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What effect does the adoption of Industry 4.0 technologies have on supply chain environmental sustainability and firm performance?

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Abstract

This research paper aims to study the mediation impact of industry 4.0 technologies on supply chain environmental sustainability and firm performance. The study is based on secondary data collected through Python text mining. Annual reports of 75 large manufacturing companies in the period from 2018 until 2022 were collected and analysed on a series of keywords related to the variables. The results show a significant relationship between the adoption of Industry 4.0 technologies and environmental sustainability. Next to this, the findings of this study do not imply any other significant relationship between the variables. Managerial implications include the importance of decision-making regarding the costs and benefits of implementing Industry 4.0 technologies.

Keywords: Industry 4.0, environmental sustainability, firm performance, manufacturing, supply chains, Python

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1. Introduction

In 2018, 2.5 quintillion bytes of data were generated daily (Forbes, 2018), and it is only expected to grow more in the future. The enormous amount of data can be gathered and analysed, using human interaction with online environments to create predictive patterns (Moat et. al. 2014), this data is called big data and many organisations use it to support decision-making. The business world is in the midst of the fourth industrial revolution, more commonly referred to as Industry 4.0. Big data is one of the key elements of Industry 4.0, a term originated by the German government in 2011. It encompasses a group of technologies that promotes the computerisation of manufacturing. Organisations are increasingly embracing new Industry 4.0 technologies to drive innovation and improve performance. In manufacturing, these technologies can be used to support sustainable supply chains (Raut et. al, 2019), creating more efficient manners to minimise its impact on the environment. The power of these new technologies is stimulated by the growth of the internet over the last few decades. Online environments provide access to digital footprints produced by diverse populations, which can be used to predict social patterns that were previously not possible due to smaller sample sizes (Kosinski et. al. 2016). Other research presents the opportunity to predict future trends in the financial markets using big data (Preis et. al. 2013). Next to using Big Data for stimulating predictive patterns, it can also be applied to enhance mechanisms in supply chain management. Industry 4.0 emergence has played a significant role in helping industry leaders implement more data-driven decisions through new technologies in manufacturing (Ren et al., 2017).

Simultaneously, there is a growing concern about the environmental impact of business activities which feeds the need to adopt sustainable business practices. Climate change is an immediate threat to our society, and according to the Intergovernmental Panel on Climate Change, climate change adaptation is “urgent to the extent that meeting important societal goals requires immediate and long-term action by governments, business, civil society and individuals at a scale and speed significantly faster than that represented by current trends. (IPCC, 2022)” According to a global survey, 82% of business executives say their organisations are concerned about climate change (Deloitte, 2021). Furthermore, consumers are more concerned about climate change as well (articles) and are increasingly asking companies to disclose more information about the environmental impacts of products and processes (Blass & Corbett, 2018). The increasing demand for environmentally friendly products drives organisations’ shift towards green innovation. Today, the generation of products is technology-based and considers sustainable objectives (Miranda et al., 2017). Supply chain management is concerned with the conflict between economic growth and environmental protection (Zhao et al., 2016). As a result, green supply chain management (GSCM) is considered crucial for manufacturers. Zhao et al (2016) define GSCM as “the creative management of a supply chain in the context of sustainable development, with the particular goal of minimising the environmental impact from suppliers to end users”. Alongside this, supply chains transform and grow increasingly more complex as our economy is shaped to grow (Fahimnia et al., 2015). Subsequently, supply chain management has seen a bigger growth in quantity and diversity of data than ever before (Waller & Fawcett, 2013). Thus, the emergence of big data, which presents a combination of resources, tools, and applications such as predictive analytics, has deep implications for supply chain management (Waller & Fawcett, 2013).

Sustainable development can be reviewed through the Triple Bottom Line (TBL) framework, initially constructed by Elkington (1997), which proposes the measurement of sustainable business performance using three lines: economic, social, and environmental. Economic sustainability aims at measurements of productivity and returns on assets, looking at profits and liquidity (Schulz & Flanigan 2016; Khan et al., 2021). Social sustainability looks at the dimension of people, focusing on providing equitable opportunities, diversity, connectedness, and quality of life (Gimenez et al., 2012). Finally, environmental sustainability is related to the impact of companies on natural systems, including ecosystems, land, air, and water (Schulz & Flanagan, 2016). It entails activities related to waste reduction, pollution reduction, energy efficiency, emissions reduction, etc. (Gimenez et al., 2012). Reviewing this framework, this research will focus on the environmental line, looking at the effect Industry 4.0 technologies have on a company’s capacity to mitigate its impact on natural systems.

2. Research objectives

Big data can play a prominent role in the development of sustainable products (Ali et. al. 2020), as well as provide supply chains with new techniques to control their environmental sustainability (Raut et al, 2019; Ren et al, 2019). The impact of big data on firm performance has been studied extensively (Ali et al, 2020; Akter et al, 2016; Garmaki et al, 2016; Upadhyay & Kumar, 2020). Literature suggests that a higher degree of big data adoption within a company positively affects firm performance. However, most literature covers this relation through the benefits of aligning company culture and/or strategy in order to benefit from big data adoption (Akter et al, 2016; Upadhyay & Kumar, 2020). The aim of this paper is to study this relation through the scope of environmental sustainability, looking at possible cost-saving and efficiency benefits in supply chains through the adoption of big data.

According to Bughin et. al (2010), information technology is a key enabler for many strategies to mitigate environmental damage. Furthermore, it is expected that big data analytics and other industry 4.0 technologies can also significantly impact the development of strategies and products to mitigate environmental damage. New technologies brought forward by Industry 4.0, such as Cyber-physical systems and Artificial Intelligence, enable Smart Manufacturing, which uses data management to create more flexibility in physical processes (Ren et al., 2019). The advancement of technologies like these can support transparency and traceability of sustainability in supply chains. In process control, big data can be applied to pollution control and sustainable management of natural resources (Zhao et al., 2016). The existing literature on the link between environmental sustainability and firm performance suggests there is a positive impact on firm performance when a firm achieves a higher level of green innovation (Porter and Van Der Linde, 1995; Chen et al., 2006; Ar, 2012). While there is some literature on the effect of Industry 4.0 technologies on achieving sustainability (Yadav et al., 2020; Jamwal et al., 2021), these studies focus on the entire triple bottom line of sustainability. This research aims to focus solely on the environmental line of sustainability. Furthermore, the literature covers most of the different Industry 4.0 technologies that influence sustainability in the supply chain (Gbededo, 2018), but there is limited literature on the impacts of adopting these technologies on environmental sustainability. Furthermore, most studies feature the impact of one of the technologies, rather than the total impact of Industry 4.0 technologies together. This research aims to look at the impact of the adoption of Industry 4.0 as a group of technologies on the environmental sustainability of manufacturers.

The aim of this study can be divided into three research questions:

1. How does a higher level of environmental sustainability in the supply chain impact firm performance?
2. Can the adoption of Industry 4.0 stimulate environmental sustainability in manufacturing processes?
3. What is the impact of Industry 4.0 adoption in manufacturing on Firm performance?

This paper aims to answer these questions by further reviewing the already existing literature on environmental sustainability in supply chains and Industry 4.0 adoption, after which hypotheses will be derived. These hypotheses will be tested, after which findings will be analysed and discussed. Furthermore, managerial implications, limitations of the study, and suggestions for future research will be reviewed.

3. Literature review

3.1 Sustainable supply chains and firm performance

In the last few decades, the growing concern for climate change has pushed corporations to be more sensitive and aware of the need for social and environmental performance, along with the traditional scope of economic focus (Elkington, 2002). Especially in developed countries, the significance of environmental sustainability is being stressed (Clarkson et al, 2008). This is because developed countries have more environmental penalties, improved awareness among customers and suppliers, and the benefit of being brand equity as a 'green company' (Porter & van der Linde, 1995; Corbett & Kleindorfer, 2001). In general, innovations in mitigating environmental harm in companies will benefit a company's environmental reputation, which creates a market advantage which can result in higher firm performance (Eiadat et al., 2008; Hart, 1995). On top of this, green products allow companies to ask for higher prices, which combined with their better reputation increases profits (Chen et al, 2006). Furthermore, consumer loyalty towards products is highly dependent on the perception that these products are ecologically friendly (Sinclair-Degagné, 2004). It can be concluded that consumer behaviour is heavily influenced by the environmental performance of product offerings.

Environmental sustainability also entails the efficient use of product inputs, as well as reusing waste, which leads to better resource productivity (Porter & van der Linde, 1995). Moreover, aiming to reduce electricity, water and gas consumption, gas emissions and switching from fossil fuels to bioenergy, all promote the efficient use of resources during the production process (Kivimaa & Kautto, 2010), which in turn provide efficiency advantages. Another cost-saving advantage of being environmentally friendly can be found in regulatory costs. With the hazards of climate change being increasingly apparent, governments also take action to mitigate its effects through the creation of laws and regulations. Actions to mitigate environmental impact within a supply chain can cause organisations to pay lower regulatory costs (Lanoie et al., 2007).

Furthermore, many organisations increasingly use environmental performance as a criterion to select new suppliers, resultingly, it can be beneficial for a company to be environmentally sustainable as this facilitates access to certain markets (Lanoie et al., 2007). As the importance of being environmentally friendly is increasingly important, solving environmental problems in manufacturing can also create business opportunities as technological breakthroughs can create 'first-mover' advantages (Lanoie et al., 2007). Additionally, many international banks have adopted the 'equator principles', which is a framework for determining, assessing, and managing environmental risks in projects (Equator Principles, 2023). Resultingly, being more environmentally sustainable, access to additional funds through banks is easier.

To conclude, environmental sustainability influences consumer behaviour, can result in lower costs, and present several market opportunities, therefore the following hypothesis can be derived:

Hypothesis 1: *More environmental sustainability will lead to higher firm performance.*

3.2 Industry 4.0 adoption and sustainable supply chains

Environmental sustainability for manufacturers comes down to creating a sustainable supply chain. A sustainable supply chain implies more than analysing and modifying the environmental performance of a manufacturing process (Haapala, 2013), it is a process where nature's ability to transform wastes into environmental nutrients and resources at a rate as fast as society consumes it, or faster, and this can only be displayed in a closed system, as shown in figure 1. (Haapala, 2013). Most literature covers three pillars when assessing a sustainable supply chain: the social, economic, and environmental (Barbosa-Póvoa et al., 2017; Galal & Moneim, 2016; Mota et al., 2017). When discussing environmental sustainability, the main pillar to focus on is the environmental pillar, which entails reducing waste, CO2 emissions, greenhouse gases, energy use and water use among various other factors such as creating renewable energy. The assessment of the environmental pillar of a sustainable supply chain can be approached in different ways. A literature review identified a total of 2555 unique metrics to analyse either green supply chain management or sustainable supply chain management (Ahi & Searcy, 2015), with the majority of these metrics being used only once, highlighting the lack of agreement on how to assess the environmental performance of a supply chain. The most used metrics of green and sustainable supply chains were quality, air emissions, energy use, greenhouse gas emissions and recycling. Most metrics used appear to be focused on a single key characteristic of sustainability, mostly assessing sustainability from a single environmental issue such as air emissions or energy use (Ahi & Searcy, 2015). However, there are also ways to evaluate the sustainable performance of supply chains by looking at those where multiple environmental impact categories are employed, such as the Life Cycle Assessment (LCA) approach (Barbosa-Póvoa et al., 2017). The International Organisation for Standardisation defines this approach as a "compilation of evaluation of the inputs, outputs and potential environmental impacts of a product system throughout its life cycle" (ISO, 2006). To understand the full environmental impacts of a supply chain, an LCA approach is more thorough than a performance metric focused on one environmental issue, however, it is also more complex to fairly assess and compare multiple supply chains using this approach.

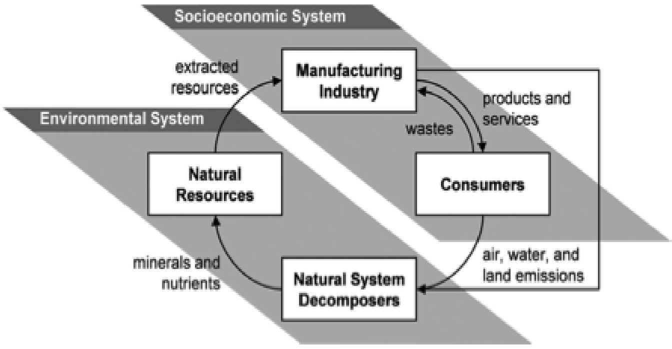


Figure 1: Sustainably supply chain (Haapala, 2013)

Identified metrics of green and sustainable supply chain management.

Metrics[a]	Frequency rate
Quality	31
Air emissions	28
Energy use	24
Greenhouse gas emissions	24
Energy consumption	21
Recycling	19
Solid waste(s)	19
Flexibility	18
Environmental management system	15
Customers' satisfaction	14
Carbon footprint	13
Life cycle assessment (LCA)	12
Profit	12
Cost	12
Water consumption	12
Product characteristics	11
Energy efficiency	11
Environmental costs	11
Market share	11
Reduction of air emission(s)	11
Reduction of solid wastes	11
Return on investment	11
Operational cost (Operating cost)	11
ISO 14001 certification	11
Level of process management	10
CO_2 emissions	10
Water waste	10

Figure 2: Metrics for sustainability (Ahi & Searcy, 2015)

Industry 4.0 and data science have opened the door for new data analytics technologies which can be implemented in supply chains. These new technologies, like Artificial Intelligence (AI), Internet of Things (IoT), and Cyber-physical systems (CPS) are integrated into the supply chain to create smart manufacturing (SM). This new manufacturing mode combines data management with process expertise to enable flexibility in physical processes (Ren et al, 2019). The traditional SM scope highlights the flexibility of physical processes in manufacturing; however, it fails to consider other product life cycle stages and the sustainability aspect (Ren et al., 2019). To incorporate all stages of the product lifecycle the term Sustainable Smart Manufacturing (SSM) is used. Whereas SM focuses on the flexibility of processes to respond to market demands, SSM is service-driven (Ren et al., 2019). Therefore, it can be used for the objectives of minimising resource inputs and emissions. SSM encapsulates the entire life cycle of a product, from the design stage to the recovery stage. All different stages in the manufacturing process generate large amounts of data which are collected and stored in different places. The overflow of data is transparent to managers, but unreadable without an ongoing system which can autonomously incorporate data from different stages in the production process, store them and interact to provide control (Thoben et al., 2017). Systems that are able to do this are called Cyber-physical systems (CPS).

Cyber-physical systems are "systems of collaborating computational entities and their ongoing processes, providing and using, at the same time, data-accessing and data-processing services available on the internet" (Montostori, 2014). CPS includes the cooperation of autonomous sub-systems which can seamlessly provide information and control. The implementation of CPS in the manufacturing sector has created the Cyber-physical production system (CPPS) (Miranda et al, 2017). CPPS can seamlessly integrate multiple points in the supply chain where information is generated into an automated process providing information for supply chain management. It enables and supports communication between humans, machines & products (Montostori, 2014). Additionally, it supports a decentralised automation hierarchy breaking a traditional automation pyramid, as it is possible to monitor multiple stages in the supply chain at once, as seen in figure 3. (Montostori, 2014).

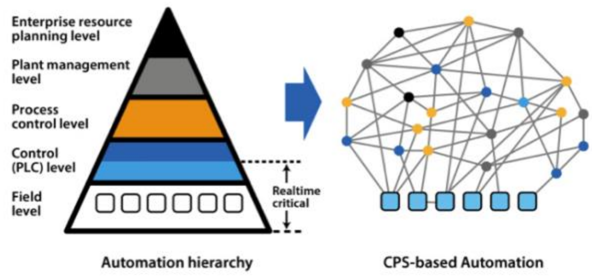


Figure 3: Cyber-Physical Systems (Montostori, 2014)

New smart enabling technologies, like the emergence of CPPS which allows for SSM, allow for data and knowledge to be effectively shared among different lifecycle management systems, facilitating more reasonable and precise decision-making throughout the product life cycle, improving a product's sustainability (Liu et al, 2019). Additionally, additive manufacturing can stimulate the reuse of waste in the supply chain when manufacturing products on demand (Nascimento et al., 2019). Industry 4.0 also provides new opportunities for improved resource control. Where energy waste problems in manufacturing are usually unobservable and costly, big data provides the potential to identify and quantify the wastage point to reduce or even eliminate them in real-time (Ren et al, 2019). The continuous application of smart sensors and smart meters during the lifecycle allows enormous amounts of energy consumption data to be collected from production and operation processes (Wang et al, 2017), and the use of RFID tags and readers are used to track and trace real-time information during the manufacturing process (Zhang et al, 2018). This data enables smarter decision-making on energy efficiency management to reduce energy consumption (Shrouf and Miragliotta, 2015). Next to this, real-time remote tracking, intelligent water measurement, and alarm-driven preventive maintenance can improve reliable resource allocation (Javaid et al., 2022). To conclude, new Industry 4.0 technologies allow for more efficient resource consumption, traceability, and support data-driven decision-making regarding resource allocation. Resultantly, the following hypothesis can be extracted:

Hypothesis 2: *A higher level of Industry 4.0 adoption will lead to more environmental sustainability*

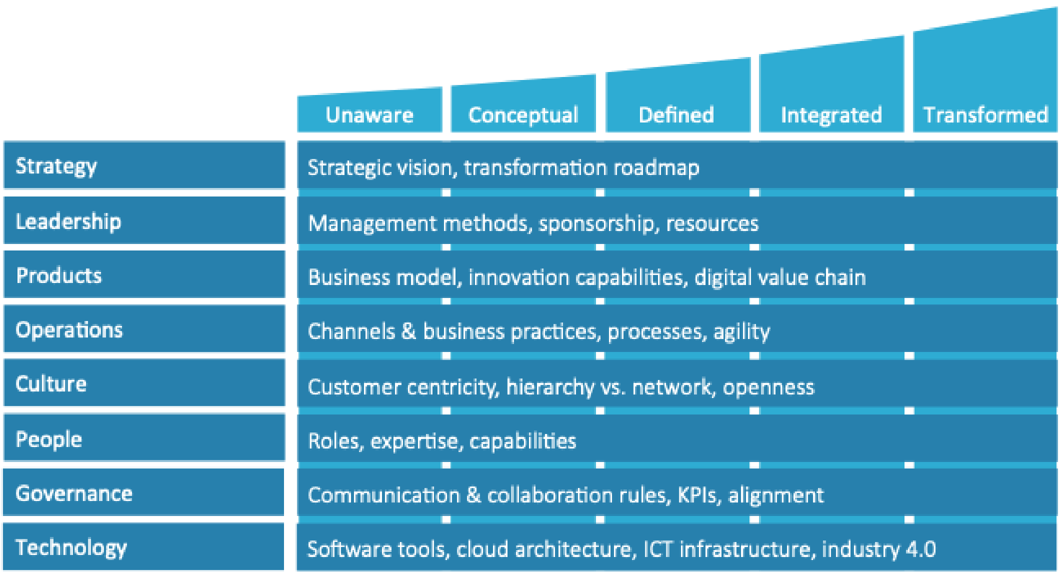
<u>*3.3 Industry 4.0 adoption and firm performance*</u>

Industry 4.0 is considered to be a new industrial stage, that incorporates emerging technologies such as Artificial Intelligence (AI), Internet of Things (IoT), and Cyber-Physical Systems (CPS) into the supply chain. Industry 4.0 is currently a top priority for organisations (Ghobakhloo, 2018), as the technologies emerging along the shift in industrial production can offer various benefits. Firstly, Industry 4.0 technologies can improve vertical integration in the supply chain through sensors and machine-machine communication (Jenschke et al., 2017). Secondly, efficiency benefits can be realised through virtualization methods like the use of Artificial Intelligence for predictive maintenance (Tao et al, 2018), simulating processes to detect bottlenecks (Jenschke et al., 2017), and using Artificial Intelligence for the planning of production (Gilchrist, 2016). Furthermore, new Industry 4.0 technologies can enhance automation in the supply chain, increasing efficiency. Next to efficiency benefits, Industry 4.0 can enhance traceability and flexibility in the supply chain. RFID systems can be integrated into the manufacturing process to improve the identification of materials and products in factories (Angeles, 2009). Furthermore, smart machines, conveyors, and products can reconfigure themselves through new technologies to allow for flexible production (Wang et al, 2016).

To measure the degree of Industry 4.0 adoption in an organisation, Azhari et al. (2014) proposes the digital maturity model. The model proposes a metric to assess the level of digital maturity in organisations from the perspective of different shareholders. The model consists of 32 individual criteria, and folds out over 8 different dimensions, as shown in Figure 1 (Azhari et al., 2014). The first dimension of "strategy" captures maturity through an organisation's digital strategy. Management has to develop a digital strategy that incorporates disruptive technological developments and accounts for changes in digital maturity (Azhari et al., 2014). This digital strategy must encapture the management's vision and needs to be documented and communicated within the company (O'Reilly, 1989; Lucas & Goh, 2009). Aligning an organisation's strategy with disruptive technologies has many potential benefits, including increases in sales and productivity, innovations in value creation and interaction with customers (Matt et al, 2015). As a result, digital business strategies can reshape entire business models (Downes & Nunes, 2013). The second dimension in the digital maturity model is "leadership", which entails the role of management in implementing digital strategy. Middle and top management must be committed to learning the new technologies and communicating the importance of the digital strategy to the organisation (Sherif & Menonm 2004). Furthermore, it is important to communicate the technologies and strategies, however, there is a risk of employees falling into a 'competence trap', where they are convinced of the superiority of the new technologies, which causes the employees to reject them (Azhari et al., 2014). Nonetheless, management has to create a sense that digital adoption is urgent to prevent the notion between employees of: "We've always done it this way, so nothing needs to change" (Leonard-Barton, 1992; Lucas & Goh, 2009). The third dimension in the digital maturity model is "product", which encapsulates the degree to which the digital transformation reaches the range of products and services an organisation offers. It includes the added customer benefits, the innovation in the business model, and the value-added share of digitization (Azhari et al., 2014). Often, disruptive technological products are not seen in time by large companies because evaluation is based on the current economic viability (Christensen, 1997; Christensen & Raynor, 2014) The fourth dimension is "operations", which deals with the agility of digital business processes, and the extent to which digital channels are integrated for both internal and external collaboration (Azhari et al., 2014). The fifth dimension is "culture", business culture defines the company's decision-making process, creating the potential to restrain innovation (Lucas & Goh, 2009; Christensen & Overdorf 2000). Next to this, an adequate business culture should feature transparency, dynamics, communication intensity and change management (Azhari et al., 2014). The sixth dimension, "people", examines the extent to which expertise and permanent learning is established in the company (Azhari et al., 2014). The seventh dimension of "governance" considers how effectively the digital strategy is implemented and what instruments control this implementation (Azhari et al., 2014). The final dimension, "technology", concerns the digital technologies and software that enable digital transformation, with the decisive factors including skills for data analysis, cross-channel management, process automation and the agility of supporting systems (Azhari et al., 2014).

The resource-based view of the firm (RBV) is an important and established framework for viewing how competitive advantage within firms can be achieved and sustained over time (Barney, 1991; Wernerfelt 1984). The perspective focuses on the internal organisation of a firm, similar to a more traditional emphasis on internal strategy to determine competitive advantage (Eisenhardt & Martin, 2000). RBV conceptualises firms as bundles of resources, which are heterogeneously distributed across them. Therefore, RBV argues that when firms have resources that are valuable, rare, inimitable, and nonsubstitutable, they can achieve sustainable competitive advantage by using these unique resources to develop value-creating strategies that cannot be easily duplicated by competitors (Barney, 1991; Wernerfelt, 1984). These resources can be divided into tangible, intangible and human resources (Grant, 1991). Bharadwaj (2000), orders IT-based resources along Grant's classification as 1) tangible resources, entailing the IT infrastructure, 2) human resources, entailing the managerial IT skills, 3) intangible resources, entailing the IT-enables resources. For Industry 4.0 technologies and their use, the same classification can be used where tangible resources include the data infrastructure capable of utilising the technologies. Human resources are the capabilities needed to utilise Industry 4.0 technologies, which can be divided into technical knowledge, needed to capture and store the data, business knowledge, needed to provide strategy and decision-making opportunities for the data, relational knowledge, needed for communication between employees using the technologies, and business analytics knowledge, needed to transform the data into models and patterns to provide useful analyses (Mikalef et al., 2020). Intangible resources for these technologies are structures and practices in a company related to managing and controlling different types of data resources. Intangible resources include the importance of developing a data-driven culture in an organisation, where decisions rely more on data-based insights (Cao & Duan, 2014). Firms that can successfully use their resources to utilise Industry 4.0 opportunities can obtain a competitive advantage (Akter et al., 2016).

As aforementioned, the adoption of Industry 4.0 technologies can create efficiency and flexibility benefits. Industry 4.0 technologies can integrate planning and scheduling activities, next to predictive analytics helping to significantly lower machine downtime and avoid production delays, which results in operational cost reductions (Bag et al. 2021). Additionally, digital technologies like CPS can reduce set-up times, processing times, and labour and material costs, resulting in higher productivity (Jeschke et al., 2017). Industry 4.0 also offers opportunities for business growth. Collaborative networks between organisations supported by new technologies combine resources, divide risks, and offer the opportunity to quickly adapt to changes in the market (Brettel et al., 2014). Consumer connection is increased through digital channels and smart products that integrate customers with an organisation (Kiel et al., 2017). For example, additive manufacturing can be used by organisations to co-produce products for their customers, leading to highly



*Abbilung: Digital Maturity Model**

customised products with high consumer value (Weller et al., 2015). To conclude, Industry 4.0 technologies can stimulate higher productivity, efficiency, flexibility, and consumer value while reducing operational costs, and risks and offering opportunities to quickly react to market changes.

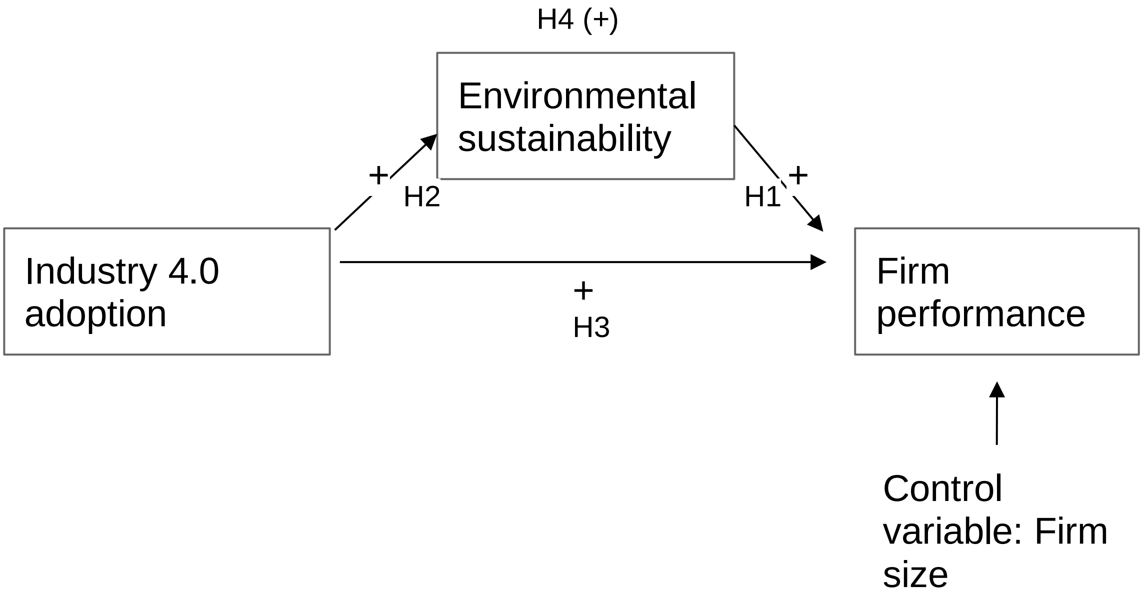
Hypothesis 3: *A higher level of Industry 4.0 adoption leads to higher firm performance.*

The adoption of new Industry 4.0 technologies into the supply chain can be instigated for several different motives. Using the Triple Bottom Line, initially proposed by Elkington (1997), the adoption of these technologies can be used to fuel all three different economic dimensions, namely the economic dimension, the social dimension, and the environmental dimension. As aforementioned, the adoption of Industry 4.0 technologies into the supply chain causes a positive effect on the economic dimension, as discussed in section 3.3, and the environmental dimension, as discussed in section 3.2. Furthermore, economic benefits can also be stimulated through technological advances focused on enhancing environmental sustainability. Research by Yu et al. (2021) shows that the implementation of Industry 4.0 technologies stimulates circular economy practices, which in order have a positive impact on operational and economic performance. The integration of new technologies focused on building sustainability will aid in organisations' long-term technological growth, which, next to environmental conservation, also results in positive economic outcomes (Tang et al., 2022). Furthermore, organisations adopt measures to evaluate supply chain sustainability with the ultimate goal not only to improve environmental performance but also to build up capabilities in a resource-based view in order to gain a competitive advantage (Khan et al., 2020). The interconnectedness of innovating the supply chain and its economic performance is embedded in the attempt to mitigate environmental impacts. Next to internal benefits for organisations, Industry 4.0 practices that assist in reducing waste and conserving energy will enhance positive reputation, market share, and government support, which all promote better long-term performance (Tang et al., 2022). To conclude, the adoption of Industry 4.0 for environmental purposes can stimulate the creation of economic benefits, therefore the following hypothesis is drawn:

Hypothesis 4: *Environmental sustainability positively mediates the relationship between big data adoption and firm performance.*

4. Methodology

4.1 Conceptual framework



4.2 Data collection

To test the hypothesis, annual reports from 75 out of the global top 100 manufacturers, ranked by market capitalisation, in the period of 2018-2022 will be collected and analysed through Python web scraping. For American firms, 10-k annual reports will be used, for firms outside of the US annual reports and 20-F SEC filings will be used. Out of the global top 100, 25 companies did not have comparable reports between 2018 and 2022, as some were not active in the same corporate structure for this period, and others did not have comparable reports to the other 75. For the variables of Big Data Analytics and environmental sustainability, the frequency of various related keywords will be analysed to establish different ranks among the two variables. The biggest global manufacturers ranked by market capitalisation provide a set of organisations that can assess the data on a worldwide scale, with data from companies in 19 different countries among different manufacturing industries. Choosing for the ranking on market capitalisation generates a ranking off stock-listed companies, which disallows state-owned companies to enter the cut. To consider how Big Data can impact environmental sustainability and firm performance, it is beneficial to have companies that need to perform in the market, as the link between environmental sustainability and firm performance is driven by the value a company can generate for its customers.

4.3 Firm performance

For the dependent variable firm performance, this research aims to calculate each of the firm's return on assets, one of the most used financial ratios in the research field (Jewell & Mankin, 2011). A firm's return on assets can be calculated through the following formula:

$$ROA = \frac{Net\ income}{(Total\ assets\ t-1\ +\ total\ assets\ t)/2}$$

For the regression analysis, firm performance is defined as the Return on Assets and denoted by

'ROA'. Out of the 75 companies, 6 companies showed a negative return on assets, which caused them to be excluded from the regression analysis for statistical purposes.

4.4 Industry 4.0 Adoption

The independent variable of big data analytics will be measured by a firm's digital maturity level. Through web scraping in Python, a frequency analysis will categorise firms into 5 different levels of digital maturity. The five different levels of maturity are categorised into "unaware", "conceptual", "defined", "integrated", and "transformed" based on the digital maturity model by Azhari et al. (2014).

A study by Tavana et al. (2022), has provided an extensive analysis reviewing various literature on digital transformation in supply chains. Through text mining, their analysis identified current topics and trends of digitalisation in supply chains, providing an overview of terms that are currently related to the digital transformation of supply chains. Using this analysis and a continuous process of redefining the keywords and their forms to improve compatibility with the annual reports in the sample, we can construct the following keywords which indicate the degree of digitalisation of manufacturers' supply chains: "technology", "digital", "internet"," data", "rfid", "smart", "cloud computing", "transformation"," online", "sensor", "server", "algorithm", "database", "statistic", "predictive"," analytic", "industry 4.0", "internet of thing", "robotics", "automation", "connectivity", "artificial intelligence", "website". Before the frequency analysis, the annual reports were altered using some data-cleaning procedures. Using Python, all word forms were transformed into their singular form and all letters were changed into lowercase letters.

When calculating the frequency score for each term, the Term Frequency and Inverse Document Frequency method is used, denoted by TF-IDF. Term Frequency (TF) is used to measure how many times a term is present in a document, divided by the total number of terms in a document (Qaiser & Ali, 2018). The formula for TF is as follows:

$$Tf_{\mathrm{i,j}} = \frac{n\ i,j}{\Sigma k\ n\ k,j}$$

Where $n_{i,j}$ represents the number of occurrences of the term in the file and $\sum_k n_{k,j}$ represents the sum of the occurrences of all terms in the file (Liu et al., 2018).

The Inverse Document Frequency (IDF) accounts for the uniqueness of terms in a document. It assigns lower weight to fewer terms, and greater weight to more frequent terms (Qaiser & Ali., 2018). The formula for IDF is as follows:

$$Idf_{\mathrm{i}} = \log \frac{N}{Dfi}$$

Where N represents the total number of documents in the corpus, and Df_i represents the number of documents which entail the specific term (Kriebel & Debener, 2019).

The Term Frequency - Inverse Document Frequency (TF-IDF) is calculated by multiplying TF and IDF.

$$Tf - Idf_{\mathrm{i}} = Tf_{\mathrm{i,d}} \times Idf_{\mathrm{i}}$$

The frequency score can be calculated by the sum of TD-IDF scores for each annual report:

$$\textit{Frequency score:}\ \sum_{i}^{\blacksquare} \blacksquare\ Tf - Idf\ \ \mathrm{i}$$

According to Heidinger and Gatzert (2018), management awareness is linked to actual economic activities. Logically, annual reports that communicate more extensively through keywords associated with big data will be more actively engaged in this element. Likewise, firms that report more keywords related to environmental sustainability will be more engaged in this aspect. After the frequency analysis, the organisations can be ranked according to their digital maturity level, as shown in Table 1. As frequency scores for digital maturity initially had a large and wide range, the natural logarithm of the scores was taken to reduce the negative impact on the regression analysis. During the regression analysis, the categories are denoted as numbers in order to use them in the statistical software: 1=unaware, 2=conceptual, 3=defined, 4=integrated, 5=transformed. For the regression analysis the variable of Industry 4.0 adoption is denoted as 'dig_maturity'.

Digital Maturity Level (DML)	Number of firms
Unaware	11
Conceptual	14
Defined	22
Integrated	16
Transformed	12

Table 1: Frequency analysis big data adoption

4.5 Environmental sustainability

Along with the variable of big data analytics adoption, the mediating variable environmental sustainability will also be measured after analysis through Python. Similar to the digital maturity model, this variable will be divided into at least 5 categories, ranking companies in different levels of environmental sustainability. Through Python, a textual analysis will be performed to measure the frequency of multiple terms related to environmental sustainability within manufacturers. The efficiency of text mining has been demonstrated by literature in the field of sustainability before (Modapothala & Issac, 2009; Liew et al., 2014). Text mining provides the capability to extract relevant information from large amounts of textual data, providing an overview of sustainability issues and practices discussed in the reports (Liew et al., 2014).

Metrics	SSCM characteristics[a]		
	Economic focus[b]	Environmental focus[c]	Social focus[d]
Quality	√	√	√
Air emissions		√	
Energy use		√	
Greenhouse gas emissions		√	
Energy consumption		√	
Recycling		√	
Solid waste(s)		√	
Flexibility	√		
Environmental management system		√	
Customers' satisfaction	√		√
Carbon footprint		√	
Life cycle assessment (LCA)		√	
Profit	√		
Cost	√		
Water consumption		√	
Product characteristics	√	√	√
Energy efficiency		√	
Environmental costs	√	√	
Market share	√		
Reduction of air emission(s)		√	
Reduction of solid wastes		√	
Return on investment	√		
Operational cost	√		
ISO 14001 certification		√	
Level of process management	√	√	
CO_2 emissions		√	
Water waste		√	

Figure 4: metrics for sustainability (Ahi & Searcy, 2015)

Using the previous work of Ahi & Searcy (2014), we can identify various metrics used to measure environmental sustainability in supply chains. Their work included the content analysis of 445 articles, identifying a total of 2555 different metrics to analyse this phenomenon. Out of these metrics, 27 had a frequency rate of finding the metric over 10 times in their analysis. Drawing from the triple bottom line, this research focuses solely on the environmental focus. In Figure 4, (Ahi & Searcy, 2015), the 27 metrics are characterised based on the three focuses in the TBL. The scope of this frequency analysis can be concluded in the following 26 keywords, associated with environmental sustainability: “emission”, ”energy”,” gas, ”environment”,” carbon footprint”,” green”,”co2”,” sustainability”, ”biodiversity”, ”life cycle”, ”renewable”, ”circular economy”, ”conservation”, ”eco-friendly”, ”consumption”, ”waste”, ”pollution”, “iso 140001”, ”iso 14064”, ”iso 50001”, ”greenhouse” ”reuse”, ”re-use”, ”ghg”, ”recycle”, ”climate”. These keywords are chosen after consulting other research using text mining to assess sustainability and research by Deng et al. (2017) building an environmental sustainability dictionary, along with a continuous process of redefining the keywords and their forms in Python to enhance compatibility with the annual reports. As aforementioned, a higher frequency of these terms in annual reports will logically result in a firm being more engaged in the environmental sustainability of its supply chains. Resultingly, organisations can be categorised into 5 different levels of environmental sustainability: level 1 = pre-compliance, 2 = compliance, 3 = beyond compliance 4 = integrated strategy, and 5 = purpose. These categories are denoted by the number of their level in section 5 to make them compatible for statistical analysis. As scores for environmental sustainability initially had a large and wide range, which would negatively impact the regression analysis, the natural logarithm from the frequency scores was taken, after which 5 even ranges were taken to categorise the firms into the aforementioned categories. Results are shown in Table 2. For the regression analysis, the variable of environmental sustainability is denoted as ‘env_score’.

Level of Environmental Sustainability (ES)	Number of firms
Pre-compliance	18
Compliance	22
Beyond compliance	21
Integrated strategy	17
Purpose	2

Table 2: Frequency analysis environmental sustainability

4.6 Firm size

To account for differences in the dependent variable of firm performance, a control variable of firm size needs to be in place. The firms are categorised into seven categories ranking them on the number of employees. The categories are adopted from Akter et al. (2016), merging together the first five categories, as they are insignificant in the sample of this research. This results in the categorisation as shown in Table 3. The control variable is denoted as 'firm_size' in the regression analysis.

Number of employees	Number of firms
0 - 2,499	1
2,500 - 4,999	3
5,000-9,999	8
10,000 - 24,999	10
25,000 - 49,999	13
50,000 - 99,999	21
100,000+	19

Table 3: Categorisation of firms based on the number of employees.

4.7 Proposed analysis

To test the hypotheses, this research will follow the mediation procedure as written by Baron & Kenny (1986). This method proposed to analyse the mediating effect by testing four hypotheses: The independent variable predicting the dependent variable (hypothesis 1), the independent variable predicting the mediator (hypothesis 2), the mediator predicting the dependent variable (hypothesis 3), and the independent variable and the mediator predicting the dependent variable (hypothesis 4). This results in the following four formulas:

Testing hypothesis 1:

$$ROA = \beta 0 + \beta 1 * DML + \beta 2 * firm\ size + \varepsilon 1$$

Testing hypothesis 2:

$$ES = \beta 3 + \beta 4 * DML + \beta 5 * firm\ size + \varepsilon 2$$

Testing hypothesis 3:

$$ROA = \beta 6 + \beta 7 * ES + \beta 8 * firm\ size + \varepsilon 3$$

Testing hypothesis 4:

$$ROA = \beta 9 + \beta 10 * DML + \beta 11 * ES + \beta 12 * firm\ size + \varepsilon 4$$

5. Results

5.1 Descriptive statistics

	N	Mean	SD	Min	Max	Kurtosis	Skewness
ROA	69	0.0902552	0.0567502	0.0171891	0.262243	1.335	1.323
dig_maturity	69	3.115942	1.289508	1	5	0.0076	0.6213
env_score	69	2.623188	1.164442	1	5	0.0002	0.8920
Firm_size	69	5.289855	1.525291	1	7	0.9575	0.0092

Table 4: Descriptive statistics

Descriptive statistics, as shown in Table 4, were performed using statistics software Stata 17. For each of the variables, the number of observations, mean, standard deviation, minimum and maximum values, kurtosis, and skewness are shown. All variables have the same number of observations, and small standard deviations, indicating that the data is centred around the means. All four variables have platykurtic distributions, as their kurtosis values are below 3. Firm_size is symmetrically distributed, with a close to zero score, and dig_maturity and env_score have insignificantly positively skewed distributions. Return on Assets has a significantly positively skewed distribution.

When looking at the Shapiro-Wilk test (Appendix B) the threshold for accepting the null hypothesis that the data follows a normal distribution is 0.05. With the exception of the variable dig_maturity, the significance levels are below this threshold. Therefore, for these three variables, we reject the null hypothesis and conclude that there is no strong evidence the data follows a normal distribution. The Q-Q plots (Appendix A) confirm this assumption. If data is normally distributed, the points in the Q-Q plots are ideally along the straight line. For all four variables, while most points are close to the straight lines, there are too many outliers, especially for the variable of Return on Assets. The same goes for the P-P plots (Appendix A) while there are some points distributed among the straight lines, there are too many outliers, causing the conclusion that the data is normally distributed to be rejected. The possibility of remodelling the data to overcome violating the normality assumption has been explored, through the option of bootstrapping. However, the data remained largely unchanged. Furthermore, remodelling the data can have negative effects on regression analysis, due to biased point estimates. According to Schmidt & Finan (2018), for sample sizes larger than 10, violating the normality assumptions do not noticeably impact results. This conclusion is further supported by Knief & Forstmeier (2021), who note that linear regression models are generally robust to violations of the normality assumption.

5.2 Multicollinearity

The following correlation matrix as shown in Table 5 was performed by Stata 17, to check for possible multicollinearity in the data.

	ln_ROA	dig_maturity	env-score	firm_size
ln_ROA	1.0000			
dig_maturity	-0.0411	1.0000		
env_score	-0.1683	0.3233	1.0000	

firm_size	-0.5065	0.0425	0.1121	1.0000

Table 5: Correlation matrix

As all variables have correlation coefficients lower than the threshold 0.7, it can be concluded that there is no multicollinearity, and the data can be used for the regression analysis.

5.3 Heteroskedasticity

Next to multicollinearity, it is important to conduct a test checking the data on heteroskedasticity. In section 4, the natural logarithm from the frequency scores was taken which already solved some heteroskedasticity. To further check the data, a Breusch-Pagan test was conducted on all four regression models described in section 4.7. The null hypothesis assumes that there is a constant variance among the residuals. The Breush-Pagan test statistics, as calculated with Stata 17, are shown in Table 6.

Regression		Chi-square	p-value
Testing H1		6.18	0.0129
Testing H2		0.01	0.9053
Testing H3		1.51	0.2188
Testing H4		0.42	0.5163

Table 6: Breusch-Pagan test

For the regressions testing hypotheses 1,2 and 4, the p-values are higher than the threshold value of 0.05, therefore the null hypothesis can be rejected and heteroskedasticity is not present for these regressions. For the regression analysis for testing hypothesis 1, the p-value is below the threshold value, which causes the null hypothesis to be rejected, showing signs of possible heteroskedasticity. To solve this problem, this regression analysis will use robust standard errors. This involves estimating the regression model with a robust covariance matrix, providing consistent standard errors even in the presence of heteroscedasticity.

5.4 Regression analysis

Dependent variable		ROA		env_score
Independent variables	Model 1	Model 2	Model 3	Model 4
firm_size	-0.0181883***	-0.0173386***	-0.0182705***	0.0752131
env_score		-0.0099307**		
dig_maturity			0.0022907	0.2881974***
Constant	0.1864685***	0.2080238	0.1797659	1.296174**
Observations	69	69	69	69
R-Squared	0.2390	0.2800	0.2417	0.1142
F-statistic	21.04***	12.06***	10.52***	4.26**
Adjusted R-2	0.2276	0.2582	0.2187	0.0874

Standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Table 7 regression analysis results

In Table 7, the four regressions, described in section 4.7 are analysed. Hypothesis 1-3 are tested using Ordinary Least Squares (OLS) The mediation procedure as written by Baron & Kenny (1986) is followed. This method proposes three preconditions which need to be met before considering mediation: The independent variable predicting the dependent variable (hypothesis 3), the independent variable predicting the mediator (hypothesis 2), and the mediator predicting the dependent variable (hypothesis 1).

Model 1 represents the interaction between the dependent variable firm performance and the control variable firm size. Both the p-value for firm size and the F-statistic is statistically significant. Model 2 represents the interaction of firm size and firm performance, and adds the independent variable of environmental sustainability, testing precondition 3. The model has an F-statistic of 3.24 and an R-squared value of 0.0749. Model 3 represents the interaction between firm performance and digital maturity, along with the control variable firm_size, testing precondition 1. The model has an F-statistic of 3.74 and an R-squared value of 0.0942. Model 4 represents the interaction between environmental sustainability as the dependent variable and digital maturity as the independent variable, along with the control variable firm size, testing precondition 2. The model has an F-statistic of 4.25 and an R-squared value of 0.1055.

Hypothesis 1, which proposes that more environmental sustainability will lead to higher firm performance, which is examined by Model 2. The effect of environmental sustainability on firm performance is significant (p<0.05) with a negative coefficient very close to zero (0.009), suggesting a small negative effect of environmental sustainability on firm performance. **H1** is not supported. The effect of environmental sustainability on firm performance is negligible.

Hypothesis 2, which proposes that a higher level of digital maturity will lead to a higher level of environmental sustainability, is examined by Model 4. The effect of the level of digital maturity on environmental sustainability is significant, with a positive coefficient (0.272) and a significant p-value (<0.01). Therefore, **H2** is supported, there is strong evidence that the level of digital maturity impacts an organisation's environmental sustainability.

Hypothesis 3, which proposes that a higher level of digital maturity leads to higher firm performance, is examined by Model 3. The effect of the level of digital maturity on firm performance is insignificant with a negative coefficient, suggesting a negative effect, and an insignificant p-value. There is no strong evidence that environmental sustainability impacts firm performance, therefore **H3** is not supported.

For **Hypothesis 4**, which proposes that environmental sustainability positively mediates the effect of the level of digital maturity on firm performance, the proposed preconditions set by Baron & Kenny (1986) are not met. Namely, the independent variable does not predict the dependent variable and the mediator does not predict the dependent variable. Therefore, there is no possible mediation effect and **H4** is not supported.

6. Discussion and Conclusion

6.1 Conclusion

The emergence of industry 4.0 technologies has brought about many technologies applicable in the manufacturing sector and it quickly became a top priority for manufacturers (Ghobakhloo, 2018). The flexibility that new technologies offer in a supply chain can be beneficial for a firm's environmental efforts (Angeles, 2009). Next to flexibility, new Industry 4.0 technologies allow manufacturers to monitor their supply chain more precisely and use this information to reduce environmental impacts (Ren et al., 2019; Shrouf and Miragliotta., 2015). However, while the adoption of these technologies can improve reliability, visibility and trackability, it also places a significant financial burden on an organization (Bag et al. 2021; Huang et al. 2021). Furthermore, these financial burdens could be outweighed by the benefits of environmental sustainability in an organisation. Companies engaging in practices mitigating environmental outputs can create competitive advantages out of their improved brand reputation (Hart, 1995) and higher resource productivity (Porter & van der Linde, 1995). However, the results of this study do not imply higher firm performance as a result of environmental sustainability within organisations. Resultantly, no assumptions can be made in this regard based on this study. It is worth noting that the implications of adopting new technologies should not be based solely on an organisation's current financial performance. Considerations for mitigating environmental impacts are increasingly dominant and should be valued fairly along the assessment of costs and benefits for implementing Industry 4.0 technologies. Furthermore, this research can conclude that implementation of these technologies ameliorates environmental impacts of organisations. Additionally, implementing new technologies is a timely procedure, which contains a process of adaptation for management. Many Industry 4.0 related technologies are still at an early stage of adoption (Dalenogare et al., 2018), which harms the ability to measure its full potential. The results of this study cannot overstep its boundaries, and therefore it is not involved in hypothesising long-term outcomes. However, the hypothesis for a direct impact of Industry 4.0 technologies on firm performance is backed by other research (Duman & Akdemir, 2021; Akter et al., 2016). A difference in results could be accounted for by different methodologies.

6.2 Managerial implications

The main point of discussion for managers concerning this research topic is the consideration of investing in Industry 4.0 technologies. The weight-off between the high cost of adopting these technologies and the benefits they have to offer can be assessed through the scope of this paper. While this research does not focus solely on the cost and efficiency benefits, the financial performance of a firm can measure this weight-off. For global manufacturing companies, likely to be heavily investing in different types of efficiency technologies in their supply chain it is crucial to assess if the Industry 4.0 technologies are worth investing in if there is an efficient supply chain established. The results of this research suggest that for large corporations it may not benefit financial performance. However, the new technologies are impacting the environmental sustainability of a firm, which is of increasing concern for top management. It can be expected that environmental concerns will only keep growing, and the importance for global corporations to account for these concerns will increase as well. Therefore, the consideration for investment into Industy 4.0 technologies cannot be evaluated solely on its financial performance in the present. All in all, the current supply chain, its sustainability, and the compatibility of new technologies need to be crucially assessed in order to decide if the weight-off between the high costs and the efficiency benefits is fitting the company.

6.3 Research limitations and recommendations

There are several limitations to this study. Firstly, approaching a quantitative study using text mining to measure the variables of both digital maturity and environmental sustainability creates a vulnerability for regression analysis. As both variables influence each other and the dependent variable firm performance, analysing the same annual reports for both variables could impact the research design. Furthermore, this method would assume firms that are more digitally mature and environmentally sustainable would also advocate this in their annual reports. While it can be argued through Heidinger and Gatzert (2018), that management awareness and its link to actual economic activities is apparent, the actual fluency of this relationship is difficult to measure and likely to be different to each firm. For future research, a continuous process of adopting the data measures to link them to the situations of different reports would lead to a clearer view of the activities regarding digital maturity and environmental sustainability in a firm. For digital maturity, consulting with the companies themselves, and looking at the different types of technologies which are implemented could provide a clearer picture. For environmental sustainability, measures regarding the reduction of energy, water and pollution could be taken, to calculate the environmental sustainability of a firm, rather than assessing its environmental situation based on reports. Additionally, the assumption of normality is violated in the regression analysis, which could potentially harm the results of the hypothesis tests. Next to this, the sample of the firms focuses on the biggest manufacturers in the world, which could impact the overall design of the analysis. This makes generalising these results for smaller firms challenging. According to Frank et al. (2019), small and medium-sized firms lack an understanding of Industry 4.0 technologies. Next to this, the organisations in the sample operate in developed markets. According to Delanogare et al. (2018), the potential for Industry 4.0 to cause performance improvements is lower in emerging economies, as a result of a low level of information and technological infrastructure. Therefore, generalising the results of this research can be challenging.

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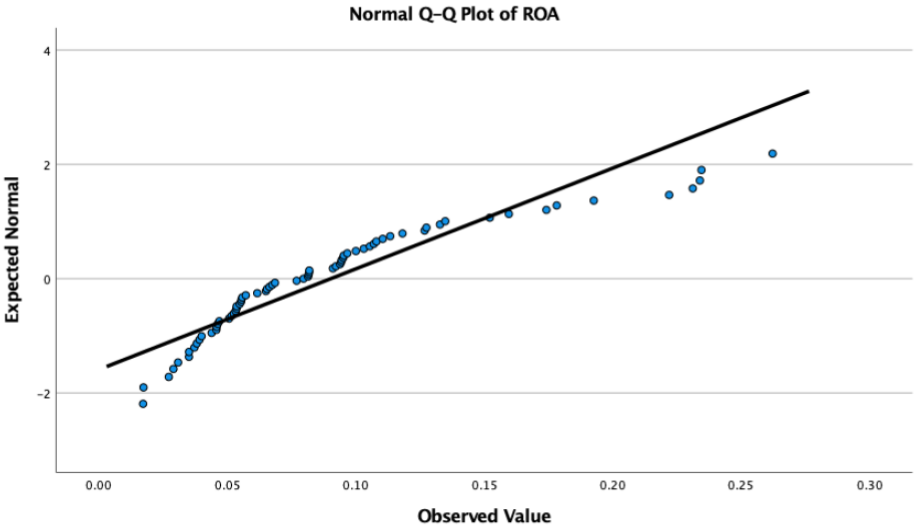
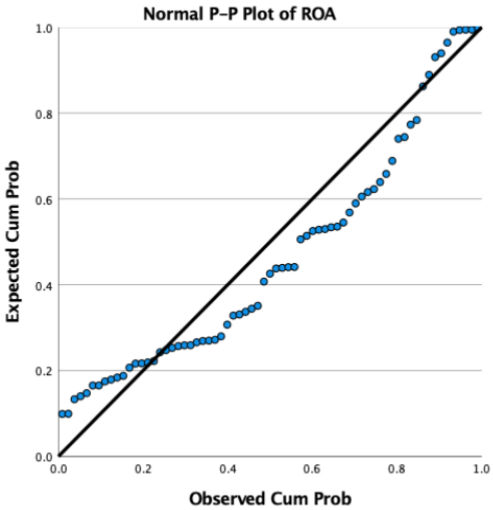
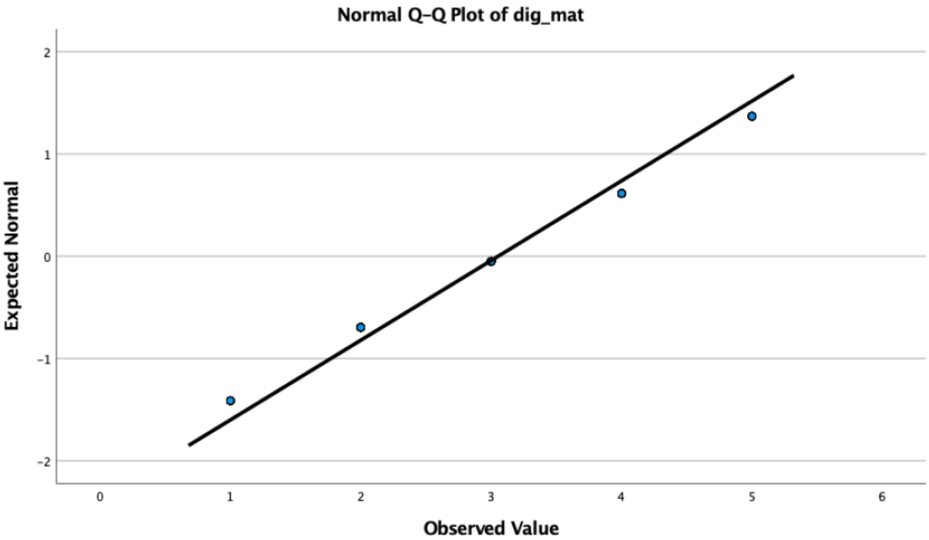
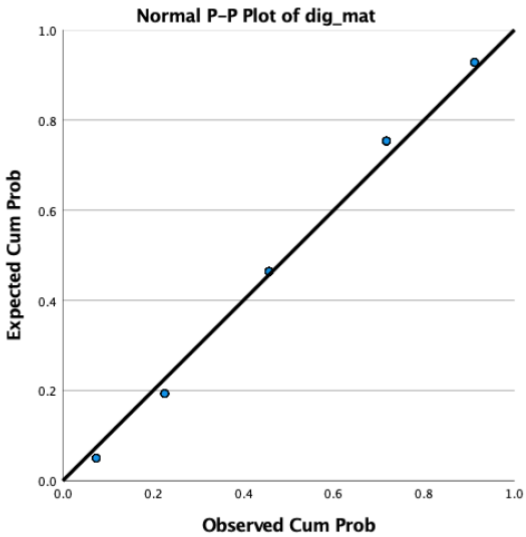
Appendix

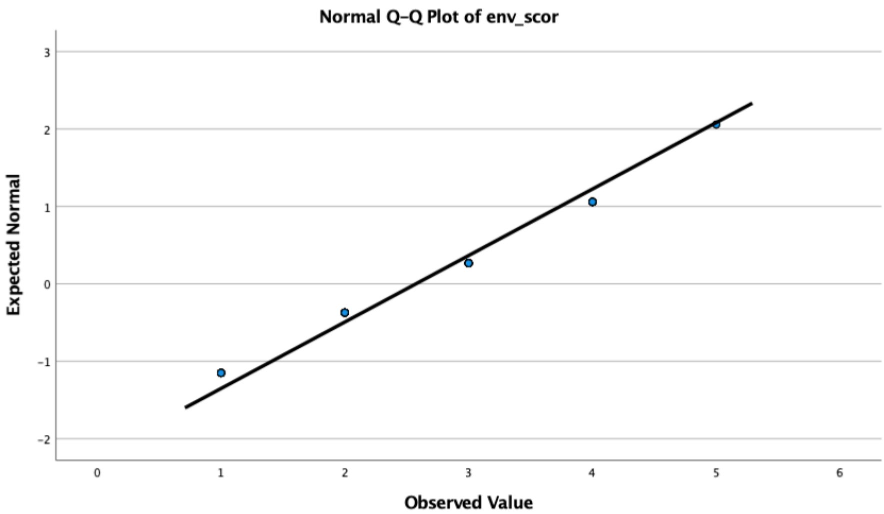
A. Q-Q and P-P Plots

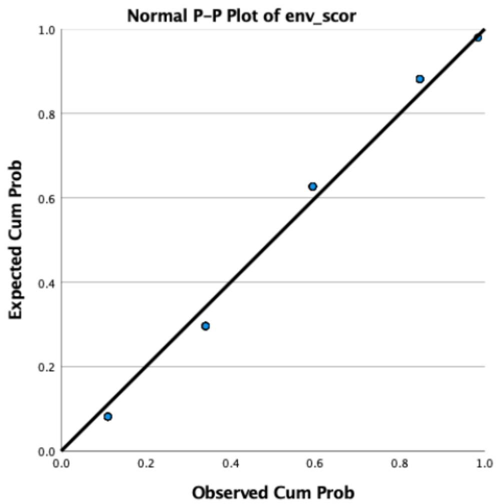


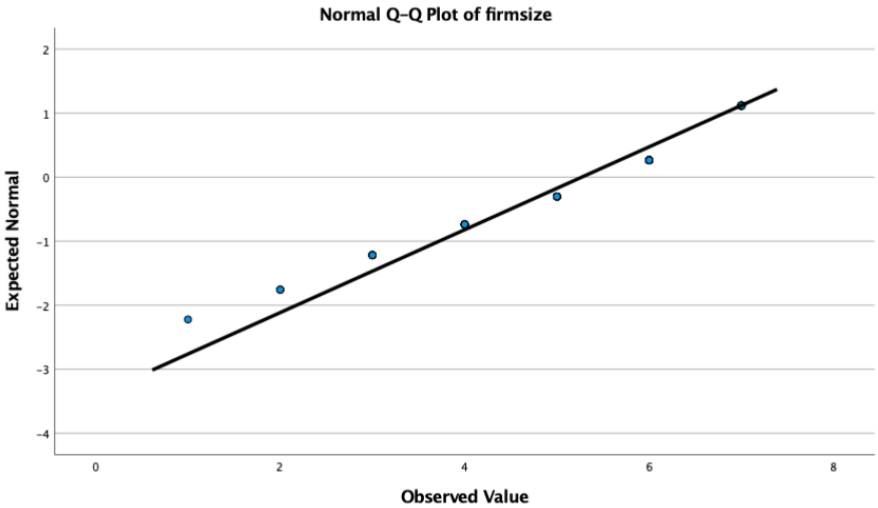


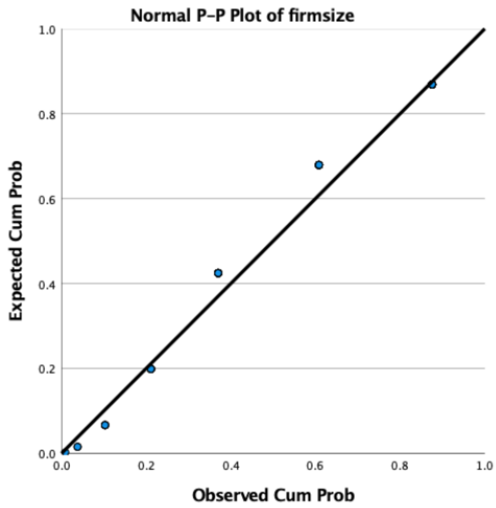












B. Shapiro-Wilk test of normality

Variable	Obs	W	V	z	prob>z
ROA	69	0.87112	7.841	4.475	0.00000
env_score	69	0.95963	2.456	1.952	0.02546
dig_maturity	69	0.99755	0.149	-4.134	0.99998
firm_size	69	0.93890	3.717	2.853	0.00217

C. Companies scores

Column 1: Company name
Column 2: Return on assets
Column 3: Digital maturity level
Column 4: Environmental sustainability score
Column 5: Firm size category

AGCO	0,0922544	2	2	5
Agilent Technologies	0,11818482	3	1	4
Airbus	0,03809122	4	3	7
Amatek	0,09532059	4	1	4
Amphenol	0,12680056	4	1	6
Analog Devices	0,05356544	3	2	4

Avery Dennison	0,09510052	5	2	5
BMW	0,06853855	3	4	7
BOE Technology	0,0173425	5	2	6
Bruker	0,08161244	3	1	3
Caterpillar	0,08140297	1	2	7
Crown Holdings	0,05159505	1	2	5
Cummins	0,07965339	1	3	6
Daikin	0,06164198	3	4	6
Dassault Aviation	0,06541479	4	4	4
Deere & Company	0,08189774	3	2	6
Denso	0,03716927	5	4	7
Dover	0,10003462	3	3	5
Emerson	0,10700979	5	3	6
Epiroc	0,15217056	4	4	4
Fanuc	0,09109178	5	3	3
Ferrari	0,12749923	2	3	2
Flex	0,05324081	3	2	7
Guangzhou Auto. Group	0,04687848	3	2	6
Geely	0,03506805	2	1	7
General Motors	0,03504634	3	3	7
Great Wall Motors	0,04582504	3	3	6
HELLA	0,02899442	4	2	5
Honda	0,03081292	1	3	7
Hoya	0,17821832	5	3	5
Illinois Tool Works	0,19264104	1	1	5
Indutrade	0,10546184	4	3	3

Intel	0,04572778	5	3	7
Jabil	0,05476891	2	1	7
Kia	0,07696915	5	5	6
Kimberly-Clark	0,10802357	2	2	5
Komatsu	0,05531652	5	4	6
Lattice Semiconductor	0,2345675	4	1	1
Lockheed	0,11049319	2	1	6
Marati Suzuki India	0,10311933	3	4	4
Mercedes-Benz	0,0557896	4	3	7
Mitsubishi Electric	0,04624408	5	4	6
Nidec	0,05546167	3	2	7
Nitto Denko	0,09428598	3	4	5
Nordson	0,13483132	1	1	3
Otis Worldwide	0,11340393	3	2	6
Porsche	0,09449363	1	1	5
Samsung Biologics	0,0650093	1	4	2
Sandvik	0,06750171	4	4	5
Snap-on	0,1327799	1	2	4
Spirax-Sarco Engineering	0,09668467	2	4	3
Stanley Black & Decker	0,03997299	3	1	6
Stellantis	0,09386961	2	3	7
STMicroelectronics	0,23117647	4	2	6
Sumitomo Denki Kõgyõ	0,05250708	5	4	6
Suzuki Motor	0,03914906	3	4	6
Techtronic Industries	0,08184053	2	4	6
Tenaris	0,15958161	2	3	4

Tesla	0,17419654	3	3	7
Textron	0,05361146	1	1	5
Toyota	0,04386272	3	3	7
TSMC	0,23394643	3	2	6
Unicharm	0,06638411	3	4	4
VAT Group	0,26224316	5	2	2
Volkswagen	0,02719455	4	3	7
Volvo Group	0,05716033	4	4	7
Volvo Car	0,05067768	4	5	5
Waters Corperation	0,22199256	4	1	3
Weichai Power	0,01718915	2	1	6