implementation of modern industry mechanisms. Based on this idea, this study sought to evaluate whether the use of digitalization and other industry 4.0 tools contributed to company performance. The preference was for companies in the Borsa Istanbul Sustainability Index because they contribute to stakeholders' knowledge by publishing sustainability reports.

Three of the four companies (Tofaş, Otokar, Ford) used in the study showed more improvement in their financial performance in 2016, 2017, and 2018, which constitute the second half of the analysis period, than in 2013, 2014, and 2015, which constitute the first half. It can be said that this is related to the increase in R&D investment rates in the second period. The fourth company (Turk Traktor) saw no improvement in financial performance in the second half of the analysis period because the share of R&D expenditures did not change much during those years.

As argued by Akgün and Akgün (2019), an increase in the share of R&D investments in the balance sheet may cause an increase in the financial performance of a company. However, a decreased or steady share of R&D investments may cause a contraction in their financial performance.

For future studies, we recommend increasing the number of years and companies in the analysis (which form the limitations of this research), using a different MCDM method, or examining the sustainability index in a different country. In addition, the relationship between financial performance and industry 4.0, which is approximately stated in this study, could be analyzed with different statistical analysis methods.

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