Kaunas University of Technology

School of Economics and Business

Digital Technologies and Environmental Performance: A Curvilinear Effects Estimation

Master‘s Final Degree Project

Lena Bostelmann

Project author

Prof. Dr. Mantas Vilkas

Supervisor

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Lena Bostelmann

Project author

Prof. Dr. Mantas Vilkas

Supervisor

Assoc. prof. Inga Stankevičė

Reviewer

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Kaunas University of Technology

School of Economics and Business

Lena Bostelmann

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Summary

With the climate crisis rapidly progressing, industries are faced with the challenge of minimizing their environmental footprint. One proven way for achieving this imperative is through the adept adoption of digital transformation (DT). However, while certain studies assert a strictly positive correlation between DT and companies' environmental performance (EP), a body of evidence suggests a more complex, non-linear relationship. This discrepancy between the two research streams leads to a research gap, requiring further exploration on the influencing factors of the relationship. Since DT is mainly built on digital technologies it appears necessary to examine the correlation between the use of these technologies and EP. Positioned within the resource-based view framework, which recognizes both digital technologies and EP as strategic resources for competitive advantage, this study contributes to the field of DT and its impact on EP.

Thus, the **research aim** is to investigate the complex relationship between digital technologies and environmental performance within manufacturing companies, specifically investigating the hypothesis of a curvilinear association.

The **research objectives** encompass:

1. To investigate the concepts of DT, digital technologies and EP

2. To review arguments and evidence for both a linear and non-linear relationship between DT and EP

3. To define a research model to analyze the effect of digital technologies on EP

4. To present the results of the effect of digital technologies on EP and propose theoretical and managerial implications of said results based on the resource-based view (RBV).

The underlying **research method** required conducting a literatur review to find evidence for both a linear positive and a curvilinear relationship to find similarities and differences in the argumentation. By leveraging secondary data from a 2022 survey, a regression analysis was conducted to examine the potentially curvilinear relationship between a selection of digital technologies and EP. The ten queried digital technologies were categorized into five groups based on the 5C architecture of Cyber-Physical Systems (CPS).

The **empirical findings** revealed a significant positive linear relationship between three technology categories, namely smart-connection, cyber and configuration, and EP. The strength of the relationships were equally weak, suggesting that the integration of these digital technologies improve the EP only slightly and there is little difference in which technologies are used. These results

contradict the expected inverted U-shape relationship, indicating a linear improvement in EP as digital technologies become more integrated into manufacturing processes. The analysis also revealed a significant relationship between company size, which was used as a control variable, and EP.

As a **final result**, this research underscores the strategic importance of DT in enhancing environmental sustainability within the manufacturing context. From a RBV perspective it is advisable for manufacturing companies to implement new and further develop existing digital technology applications, to improve their competitive advantage. This is restricted to technologies from the categories smart-connection, cyber and configuration. However, research suggests that digital technologies have their main environmental impact outside of the operative using stage in their production and end-of-life disposal. Therefore it is possible, that EP of companies that use these technologies does not reflect this impact accordingly.

This research also emphasizes the need for further qualitative investigation into how digital technologies can be utilized in a targeted approach to improve EP. By outlining how the use of digital technologies already improves EP and enhances the competitive edge of manufacturing enterprises, this study contributes theoretically to the existing body of literature while adding to the global empirical evidence base, particularly through the evaluation of data from Lithuania.

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Santrauka

Sparčiai progresuojant klimato krizei, pramonės įmonės susiduria su iššūkiu sumažinti savo ekologinį pėdsaką. Vienas iš patikrintų būdų tai pasiekti yra veiksmingas skaitmeninės transformacijos (DT) įgyvendinimas. Tačiau, nors kai kurie tyrimai rodo, kad tarp skaitmeninių technologijų diegimo ir įmonių aplinkosauginio veiksmingumo yra teigiamas ryšys, yra ir įrodymų, rodančių sudėtingesnį, netiesinį ryšį. Šis dviejų tyrimų srautų neatitikimas lemia tyrimų spragą, todėl reikia toliau tirti ryšius įtakojančius veiksnius. Kadangi DT daugiausia paremta skaitmeninėmis technologijomis, atrodo, kad būtina išnagrinėti ryšį tarp šių technologijų naudojimo ir EP.Ištekliais grįsto požiūrio teorijos kontekste, kurioje skaitmeninės technologijos ir aplinkosauginis veiksmingumas pripažįstami strateginiais konkurencinio pranašumo ištekliais, šis tyrimas prisideda prie skaitmeninių technologijų poveikio aplinkosauginiams pasiekimams žinių.

Taigi, šio darbo tikslas – ištirti kompleksinį ryšį tarp skaitmeninių technologijų ir aplinkosaugos veiksmingumo gamybos įmonėse išnagrinėjus netiesinio poveikio galimybę.

Tyrimo tikslai apima:

1. Išnagrinėti DT, skaitmeninių technologijų ir EP sąvokas

2. Apžvelgti argumentus ir įrodymus, patvirtinančius tiek tiesinį, tiek nelinijinį ryšį tarp DT ir EP

3. Nustatyti tyrimo modelį skaitmeninių technologijų poveikiui EP analizuoti

4. Pateikti skaitmeninių technologijų poveikio EP rezultatus ir pasiūlyti šių rezultatų teorines bei vadybines pasekmes remiantis ištekliais pagrįstu požiūriu (RBV).

Pagrindinis tyrimo metodas reikalavo atlikti literatūros apžvalgą, kad būtų galima rasti tiek tiesinio teigiamo, tiek kreivinio ryšio įrodymų, kad būtų galima rasti argumentacijos panašumų ir skirtumų.Remiantis antriniais 2022 m. tyrimo duomenimis, buvo atlikta regresinė analizė, siekiant ištirti galimai netisinį ryšį tarp pasirinktų skaitmeninių technologijų ir poveikio aplinkai. Dešimt skaitmeninių technologijų buvo suskirstytos į penkias grupes, remiantis kibernetinių fizinių sistemų (CPS) 5C architektūra.

Empirinės išvados atskleidė reikšmingą teigiamą tiesinį ryšį tarp trijų technologijų kategorijų, būtent išmaniojo ryšio, kibernetinės ir konfigūracijos bei EP. Ryšių stiprumas taip pat buvo silpnas, o tai rodo, kad šių skaitmeninių technologijų integravimas tik šiek tiek pagerina EP ir mažai skiriasi, kokios technologijos naudojamos Šie rezultatai prieštarauja anksčiau nustatytam U formos ryšiui, ir rodo tiesinį aplinkosaugos veiksmingumo pagerėjimą, kai skaitmeninės technologijos tampa labiau

integruotos į gamybos procesus. Analizė taip pat atskleidė reikšmingą ryšį tarp įmonės dydžio, kuris buvo naudojamas kaip kontrolinė kintamoji, ir EP.

Šis tyrimas pabrėžia strateginę skaitmeninės transformacijos svarbą didinant aplinkos tvarumą gamybos kontekste.Iš RBV perspektyvos rekomenduojama gamybos įmonėms įdiegti naujas ir tobulinti esamas skaitmenines technologijų programas, siekiant pagerinti savo konkurencinį pranašumą. Tai ribojama iki išmaniojo ryšio, kibernetinės ir konfigūracijos technologijų kategorijų. Tačiau tyrimai rodo, kad skaitmeninės technologijos turi pagrindinį aplinkos poveikį neoperatyvinėje naudojimo stadijoje, jų gamyboje ir galutinio naudojimo atliekų tvarkymo procese. Todėl yra galimybė, kad įmonių, naudojančių šias technologijas, aplinkos poveikis nepakankamai atspindi jų EP.

Šis tyrimas pabrėžiama, kad reikia atlikti tolesnį kokybinį tyrimą, kaip skaitmenines technologijas galima panaudoti tikslingai siekiant pagerinti įmonių poveikio aplinkai minimizavimą. identifikuodamas, kaip skaitmeninių technologijų naudojimas gerina aplinkosaugos pasiekimus ir didina gamybos įmonių konkurencinį pranašumą, šis tyrimas prisideda prie esamos literatūros ir papildo pasaulinę empirinių įrGneuaodymų bazę, ypač vertinant Lietuvos duomenis.

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List of Abbreviations and Terms

Abbreviations:

AI	Artificial Intelligence
AM	Additive Manufacturing
AR	Augmented Reality
CAD	Computer Aided Design
CNC	Computerized Numerical Control
CPS	Cyber-Physical-System
CRP	Corporate Responsibility Performance
CSRD	Corporate Sustainability Reporting Directive
CSDDD	Corporate Sustainability Due Diligence Directive
DT	Digital Transformation
EMS	Environmental Mangement System
EP	Environmental Performance
EPI	Environmental Performance Index
ERP	Enterprise Resource Planning
ETS	EU Emission-Trading-Scheme
IoT	Internet of Things
MES	Manufacturing Execution System
NACE	European Classification of Economic Activities
RBV	Resource Based View
T&T	Tracking and Tracing
VR	Virtual Reality

Terms:

Digital Technologies:	electronic tools, devices, systems, and resources which generate, store or process data

Digital Transformation:	a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies.
Digitalization:	the adaptation of a system, process, etc., to be operated with the use of computers and the internet.
Digitization:	the conversion from analogue to digital means or systems.
Digital Innovation:	the use of digital technologies to create digital and physical components of products.
Environmental Performance:	the outcome of an environmental management system that provides environmetal benefits for a company and its stakeholders and is measured in appropriate KPIs.

Introduction

Relevance:

Against the background of the simultaneous challenges posed by the climate crisis and the transformative progress of the fourth industrial revolution, the question arises, of how the digital ages shape today's environment, especially in terms of sustainability (Le Ha, Huong, & Thanh, 2022). Although digital technologies can support businesses in various aspects, companies are increasingly under pressure to work towards becoming more sustainable and try to find out how these two issues could be balanced or even combined (Kraus, Rehman, & García, 2020). Lithuania as a country exhibits an overall digitalization level that resembles the European average (European Commission, 2022). While overall, the country is in the top 35 countries concerning the environmental performance index (EPI), it is substandard when it comes to air quality factors such as NOx, SO_2 or CO emissions, which can be caused by manufacturing industries (Wolf, Emerson, Esty, & Sherbinin, 2022).

Problem Analysis:

With the research landscape focussing on different aspects of digital transformation (DT), one subject to discussion is its effect on the environmental performance (EP) of companies (Feroz, Zo, & Chiravuri, 2021). In recent years, two main research streams have emerged, one suggesting a strictly positive impact and the other proposing a more nuanced, potentially curvilinear relationship between DT and EP (Chen, Despeisse, & Johansson, 2020; Feroz et al., 2021). Both research streams are supported by empiric data and diverse circumstantial evidence. One side argues that the availability of data and the decision support through algorithms enable great possibilities for fact-based eco-efficiency plans and that smart manufacturing tools can reduce waste, energy consumption and emissions (Feroz et al., 2021; Le Ha et al., 2022; Wu, Goepp, & Siadat, 2019). The other side refers to the high energy consumption of the required servers and the pollution caused by the production, use and end-of-life disposal of new machines and tools (Ahmadova, Delgado-Márquez, Pedauga, & La Leyva-de Hiz, 2022; Chen et al., 2020).

Research Gap:

Thus, a research gap results from the existing divergent opinions as well as a noticeable preponderance of research on a positive linear effect. This indicates a need for broader evidence across various countries and industry segments. The exploration of influential factors contributing to the complex relationship between DT and EP becomes important within this context. As one central aspect that DT builds on is digital technologies, this thesis aims to evaluate the difference between various digital technologies and their effects on EP, with a focus on Lithuanian manufacturing companies. Therefore, the central **research question** guiding this thesis is: "Do different kinds of digital technologies vary in their effect on EP in manufacturing companies?".

Research object:

The research object is the relationship between digital technologies and EP in Lithuanian manufacturing companies.

Research aim:

The research aim is to evaluate the relationship between digital technologies and EP and give recommendations as to which technologies lead to a competitive advantage in terms of their environmental effect.

Research objectives:

1. To investigate the concepts of DT, digital technologies and EP
2. To review arguments and evidence for both a linear and non-linear relationship between DT and EP
3. To define a research model to analyze the effect of digital technologies on EP
4. To present the results of the effect of digital technologies on EP and propose theoretical and managerial implications of said results based on the resource-based view (RBV).

Methodology:

In order to answer the research question, firstly the concepts of DT, digital technologies and EP have to be defined and must be placed in context with each other. Furthermore, there will be an analysis of the existing body of literature identifying evidence and arguments for both research streams as well as already-found influential factors. To continue with the analysis, there has to be a meaningful categorization of the chosen technologies in order to abstract the findings. Finally, by using a dataset obtained from a 2022 survey of Lithuanian manufacturing companies, the relationship between digital technologies and EP will be analyzed and discussed to answer the research question.

The methodology encompasses a comprehensive literature review for establishing a theoretical framework and a regression analysis to evaluate the relationships within the identified technology categories and their impact on EP. From a managerial perspective, this research applies a resource-based theory view and seeks to contribute nuanced insights to the ongoing discourse surrounding the environmental consequences of DT, offering valuable perspectives for sustainable development in manufacturing industries. The adoption of a RBV will help in understanding how companies can make targeted use of digital technologies to reach environmental sustainability goals and gain a competitive advantage from that.

This thesis will contribute to existing research by expanding the knowledge base with quantitative evidence from Lithuania, adding to the solving of the conflict between the two research streams. Additionally, it will provide recommendations for organizations and managers on which digital technologies can benefit their company by creating or increasing a competitive advantage.

1. Problem Analysis

Nowadays, the connection between DT and EP in manufacturing companies has become a focal point for investigation. This chapter will first introduce the concept of DT, establishing the distinction between the terms “digitalization“, “digitization“, “digital innovation“ and “digital technologies“. Secondly, it will explore barriers and the application of DT in manufacturing companies. Afterwards, EP is discussed in more detail by looking at possible definitions, dimensions and the companies‘ motivations. Finally, the bridge between DT and EP is forged, building a basis for the following analyses.

1.1. The Need for Digital Transformation in Manufacturing Industries

In this chapter, the concept of DT and digital technologies, specifically with regard to manufacturing industries, is thoroughly explained, creating a foundation for further discussion.

1.1.1. Definition of Digital Transformation

DT is a relatively new concept that is often used interchangeably with "digitalization“, "digitization“ or "digital innovation“ (Chen et al., 2020; Osmundsen, Iden, & Bygstad, 2018). This makes it important to find a definition that differentiates between these terms. Furthermore, this chapter will introduce the relationship between these concepts and digital technologies.

According to the Oxford Dictionary, digitalization is the "adaptation of a system, process, etc., to be operated with the use of computers and the internet." Specifically the word "operated“ illustrates the difference to digitization. While digitization purely involves the conversion from analogue to digital, digitalization introduces a social aspect of adopting and using digital technologies (Yoo, Henfridsson, & Lyytinen, 2010). Finally, Yoo et al. (2010) define digital innovation as the use of digital technologies to create digital and physical components of products.

As stated above, given the novelty of DT, various definitions exist in research, causing a lack of clarity. This thesis will utilise the term as characterized by Vial (2019), defining it as “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” based on an analysis of 28 publications. This understanding, especially with an emphasis on business improvement, is widely supported (Feroz et al., 2021; Osmundsen et al., 2018). Using the expression "significant changes“ underlines DT not only encompassing technological change but also the organizational way of working (Ahmadova et al., 2022). Here also lies the differentiation to digital innovation, which refers to innovative products or services based on digital technologies or the process of creation (Vial, 2019). In contrast to several other sources, Vial (2019) does not use “digital technologies“ as a keyword in the definition and instead employs a list of its components as proposed by Bharadwaj et al. (2013). By doing so, the author agrees with the consensus that digital technologies are a critical enabling element in DT (Feroz et al., 2021; Liere-Netheler, Packmohr, & Vogelsang, 2018; Matt, Hess, & Benlian, 2015), while aiming to be more specific in the phrasing.

Similar to Bharadwaj et al.'s (2013) characterization, digital technologies are often described by listing the individual technologies or technology groups that are considered as such (Varriale, Cammarano, Michelino, & Caputo, 2024). However, this leads to a number of mutually inconsistent lists, changing continuously with ongoing technological development. A more generalized definition is provided by Salmons and Wilson (2009), describing digital technologies as “electronic tools, devices, systems, and resources which generate, store or process data“. This is a broader definition, including all sorts of technologies that will be specified in chapter 1.1.3 and used in this thesis.

Finally, it can be summarized that DT is not synonymous with digitalization, digitization or digital innovation, but rather builds upon these concepts as illustrated in **Fig. 1**. It also becomes apparent that digital technologies are a key element of DT and digital innovation and can be created through but are also used for digitalization.

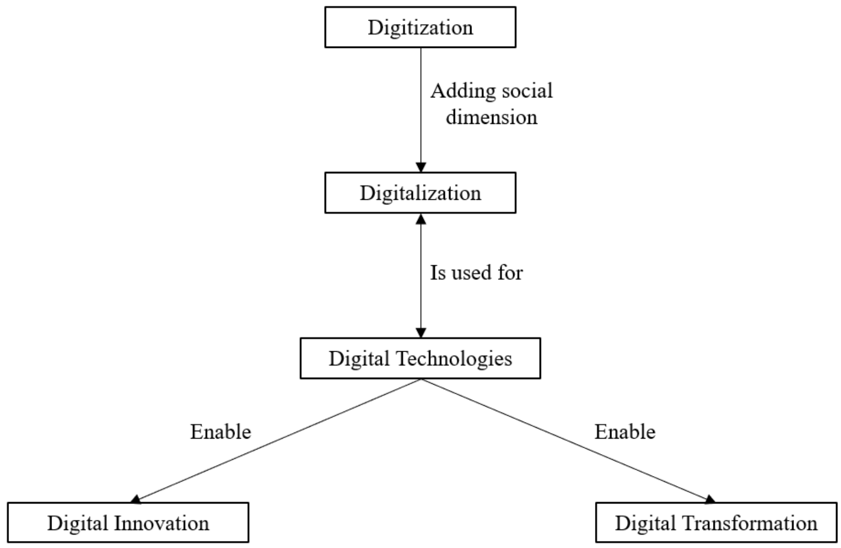

Fig. 1. Visualization of relationships between digitization, digitalization, digital technologies, digital innovation and DT (source: own depiction)

1.1.2. Drivers and Barriers

As defined, DT is a way to alter value creation in organizations in a potentially disruptive way (Vial, 2019). Nevertheless, to enable this kind of change through the implementation of digital technologies, certain conditions have to be given or created and risks mitigated. Thus, various research highlights drivers and objectives of DT that act as motivation or enablers, which will be summarized in this chapter to help understand the organizational environment of DT.

First of all, there is a differentiation between internal and external drivers (Liere-Netheler et al., 2018). On the one hand, internal or organizational drivers often manifest themselves by creating a favourable cost-benefit ratio (Bhatia, Meenakshi, Kaur, & Dhir, 2024). This means that they help in reducing existing costs more than the initial investment required for technology implementation. This can take place through process and workplace improvement, management support, or enhancement of operation efficiency (Liere-Netheler et al., 2018). Furthermore, digital technologies can support business growth by setting up options for vertical and horizontal integration or promoting global agility (Bhatia et al., 2024). Recent studies identified environmental consciousness in company values and leadership as upcoming strong drivers for DT (Bhatia et al., 2024). As awareness of the impact businesses have on the climate increases, companies are making efforts to achieve energy efficiency and waste reduction by using digital technologies.

On the other hand, external drivers characterize pressure from stakeholders such as customers, the government, the market or the supply chain, as well as an innovation push (Liere-Netheler et al., 2018). Companies seeking a competitive advantage choose DT as a way to stay ahead and be equipped for future changes in the market (Bhatia et al., 2024). Finally, employee support is identified as another main driver. However, this can also be categorized as a success factor, which is not actively driving the transformation but is a key element to generate success, as elaborated by Osmundsen et al. (2018). The authors also explain that a supportive organizational culture and values that align with change and customer-centricity can aid DT. Other success factors can be well-structured knowledge management, a digital business strategy and the development of dynamic and information system capabilities (Li, 2022; Osmundsen et al., 2018).

Nevertheless, some barriers can impede the exploitation of DT for manufacturing companies, most of which are grounded in a lack of organizational readiness (Lokuge, Sedera, Grover, & Dongming, 2019). For instance, inertia poses a significant challenge, as established processes and practices often stand in the way of change (Vial, 2019). This appears in the form of path dependency, suggesting that the historical choices and investments made in specific technologies shape the current technological trajectory. Oftentimes, this aggravates deviating from established paths. However, inertia can also be provoked by resistance, fostered by an unfavourable organizational culture with a lack of visibility regarding potential benefits further amplifying concerns (Schmid, Recker, & vom Brocke, 2017). In addition to that, cybersecurity emerges as a critical concern, since the negative consequences can be severe - ranging from damage to company software and reduced productivity to the potential loss of intellectual property and customer confidence (Jones, Hutcheson, & Camba, 2021). The associated costs, including those for investigating violations and litigation, as well as the risk of reputational damage, make cybersecurity a serious barrier (Barmuta et al., 2020). Furthermore, a lack of digital capabilities, which refers to the organization's proficiency in leveraging digital technologies, skills, and resources effectively, can impede the smooth progression of DT (Ding, 2022). These capabilities have to be built on a company-wide and individual employee level to avoid push-back (Cichosz, Wallenburg, & Knemeyer, 2020).

Apart from organizational barriers, the implementation of digital technologies can also fail due to financial restrictions (Bhatia et al., 2024). Although with sensible and thorough planning of DT applications, a positive cost-benefit ratio can often be achieved, a high initial investment is necessary for the acquisition of software, equipment and possible licenses, as well as for the training of employees. As with the drivers, there are also external barriers, preventing companies from leveraging DT, such as stakeholder acceptance or uncertainty of potential future regulatory changes (Vogelsang, Liere-Netheler, Packmohr, & Hoppe, 2019).

1.1.3. Digital Technologies in Manufacturing

Digital technologies are used in all kinds of organizations and industries, from agriculture to healthcare (Ciarli, Kenney, Massini, & Piscitello, 2021). As this thesis covers the DT in Lithuanian manufacturing companies, this chapter will examine the peculiarities that are specific to these types of organizations. Therefore, the chapter will discuss key digital technologies, levels of DT in companies, as well as strategies and approaches for the integration of technologies.

As explained in chapter 1.1.1, the DT of manufacturing companies is based on digital technologies and innovations that have reshaped the industry. Jones et al. (2021) mention in their review the presence of the following technologies in literature: additive manufacturing (AM), cloud computing, connectivity, robotics, and automation, big data and manufacturing analytics, artificial intelligence (AI), digital twins, and Model-Based Enterprise environments. Chen et al. (2020) supplement this list with the (IoT), virtual reality (VR), and augmented reality (AR). These lists, while not necessarily being comprehensive, depict the characteristics of innovations that are connoted with DT. They enable data-driven processes and manufacturing and real-time exchange (Chen & Hao, 2022). A categorization of the technologies used in the scope of this thesis will take place in Chapter 2.4.

The implementation of DT in manufacturing companies requires a well-organized process as well as structural changes (Vial, 2019). In the initial stages, companies typically focus on assessing their current technological landscape and identifying areas for improvement (Zaoui & Souissi, 2020). This involves conducting thorough digital readiness assessments and evaluating organizational culture. As companies advance, the establishment of a clear digital strategy becomes essential, outlining specific goals and aligning technology adoption with business objectives (Zaoui & Souissi, 2020). The implementation of cross-functional collaboration and change management initiatives was found to be important to fostering a digital-ready culture among employees (Berghaus & Back, 2016). Concurrently, data governance and management processes are refined to ensure the availability of accurate and reliable information for decision-making. Additionally. companies often invest in upskilling and training programs to enhance workforce capabilities in line with emerging digital technologies (Berghaus & Back, 2016). Another integral step is the collaboration with external partners and suppliers for digital integration throughout the supply chain. During these stages, continuous monitoring, evaluation, and iterative improvements are fundamental to the success of the DT journey (Berghaus & Back, 2016). Furthermore, the development and strengthening of dynamic capabilities are necessary for preventing dependency on certain technologies and rapid changes in the market (Li, 2022; Warner & Wäger, 2019). Finally, it has to be emphasized that DT has to be a continuous process to adjust to innovations and development and keep up with the competitive landscape (Warner & Wäger, 2019).

To analyze the maturity level of DT in companies, different models can be applied. Maturity models describe the stage of transformation and organization (Santos & Martinho, 2020). It can be seen that companies with a more advanced digital maturity level reach this state by applying a clear and comprehensive digital strategy (Salume, Barbosa, Pinto, & Sousa, 2021). Additionally, digital maturity can enhance the economic performance (Westermann & Dumitrescu, 2018). An analysis of different industry 4.0 maturity models, performed by Santos and Martinho (2020), for instance, leads to a framework encompassing six maturity levels, reaching from no implementation over pilot projects and partial implementation to the full application of all proposed concepts. This is evaluated in the dimensions of organizational strategy, workforce, smart factories, smart processes, and smart products and services (Santos & Martinho, 2020). In contrast to measuring the transformation process, the maturity level can also be measured on an absolute scale, where the state of different aspects of the company is examined. An example can be found in Klötzer and Pflaum (2017), where the five stages go from "digital awareness“ to "data-driven enterprise“.

1.2. The Problem of Environmental Sustainability in Companies

As digital advancements continue to progress, it is important to evaluate the impact these changes have on other aspects of modern businesses. For example, many western companies strive to improve their sustainable performance (Kraus et al., 2020). In Lithuania, the industrial sector accounts for approximately 15% of the annual greenhouse gas emissions, as shown in Fig. 2 (Aplinkos Apsaugos Agentūra, 2022). Although there is already a noticeable downward trend, enterprises are actively working to further strengthen this development.

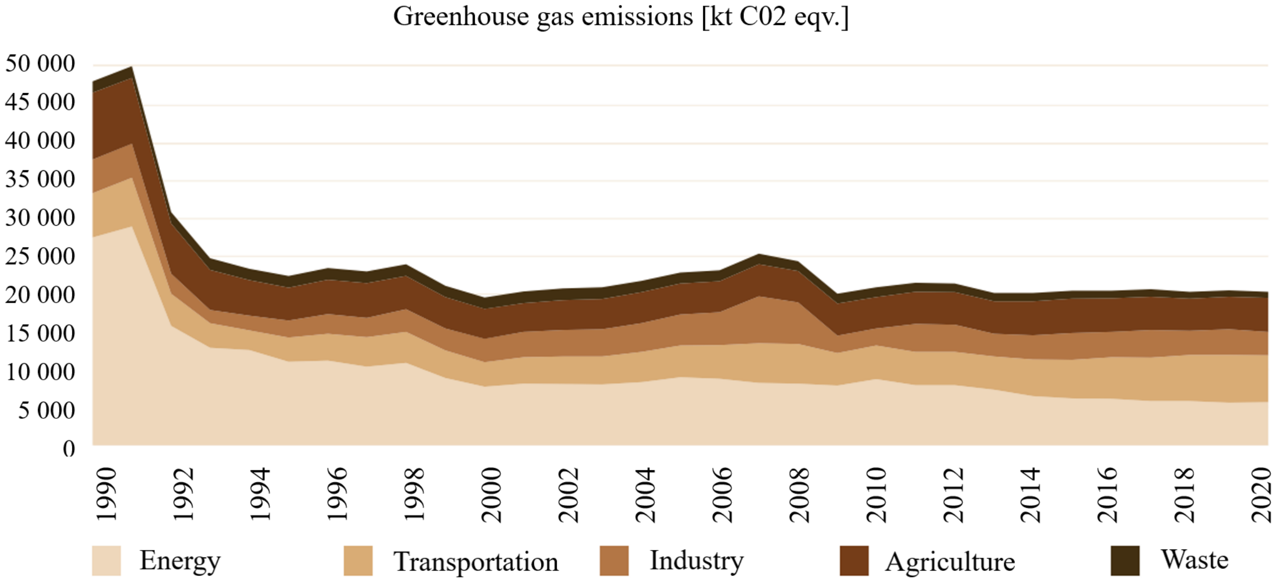

Fig. 2. Greenhouse gas emissions in Lithuania divided by sector (source: Aplinkos Apsaugos Agentūra, 2022)

There may occur an underlying intrinsic motivation, coming from managers or employees (Lisi, 2015). However, companies also face severe external pressure from stakeholders to reduce their environmental impact (Chen & Hao, 2022). This can take the form of government regulations, such as the European "Green Deal" of 2019, which provides for a comprehensive package of principles as well as funding options for companies (European Commission, 2023b). A further sense of urgency can be created by society and customers as well as investors, who may view companies with environmental efforts as a more attractive investment opportunity (Chen & Hao, 2022). Therefore, companies are encouraged to look into opportunities for enhancing their environmental sustainability in a way that allows business continuity while at the same time maintaining or improving economic efficiency.

1.2.1. Environmental Performance Definition

There are several ways to define EP, depending on the context. The keyword "EP" was first mentioned in the literature in the late 1980s, when research indicated that EP can create a competitive advantage (Clemens & Bakstran, 2010). According to DIN EN ISO 14001, it is defined as the outcome of an organizational (EMS) (DIN e.V., 2020). Furthermore, EP is said to relate to the control which the organization exercises over its impact on the environment based on its environmental policy, since this is reflected in measurable values (Albertini, 2016). However, Nawrocka and Parker (2009) criticize that this definition only considers these short-term outcomes and neglects more complex impacts, for example, on the stakeholders. They propose the use of a broader definition that includes environmental benefits for the company, such as savings generated by an EMS or a competitive advantage (Nawrocka & Parker, 2009).

The EP concept can be applied to a variety of organizations, such as companies or industries as well as to countries. Commonly, the EP of a company refers to a set of indicators that measure the direct or indirect influence on a specific environmental problem (Campos, Melo Heizen, Verdinelli, & Cauchick Miguel, 2015). These indicators can look very different across different industries or stages in the value chain at which they are measured. El Saadany et al. (2011) for instance elaborate that for supply chains, EP measures assess the amounts of air pollutants emitted from industrial plants and hazardous substances released, affecting soil and water quality. Albertini (2016) argues that variables can be of different origins, as long as they are observable and quantifiable. Performance is usually measured as positive when pollution of any kind is reduced and negative when it augments (Albertini, 2016). On a country level the EPI, published by the Yale Centre for Environmental Law and Policy, is a tool that provides a data-driven ranking with a set of 40 different indicators coming from the categories climate, environmental health and ecosystem vitality (Wolf et al., 2022). Every two years, 180 countries are assessed according to these indicators, but can also use them for self-monitoring (Wolf et al., 2022).

According to Albertini (2016), the dimensions of EP can be displayed on two axes. Within these dimensions, companies or organizations have various possibilities of actions to exercise influence over said dimension. Firstly, the internal/external axis shows whether action is taken solely within the company or with third parties involved. The second axis, process/outcome, captures whether the emphasis is on the end result or on the internal processes and methods employed to achieve environmental objectives. The dimensions derived from those are (1) organizational systems, (2) relations with stakeholders, (3) conformity to regulations, and (4) environmental impacts (see Fig. 3) (Albertini, 2016).

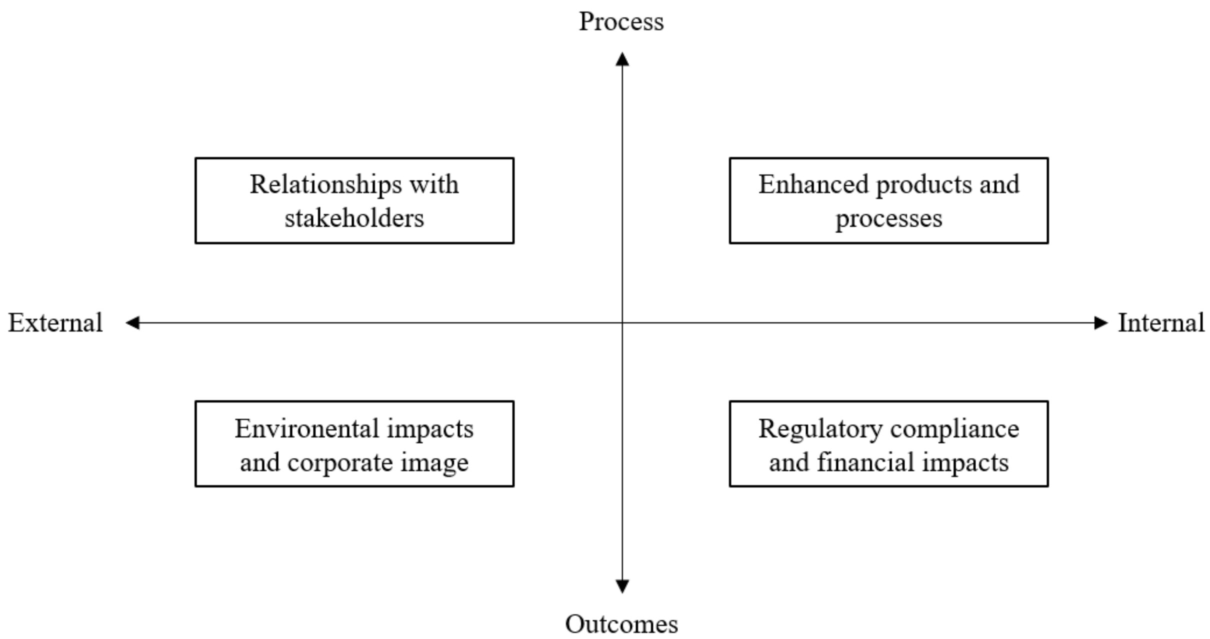

Fig. 3. Dimensions of EP (based on Albertini, 2016)

The showcased framework harmoniously corresponds with Nawrocka and Parker (2009) interpretation of EP, highlighting that it surpasses a mere list of indicators and emphasizing the interconnectedness of diverse dimensions and processes.

For purposes of consistency, the following thesis will use a definition as implemented by DIN EN ISO 14001, extended by the means proposed by Nawrocka and Parker (2009). Therefore, EP will be seen as the extent to which an organization, in this case companies, can decrease its negative environmental impact and simultaneously benefit from its efforts.

1.2.2. Motivation for Environmental Performance Improvement

To understand how companies can improve their EP, it is necessary to know, why they aspire to do so in the first place. As aforementioned, there are several potential motivations for a company to improve its EP.

While research commonly acknowledges a range of both intrinsic and extrinsic motivations to be driving forces, most scholars agree that the main motive for taking environmental action is based on economic interests and rather seldom derives from ecological awareness (Cainelli, Marchi, & Grandinetti, 2015). Applying an RBV can help managers understand the opportunities they hold to gain a competitive advantage by investing their available resources. Research suggests that being mindful of a company's resources is a key factor in achieving environmental sustainability and thus improving EP (Cainelli et al., 2015; Makhloufi, Laghouag, Meirun, & Belaid, 2022). In addition to that, EP has been found to be closely linked to the profitability and performance of companies (Miroshnychenko, Barontini, & Testa, 2017; Russo & Fouts, 1997).

Additional intrinsic motivations can also be derived from the four dimensions of EP identified by Albertini (2016) (see Fig. 2). One of the strongest motivators is an improved corporate image (Del Río González, 2005; Puttawong & Kunanusorn, 2020). This, in turn, indirectly affects a company's performance by influencing customers' opinion and their inclination to engage with the organization. While this effect is more commonly observed in B2C sectors, it is still a valuable aspect for B2B companies as well (Puttawong & Kunanusorn, 2020).

Concurrently, extrinsic motivational factors mainly exert pressure on companies to take action, to avoid negative consequences (Graafland & Bovenberg, 2020). This is evident in the form of regulations, financial sanctions, and pressure from stakeholders. Regulations are one of the key extrinsic motivational factors that drive companies to act (Nyahuna & Doorasamy, 2022). Governments and regulatory agencies establish rules and guidelines that businesses must adhere to. Failure to comply with these regulations can lead to legal consequences, fines, or the suspension of business operations (Nyahuna & Doorasamy, 2022). This serves as a powerful incentive for companies to actively address the issues at hand. The European Union has developed a framework of rules and guidelines, comprised in the so-called Green Deal (European Commission, 2023b). It contains for example the Corporate Sustainability Reporting Directive (CSRD), which obliges companies to include their sustainability governance, strategy and measures in the annual reports, creating accountability for taking environmental, social and economic action (European Commission, 2023a). In case of non-compliance with the regulation, there will be financial penalties and other legal actions.

In addition to regulations, the European Union (EU) has introduced a “cap and trade” system to incentivize a decrease in CO2 emissions (European Parliament, 2003). This system, known as the Emissions Trading Scheme (ETS), requires companies to hold a certain amount of emissions allowances to legally emit greenhouse gases. If a company exceeds its allocated allowances, it must either purchase additional allowances or reduce its emissions. This creates a financial motivation for companies to lower their carbon footprint. In addition to that, many countries introduced taxes on CO2 or greenhouse gas emissions. However, Lithuania has not implemented such a thing as of now.

Finally, the pressure from stakeholders, including investors and customers, plays a central role as well in driving companies towards action (Graafland & Bovenberg, 2020). These stakeholders have an interest in the environmental practices of companies and are increasingly demanding sustainable actions (Nyahuna & Doorasamy, 2022). Any failure to meet these expectations can lead to a loss of reputation, a decline in the number of customers, or a decrease in investments (Graafland & Bovenberg, 2020). Consequently, companies are compelled to address these concerns to ensure stakeholder satisfaction and uphold their reputation.

1.2.3. Connecting Digital Transformation and Environmental Performance

As the industrial revolution unfolded, it became evident that technological advancements have negative impacts on the environment across diverse dimensions, thereby adding to the emergence of a climate crisis (Chen & Hao, 2022). The Industry 4.0 movement has positioned itself intending to mitigate these effects, harnessing smart factories to work towards a sustainable economy. Consequently, a substantial body of research is dedicated to addressing the inquiry regarding the efficacy of DT in enhancing the EP of corporations, particularly regarding manufacturing entities (Bendig, Schulz, Theis, & Raff, 2023). Moreover, researchers are trying to determine the most effective way to implement digital technologies for the benefit of the environment (Plekhanov, Franke, & Netland, 2023). Schöggl et al. (2023) discovered that companies that use digital technologies in manufacturing rarely prioritize EP. Instead, their main focus is on achieving production excellence.

Albertini (2016) defines five categories to measure EP related to business strategy: general management, resource consumption, production process, achieved production, and financial and nonfinancial results. DT and digital technologies, mentioned in Chapter 1.1.3, mainly belong to the third and fourth categories as they are all production-related. However, it can also be argued that some of them have an effect on resource consumption and general management (Ahmadova et al., 2022).

It is important to note that there is a consensus in research regarding the existence of a correlation between DT and EP (Chen et al., 2020). However, the specific nature of this relationship is still under debate, as scholars have expressed differing viewpoints (Li, 2022). While certain studies suggest a purely positive influence on EP, other research indicates that the correlation may take on a curvilinear trajectory. In such cases, the environmental benefits of digitalization may diminish or have unintended consequences under certain conditions (Chen et al., 2020). However, Chen et al. (2020) state that only 14% of sources in their literature review investigated a U shape-relationship. Consequently, further investigation testing this kind of relationship is required. Additionally, the research field is lacking data from diverse countries and regions (Feroz et al., 2021). Currently, the knowledge base primarily encompasses insights from Eastern Asian countries (Chen & Hao, 2022; Li, 2022; Lin, Zeng, Wu, & Luo, 2024; Sarfraz, YE, Dragan, Ivascu, & Artene, 2022; Wen, Lee, & Song, 2021; Yang, Yang, Xiao, & Liu, 2023), with fewer examples from other global regions (Ahmadova et al., 2022; Bendig et al., 2023; Le Ha et al., 2022). Furthermore, there is evidence suggesting that the relationship between DT and EP might differ between various regions based on differences in their digital and environmental development level (Xu, Li, & Guo, 2023; Yang et al., 2022).

Therefore, a more comprehensive understanding needs broader geographical coverage and a diversified dataset as well as a focus on a potential non-linear relationship between DT and EP to close these research gaps and contribute towards gathering more data in Europe.

2. Theoretical Solution for the Effect of Digital Transformation on Environmental Performance

As concluded in chapter 1.2.3, the problem that this thesis aims to address is determining whether the relationship between different digital technologies and EP varies in terms of strength and significance and if a non-linear model is appropriate to represent this relationship. To accomplish this, this chapter will provide an overview of the theoretical evidence supporting both linear and curvilinear models, as well as a categorization of technologies. This will then lead to the development of the research model and hypotheses.

2.1. Theoretical Evidence

Over the past decade, research on the relationship between DT and EP has become more concentrated (Chen et al., 2020). Although the number of published papers on this topic has strongly increased, with Chen et al. (2020) finding 65 papers between 2018 and 2020, evidence for various forms of the relationship has emerged. While scholars acknowledge the existence of a relationship, it remains unclear whether it is linear or non-linear. This chapter will summarize the arguments and findings from both research streams, which will be considered when developing hypotheses.

2.1.1. Evidence for a Linear Relationship

Firstly, when examining the research stream which supports a strictly positive relationship between DT and EP, it has been found that the implementation and use of digital technologies have a direct impact on the environmental sustainability of a production (Wen et al., 2021). One of the main effects is proposed to be a decrease in energy consumption during the design and production phase (Ahmadova et al., 2022; Bendig et al., 2023; Wen et al., 2021). On the one hand, machines become increasingly energy efficient, and on the other hand, data collection and evaluation can analyze the energy consumption behaviour, waste and root causes and thus help create environmental goals and paths (Bhatia et al., 2024).

Furthermore, digital technologies can lead to a decrease in emissions such as carbon dioxide or other greenhouse gases and a reduction in waste (Ahmadova et al., 2022; Yang et al., 2023). In particular, the management of waste and the reduction of discarded materials through new manufacturing technologies like AM have been highlighted. Another aspect when considering energy and waste reduction is predictive maintenance. By using digital technologies, companies can monitor and predict equipment failures, enabling timely maintenance interventions and reducing the environmental impact associated with unplanned downtime and resource wastage (Bhatia et al., 2024).

Additionally, the new level of knowledge acquisition facilitated through DT, in connection to computer-aided design (CAD) and simulations, can lead to the design of eco-friendly products, which are constructed for a longer lifespan and easy repair, refurbishment or recycling at the end-of-life (Yang et al., 2023). Also, the collected data can be used to implement more resource-efficient manufacturing practices with modular production and shorter lead-times (Plekhanov et al., 2023). Finally, an indirect way, digital technologies can affect EP, is through enhanced knowledge exchange within the company or throughout the supply chain (Schöggl et al., 2023).

2.1.2. Evidence for a Non-linear Relationship

On the other side, there are some studies suggesting a curvilinear, or also inverse-U-shaped, relationship. Although this research stream agrees with the positive findings, the scholars assume there to be a tipping point at which digital technologies can no longer serve to an improvement of EP but rather foster a negative impact (Ahmadova et al., 2022). These impacts often show a more indirect and longterm nature than their positive counterparts (Wen et al., 2021).

For instance, the systems that are in place to generate and process a vast amount of data require the support of an equally large amount of servers, which in turn intensifies energy consumption (Chen et al., 2020). Li (2022) adds that approximately 90% of the collected data is not productively used, but still stored. Moreover, most digital technologies use some form of sensors or micro-chips, which tend to cause pollution in their fabrication, specifically through semi-conductor production, as well as at their end of life, since nowadays only a mere fraction of sensors and chips are recycled (Chen et al., 2020; Ruberti, 2023).

Concurrently, rapid technological change leads to technologies having a shorter lifetime than they were intended to have, which increases the electrical waste of valuable resources in all lifecycle stages (Ahmadova et al., 2022). Researchers agree that while there are ways that DT can improve EP, there is a rebound effect, which occurs when more and more technologies are used due to their positive impact so that these are overcome by negative effects (Ahmadova et al., 2022; Chen et al., 2020; Chen & Hao, 2022; Li, 2022).

In addition to the direct and indirect impacts, research suggests, that there are several moderating and influencing factors that play a role in the effect DT has on EP. Firstly, there are industry factors, recognizing elements such as market turbulence (Li, 2022) as significant determinants. Secondly, there are technological factors, encompassing considerations like overall technological capabilities (Sarfraz et al., 2022), have been investigated for their role in influencing the environmental outcomes of digital initiatives. Furthermore, organizational factors within companies, spanning production and product characteristics, digital strategies (Sarfraz et al., 2022), and organizational and leadership culture (Chen & Hao, 2022; Lisi, 2015), are seen to play a role in this context. Understanding these factors is essential for a comprehensive exploration of how technologies may contribute to EP in varied ways. This realization lays the basis for considering different aspects within the field of technology adoption and its implications for environmental sustainability in the manufacturing sector.

2.2. A Resource-based View on Digital Technologies and Environmental Performance

When looking at digital technologies and EP, researchers often make use of the so-called resource-based view of strategy, which traces back to Wernerfelt (1984). The RBV as opposed to the market-based view is a strategic management framework that shifts the focus from market factors as key influencers on a company's long-term success to the uniqueness and quality of a company's resources (Thudium, 2005). It‘s main idea is to build resources for a competitive advantage instead of deriving the required resources from the market position and needs. This enables a new perspective on growth as well since strategic acquisitions can be planned as the intake of new resources (Wernerfelt, 1984).

Barney (1991) identified four attributes that contribute to the attractiveness of a resource in this context: value, rarity, imperfect imitability, and lack of substitutability. The author also classified firm resources into three categories: physical capital resources, human capital resources, and organizational capital resources. Digital technologies generally fall into the category of physical capital resources and they possess the ability to fulfill all four attributes (Barney, Wright, & Ketchen, 2001). They have been found to enable manufacturing companies to create capabilities that improve value creation in various ways, depending on their specific application area, thereby improving profit generation (Schöggl et al., 2023). For example, digital technologies allow for the adoption of new manufacturing methods (Plekhanov et al., 2023). By employing innovative techniques such as AM and modular production design, companies can leverage their physical resources differently, facilitating mass customization. Furthermore, digital technologies simplify data collection and processing in an intelligent way which advances the distribution of resources of all kinds to become more sensible, learning from their production through machine learning and AI applications (Bhatia et al., 2024). These examples demonstrate how digital technologies can enhance the overall efficiency of manufacturing entities, offering a competitive advantage through increased efficiency.

Moreover, digital technologies foster digital innovations, as discussed in Chapter 1.1.1, which can help companies establish technological leadership (Plekhanov et al., 2023). Such differentiation options can also lead to the possibility of generating higher profit margins. Additionally, they strengthen the resilience of production systems, empowering companies to react to unforeseeable market situations or new external threats (Osmundsen et al., 2018). Additionally, well-rounded digital resources might open up the possibility of vertical or horizontal expansion to markets that require similar resources (Barney, 1991). This counteracts the threat of being locked into one market by a set of competencies in case the market changes (Yadav, Han, & Kim, 2017).

Indirectly, DT can also lead to a competitive advantage if it is positively affecting the EP of a company, as explained in chapter 2.1.1. Originally, Wernerfelt (1984) defined a resource as "anything which could be thought of as a strength or weakness of a given firm" and which is tied semi-permanently to it. Hence, EP can also be seen as a resource, albeit an intangible one. From a RBV, EP can have several beneficial effects on the competitive position of a company. In today's more environmentally conscious society, public environmentally sustainable behaviour elevates a company's reputation if done right (Yadav et al., 2017). A positive reputation is seen as a strong intangible resource that can reinforce a sustainable competitive advantage, as it is a central aspect of brand recognition (Wernerfelt, 1984). This does not only apply to customers or potential investors but also affects the job market's reputation. Skilled personnel might be inclined towards working for a company with a good EP (Graafland & Bovenberg, 2020). A good reputation can also lead to beneficial conditions in bargaining situations in both customer and supplier positions.

Financially, Surroca et al. (2010) revealed corporate responsibility performance (CRP) to be directly related to the overall business performance. With EP being part of the CRP, it contributes to a general profit improvement by reducing the spending on governmental induced carbon taxes, emission trading or other regulatory expenses that incentivise companies to reduce their environmental footprint (Graafland & Bovenberg, 2020). Moreover, in the internal process dimension (see **Fig. 3**), EP is often demonstrated through improved products and processes (Albertini, 2016). Efficiency, in particular, is closely associated with effective EP (Yadav et al., 2017). This entails reducing unnecessary waste, energy consumption, and other resources (Schöggl et al., 2023). While initial investments may be necessary, this can ultimately lead to lower production costs in the long term (Yadav et al., 2017).

As a result, digital technologies, DT and EP are all individual resources that help ensure a competitive advantage. By understanding the relationships between them, this effect can be reinforced. As this thesis aims to answer the question of the nature of the relationship, digital technologies and EP have, it can help companies to make strategic decisions on how to develop and expand their technological capabilities to profit from the competitive advantages, EP offers.

2.3. Categorization Framework Selection

This thesis ought to offer recommendations on which technologies to implement to which level for achieving a positive impact on EP. In order to create an abstractable outcome that can potentially be transferred to technologies not examined in this research, this chapter aims to classify the studied technologies. It will present requirements for the categorization, three potential classifications and reasoning for the decision for one of the options.

As mentioned in Chapter 1.1.1, numerous scholars attempt to define the term "digital technologies" by providing a list of recent technologies. In this context, there have been several efforts to create a meaningful categorization for digital technologies (Varriale et al., 2024). However, there is currently no academic consensus on the best approach to categorize them. Therefore, this chapter aims to analyze and compare different categorization methods.

2.3.1. Categorization Requirements

Before introducing the options, it is important to establish the criteria based on which they will be evaluated and selected (Kwasnik, 1999). This step is necessary to ensure a well-informed decision that is based on objective requirements. To achieve this, a comprehensive number of attributes and characteristics must be clearly defined (Tan, Steinbach, & Kumar, 2006). This will endow a meaningful and accurate characterization of the options, ultimately leading to the creation of consistent and empirically valuable categories. The four qualities that will be taken into consideration for the choice of the categorization framework will be category broadness, scalability, consistency and academic recognition.

Categorization is the process of organizing different objects into groups based on their shared characteristics (Apostel & Rose, 2022; Spivak, 2014). A descriptive model allows for a more structured and organized understanding of the objects being classified and their characteristics (Tan et al., 2006). It is necessary to ensure that each category has the ability to include multiple objects. This is because a too narrow definition of a category may restrict its usefulness and limit the objects that can be included within it. By having broader categories, we can capture a wider range of objects and increase the effectiveness of the categorization system. This is also a way to ensure scalability.

Scalability, or generalization ability, refers to the ability of a system to expand and adjust as needed (Tan et al., 2006). In the context of a categorization framework, it means that the framework should have the capability to accommodate additional objects or data without requiring extensive modifications, such as the inclusion of new categories. This flexibility allows the framework to easily adapt to evolving needs and accommodate a growing range of objects without hindrance and include new objects based on the attributes of each category. In other words, scalability ensures that the categorization framework can effectively handle increasing amounts of information without causing disruptions or the need for substantial changes to its structure.

In addition to that, it is important to maintain consistency not only within each category but also across different applications (Brucks, 1986). This means that the classification and organization of items should be uniform and coherent within the entire system. By ensuring consistent and distinct categories, users will have a seamless experience and be able to easily navigate and comprehend them.

Finally, for the purpose of this thesis, the chosen categorization framework should ideally have a considerable level of consensus within the academic community. As mentioned earlier, there is currently no academic consensus regarding a single form of categorization. However, some papers and authors have expressed support for a particular idea or approach.

2.3.2. Option 1: Technology-based categorization

The first option introduces a comprehensive framework that was developed to establish a connection between digital technologies and supply chain risks. Ivanov et al. (2019) formulated this framework by reviewing existing research and identifying four distinct categories. Although this framework was originally designed for a study focused on supply chain management, it is still relevant and applicable to the specific case being examined in this thesis, given that the study is exclusively centred around manufacturing applications. The four categories for this option are predictive analytics, Industry 4.0, 3D printing and advanced tracking and tracing (T&T) technologies.

Ivanov et al. (2019) discuss the concept of predictive analytics and its application by using big data analytics as an exemplary enabler. Big data refers to the large volume, velocity, and variety of data that is generated from various sources such as social media, sensors, and online platforms (Buhl, Röglinger, Moser, & Heidemann, 2013). Predictive analytics involves the use of statistical techniques and algorithms to analyze these large sets of data in order to make predictions and forecast future outcomes. Due to their close relationship, they are often referred to as a combined entity (Gunasekaran et al., 2017).

The concept of Industry 4.0 lacks an overall definition (Ivanov et al., 2019). However, it is widely used as an umbrella term for a large variety of technologies, such as IoT, smart products, robotics or augmented and VR, as used by Ivanov et al. (2019). The technologies are characterized by enabling smart and interconnected manufacturing processes (Queiroz, Pereira, Telles, & Machado, 2021).

The third category, 3D printing, specifically encompasses additive manufacturing as a technology (Ivanov et al., 2019). However, it is important to note that AM comprises several technologies that fall under this umbrella term (Mehrpouya et al., 2019). These technologies include material jetting, selective laser melting, and screen printing, among others. AM processes involve the creation of three-dimensional objects by adding layers of material on top of each other (ASTM, F2792-12a).

Finally, the last category, advanced T&T technologies, includes sensors and RFID technology (Ivanov et al., 2019). This category is the only one out of the four, which is specific to supply chain management, as tracking and tracing throughout the supply chain build the foundation for decision-making in this context (Bearzotti, Salomone, & Chiotti, 2008). By accurately monitoring the movement and location of goods, this technology establishes a strong foundation for effective and informed decision-making within the supply chain context.

This method of categorizing technologies is widely used in various disciplines. Many authors use overarching terms like Big Data, Industry 4.0, CPS, IoT, or cloud computing, and then include additional categories for technologies that do not fall under these broad labels (Varriale et al., 2024). Examples of this can be found in research by Dantas et al. (2021)or Zheng et al. (2021). The first one, on the one hand, used Industry 4.0 as a general term to describe all of the digital technologies, which were then categorized into big data, CPS, AM, IoT, Internet of Services, cloud computing, systems integration, AR, autonomous robots, and cybersecurity (Dantas et al., 2021). Zheng et al. (2021) on the other hand used the categories CPS, IoT, cloud technology, blockchain, big data and analytics, AI, simulation and modelling, automation and industrial robotics, visualization technology, and AM. Hence, it can be seen that the way of performing the classification as proposed by Ivanov et al. (2019) is generally accepted and serves as a common framework for organizing and understanding various technological advancements.

Nevertheless, it has to be noted that some categories within the classification system are relatively broad and lacking in precise definitions, such as Industry 4.0. On the other hand, the category AM is more narrowly defined. This lack of specificity could potentially hinder the consistency and scalability of the classification system. It may pose a challenge to incorporate new technologies that were not previously included in the taxonomy proposed by Ivanov et al. (2019) due to this issue.

2.3.3. Option 2: 5C Architecture of CPS

The second option is the 5-level architecture of cyber-physical-systems (CPS), a model created by Lee et al. (2015). The paper provides a systematic guideline for the implementation of CPS particularly in the manufacturing industry. The U.S. National Science Foundation (2021) defines CPS as "systems that are built from, and depend upon, the seamless integration of computation and physical components“. They consequently permit close monitoring and synchronization of information between the physical factory and the cyber computational space, facilitating connected machines to operate more efficiently, collaboratively, and durably through advanced information analytics.

While the framework aims to provide a guideline for the deployment of the technologies, it concurrently offers a form of categorizing them (Lee et al., 2015). Although some sources differentiate between CPS and digital technologies, others see them as part of CPS (Piardi, Leitão, Queiroz, & Pontes, 2024; Wu et al., 2019). Therefore, the categorization can be applied to all kinds of digital technologies, as proposed by Chen et al. (2020). The five levels, as shown in Fig. 4, are the smart connection level, data-to-information conversion level, cyber level, cognition level and configuration level. As shown, the levels build upon each other and from progress level to level in automation and autonomy of the CPSis attained.

The smart connection level enables seamless communication and data acquisition from machines and their components (Lee et al., 2015). Its main objective is the acquisition of accurate and reliable data, ensuring that it is seamlessly transferred to the central server. To achieve this, for instance, advanced smart sensors can be employed to gather precise data from the machines.

The data-to-information conversion level focuses on transforming raw data acquired from the smart connection level into meaningful and actionable information for decision-making processes (Lee et al., 2015). The primary objective is to convert vast and often complex datasets into a comprehensible format that facilitates analysis and supports informed decision-making. The data-to-information conversion level acts as a bridge between the raw data collected from the smart connection level and the more abstract and meaningful information needed for higher-level decision-making at the cyber and cognition levels.

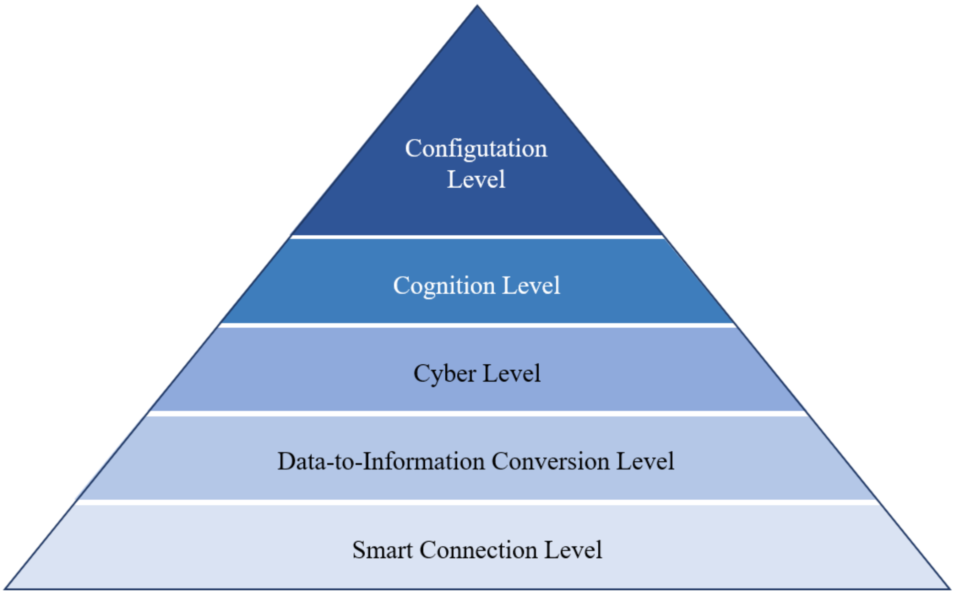

Fig. 4. 5C levels (Lee et al., 2015)

The cyber level is often referred to as a central information hub (Lee et al., 2015). All gathered data is centralized and supports self-comparison amongst the machines of a fleet in terms of health and performance. This leads to the ability to compare and rank the performance of single machines in a fleet in order to operate the fleets in a long-lasting way (Jiang, 2018).

The cognition level is primarily responsible for higher-order decision-making, reasoning, and intelligent behaviour based on the information processed and generated in the lower levels of the architecture (Lee et al., 2015). The cognition level integrates advanced computational methods, simulation, and human-machine interaction to derive insights and make informed decisions.

Finally, at the configuration level, the systems can give corrective or preventative feedback from the cyber world to the physical world (Lee et al., 2015). This level oversees the management and adaptation of the system to meet specific objectives and requirements (Jiang, 2018). Accordingly, it is instrumental in ensuring the flexibility, scalability, and optimal functioning of the entire CPS and is responsible for resilience control (Wu et al., 2019).

Each of the categories is defined by Lee et al. (2015) with a specific set of attributes. According to the author, these categories are interconnected, and as the level of complexity of technologies, self-management capabilities, and independence of human input increases, so does the level of the category. This allows for smooth scalability if needed. It also ensures consistency within the framework. However, Chen et al. (2020) point out that categorizing technologies into these categories can be challenging because they often fit into multiple categories. This complicates the application of this framework. Nevertheless, since its creation, several authors have reviewed and successfully applied this framework (Ahmadi, Cherifi, Cheutet, & Ouzrout, 2017; Chen et al., 2020; Wu et al., 2019), thereby confirming its academic relevance.

2.3.4. Comparison and Selection

When comparing the two options for categorizing digital technologies, namely the framework proposed by Ivanov et al. (2019) and the 5C architecture of CPS introduced by Lee et al. (2015), several factors come into play. As discussed in Chapter 2.3.1, the comparison will focus on scalability, the broadness of categories, consistency, and academic acceptance. It is clear that different authors have different understandings of technologies and technology categories. For instance, some consider CPS as a distinct group of technologies among others (Dantas et al., 2021; Zheng et al., 2021), while others include all digital technologies under CPS since they all have a digital and physical component (Lee et al., 2015).

Firstly, the 5C architecture of CPS offers an advantage in terms of scalability due to its hierarchical structure and interconnected levels. As the complexity of technologies increases, the architecture allows for smooth scalability by accommodating higher levels of complexity, self-management capabilities, and reduced human dependency. Each level builds upon the previous one, enabling the system to adapt and grow as needed. On the contrary, the framework proposed by Ivanov et al. (2019) might face challenges in scalability due to both relatively broad and narrow categories. Incorporating new technologies into the framework could be inconvenient and may require modifications to the existing categories.

In terms of the broadness of categories, the framework by Ivanov et al. (2019) offers a more specific approach, with four distinct categories: predictive analytics, Industry 4.0, 3D printing, and advanced T&T technologies. While this provides a broad overview of digital technologies, some categories lack generalizability, which could hinder consistency and scalability. On the other hand, the 5C architecture of CPS provides a more granular categorization, with five distinct levels that encompass different aspects of CPS, from data acquisition to decision-making and system configuration. This allows for a more detailed understanding of how digital technologies are sorted within the CPS framework, enhancing both consistency and scalability.

Considering consistency, both options demonstrate a certain level within their respective frameworks. The 5C architecture of CPS maintains consistency by defining clear attributes for each category and ensuring that the levels are interconnected and build upon each other. This consistency contributes to a cohesive framework that facilitates understanding and application. The framework proposed by Ivanov et al. (2019) is very specific in determining which digital technologies fit into which category, indicating a certain level of consistency and ease in its application. However, some categories within this framework may lack generalized definitions, which could lead to lower consistency.

Finally, both papers have been well-received in the academic community, with numerous studies citing and applying these frameworks in various contexts. The 5C architecture of CPS has been reviewed and successfully applied by several authors, confirming its academic relevance and practical utility (Chen et al., 2020; Venancio Teixeira, da Silva Hounsell, & Wildgrube Bertol, 2023; Wu et al., 2019). Meanwhile, the framework proposed by Ivanov et al. (2019) has strong similarities with the way that numerous other authors have categorized digital technologies in their field of application (Dantas et al., 2021; Varriale et al., 2024; Zheng et al., 2021).

After a comprehensive comparison, it is evident that both options have their own strengths and weaknesses. However, for the purpose of this thesis, the 5C architecture of CPS appears to be the more suitable choice. Its hierarchical structure and clear attributes provide advantages in terms of scalability and consistency. In addition to that, the detailed and descriptive categorization offered by the 5C architecture enables an easy allocation of technologies for each category. Therefore, the 5C architecture of CPS will be used as the primary framework for categorizing digital technologies in this study.

2.4. Categorization Application

As explained, the 5C architecture of CPS will be used to categorize technologies to receive clear and abstractable outcomes. In the following, the model will be reviewed and applied for a selection of digital technologies, which were mentioned in Chapter 1.1.3: Enterprise resource planning system (ERP) supported manufacturing, industrial automation, CAD manufacturing, digitalization of production, real-time control of inventory, real-time control of manufacturing, machine learning and AI, simulation, AR solutions, and fully-automated/smart manufacturing

2.4.1. 5C Architecture of CPS Review

This chapter will provide additional insights into the 5C architecture framework and adjustments or alterations proposed by scholars. This will create a base for a detailed explanation of the allocation of technologies to each category.

According to Jiang et al. (2018), the five levels as proposed by Lee et al. (2015) can also be interpreted as a cycle in terms of data flow instead of a strictly hierarchical order. Data is collected via sensors and converted into useful information first on a machine level, then on a fleet level. After a critical mass of data has been collected, it can be used for simulation or machine learning purposes. Concurrently, during the operation of smart manufacturing, the data collection continues. While IT used to have a more supportive function in the manufacturing process, Industry 4.0 transformed it into a central key element in the value creation (Javaid, Haleem, Singh, & Suman, 2023). Despite that, safety must be prioritized when talking about collaboration between human operators and CPS (Venancio Teixeira et al., 2023). All levels of the 5C architecture can be connected to several norms and standards which allow standardization within industries and can support the implementation of digital technologies (Ahmadi et al., 2017).

A systematic review by Venancio Teixeira et al. (2023) stated that more often than not, not all levels of CPS are reached and companies tend to focus on two to three of the categories. Reasons might be that companies face barriers to implementation as mentioned in Chapter 1.1.1, such as cyber security issues or a lack of digital capacities to handle this large amount of data (Bruton, Walsh, Cusack, O'Donovan, & O'Sullivan, 2016). While Wu et al. (2019) claim that the configuration level is still widely underresearched, most of the papers analyzed by Venancio Teixeira et al. (2023) emphasize the importance of examining the configuration and cognition levels, as well as the technologies associated with them. This suggests that research, specifically on the more complex parts of the model, has increased over the past few years. While improvements were mostly measured concerning operation time, the authors argue that a more comprehensive comparison to traditional industry could be seen as beneficial (Venancio Teixeira et al., 2023).

Jiang (2018) proposes an integration of three additional components to the architecture, making it an 8C framework. The author argues that the model focuses mainly on vertical integration and suggests adding the horizontal facets of coalition, content and customer. Firstly, the coalition sphere refers to value chain and product chain integration. Secondly, the customer facet highlights the role of the customer in the production process. Third, the content facet is centered around extracting, storing and retrieving all product-related content. Although these are important factors to take into account in the implementation of digital technologies and achieving a smart factory, they do not extend or change the levels of technologies but rather surround them (Jiang, 2018). Thus, in this thesis, the additional 3C facetts can be neglected, since the focus lies on the digital technologies and their categorization.

When it comes to the categorization according to the 5C architecture, some technologies can be associated with more than one of the five levels. Nevertheless, for reasons of clarity, they will be assigned to the level they are most compliant with (Chen et al., 2020). A detailed evaluation of the allocation, summarized in Table 1, follows in Chapters 2.4 to 2.4.6.

Table 1. 5C Categorization of Technology

5C-Level	**Technologies**
Configuration	Fully-automated/smart manufacturing Machine-learning / AI
Cognition	Simulation Augmented and virtual reality solutions
Cyber	Real-time control of inventory Real-time control of manufacturing
Data-to-Information-Conversion	Industrial Automation CAD Manufacturing
Smart Connection	ERP Supported manufacturing Digitalization of production

2.4.2. Smart Connection Level

As the base layer of the 5C architecture, the smart connection level ensures the connection between all systems and the machines (Lee et al., 2015). Efficient management of data acquisition procedures and the selection of appropriate sensors are key aspects of the smart connection level (Chen et al., 2020). Appropriate sensors can transmit valuable information on for example temperature, vibration, rotating speed, feed speed, and oil concentration of machines (Jiang, 2018). Nevertheless, since all the components collect an enormous amount of data, suitable acquisition approaches and data cleansing models are needed and subject to a broad research stream (Wu et al., 2019). In addition to that, standard protocols, interfaces, and information models are critical elements in handling data from diverse sources.

On the smart connection level, ERP systems, manufacturing execution systems (MES) and digitalization of documentation and reporting are chosen as the representative technologies. ERP and MES systems in this context are used for identifying the order delivery process of each production batch and integrating data from the sales, manufacturing planning, warehouse and accounting (Ghobakhloo et al., 2023). The digitalization of documentation and reporting involves the transition from traditional paper-based methods to electronic formats. This empowers the creation, storage, and retrieval of documents and reports in digital form, eliminating the need for physical copies and reducing the risk of loss or damage (Lee, Azamfar, Singh, & Siahpour, 2020). By digitizing instructions, organizations can enhance accuracy, speed, and accessibility, allowing employees to quickly access relevant information and perform tasks more effectively. Both technologies facilitate tether-free communication and enable data collection and management (Chen et al., 2020). While the digitalization of documentation and reporting could theoretically fall into various categories depending on its purpose, the given application in this context (see Chapter 3.1) is the use of electronic instructions, performance reporting, and documentation. Consequently, in this case, digitalization aligns mostly with the objectives of the smart connection level.

2.4.3. Data-to-Information Conversion Level

On the data-to.information conversion level the collected data is transformed into useful information that humans can work with (Lee et al., 2020). Algorithms and data processing techniques are employed to filter, aggregate, and contextualize the raw data. This transformation is necessary to extract valuable insights, identify patterns, and generate information that is relevant to the specific requirements but also health and remaining useful life of the physical components (Jiang, 2018). This allows transformation to reduce equipment failures and downtime, which enhances the efficiency and effectiveness of the overall system (Javaid et al., 2023). To manage the amount of data proficiently, tools and methodologies such as data processing, big data analysis and data mining approaches must be incorporated (Wu et al., 2019). The data-to-information conversion level can also involve transforming input data into actionable output data, carried out by machines or robotic applications (Chen et al., 2020).

For this level, the decision was made to incorporate the technologies of industrial automation and CAD manufacturing. Industrial automation, as a concept, revolves around the integration of robots within the manufacturing environment in order to optimize and streamline processes (Ciarli et al., 2021). These robots possess the ability to transform input data into physical, automated tasks, thus effectively carrying out a variety of manufacturing operations. This also involves implementing AM for the prototyping of new products, parts or tools. Additionally, CAD and computer numerical control (CNC) manufacturing equipment or production lines are also essential components of this system(Nee, 2014). These technologies use the existing CAD data and transform it into automated routines, resulting in efficient and precise manufacturing processes.

2.4.4. Cyber Level

As the cyber level serves as an information hub with centralized and interconnected data, it already permits a higher level of self-management (Lee et al., 2015). This means that it has the capability to compare the status of various components such as machines and fleets. This level establishes a communication infrastructure necessary for seamless interaction between the components of the whole manufacturing system (Wu et al., 2019). This includes communication protocols, networking technologies, and data transmission mechanisms. The reliability and efficiency of communication systems are important to ensure continuous information exchange. One of the main benefits of having strong systems on the cyber level is the opportunity to have real-time data and control (Lee et al., 2020). A key technology is the digital twin, which allows computational resources to process and analyze information quickly, allowing for timely responses to changing conditions in the physical environment. Accordingly, technologies for real-time control of inventory, raw material and finished goods, as well as manufacturing will be evaluated in the following, to allow a holistic view and management of all data in the network.

Cybersecurity appears to be one of the main concerns at the cyber level (Yeboah-Ofori, 2019). The implementation of robust security measures to protect the system from unauthorized access, data breaches, and cyber-attacks is a central activity when concentrating on this level (Wu et al., 2019).

Therefore, encryption, authentication mechanisms, and intrusion detection systems are employed for the protection of sensitive information.

2.4.5. Cognition Level

On the cognition level, complex systems are already able to support human decision-making processes (Lee et al., 2015). This is achieved by leveraging the data collected and processed in the lower stages of the CPS architecture. One common field of application is the maintenance and possible predictive maintenance of machines (Jiang, 2018). A well-implemented CPS on the cognition level offers the opportunity to take over diagnostics and prioritization of tasks related to the physical health of production facilities. This collaboratively takes place between humans and the system. However, what is needed for a successful implementation is the purposeful adaption of the system to the existing expertise within the company to enable a functioning collaboration, since on this level the systems are made for decision support and not fully independent operation (Wu et al., 2019). This also necessitates appropriate presentation tools to illustrate the data in an aesthetically pleasant and more importantly clear way, enabling easy interpretation by users.

Technologies that fall into the cognition category include simulation and augmented and virtual reality solutions. Simulations are versatile and can be used to visualize technological problems and their sources of error and for the solution process, making it easier to identify and understand potential issues (Nee, 2014). They are also useful from a process planning perspective, to prevent bottleneck situations and optimize the manufacturing work flow. Furthermore, manufacturing companies can use simulation technologies to predict plant performance and test the effectiveness of the production schedule

AR and VR can serve as a supplementary tool in production environments, helping workers by providing practical information and visualizations (Nee, 2014). For instance, it can display instructions or reference material that can enhance productivity and accuracy. AR can also be used during maintenance or logistics operations, enabling workers to view and interact with digital overlays on physical objects, which can simplify complex tasks and reduce the risk of failure. Furthermore, it can be used as a tool for employee training, allowing for an interactive learning experience (Le Ha et al., 2022).

2.4.6. Configuration Level

The configuration level is considered the most independent component out of the whole CPS architecture, making it the most complex (Lee et al., 2015). The systems in place at this level allow feedback between the physical and digital worlds. This enables them to fulfil objectives and tasks almost fully self-managed (Wu et al., 2019). Consequently, the configuration level poses significant challenges in terms of both implementation and maintenance, demanding the expertise of highly skilled and well-trained personnel.

Next to performance optimization, this CPS level sets up companies to improve resource managment and create dynamic capabilities (Chen et al., 2020). This is one of the main areas where the EP of the company can be altered on a daily basis, depending on the decisions the system makes. It has a direct influence on the "enhanced products and processes“ dimension of organizational EP and can lead to a decrease in energy, raw material and water consumption (Albertini, 2016).

Technologies such as AI, machine learning or smart manufacturing systems fall into this category due to their ability to self-adapt, -configure and -optimize at this stage (Wu et al., 2019). These technologies demonstrate their ability to continuously learn and enhance performance through the utilization of algorithms and data analysis (Chen et al., 2020). AI and machine learning can be used in a production scenario for demand forecasting, quality control or predictive maintenance through real-time anomaly detection (Feroz et al., 2021; Le Ha et al., 2022). Meanwhile, smart manufacturing systems are characterized by manufacturing processes that are integrated into continuous automated production lines. These systems are built upon real-time and historical data, as well as patterns collected throughout the production processes.

Javaid et al. (2023) emphasize that, despite the processing power and strength of the underlying algorithms, humans still act as the "highest level controlling instance". disparity between artificial machines and humans in terms of flexibility and intelligence, despite the impressive processing power and advanced algorithms possessed by machines. Similar to the cognition level, this requires interfaces to be designed with a profound understanding of human cognition, aiming to deliver seamless and intuitive user experiences.

2.5. Research model

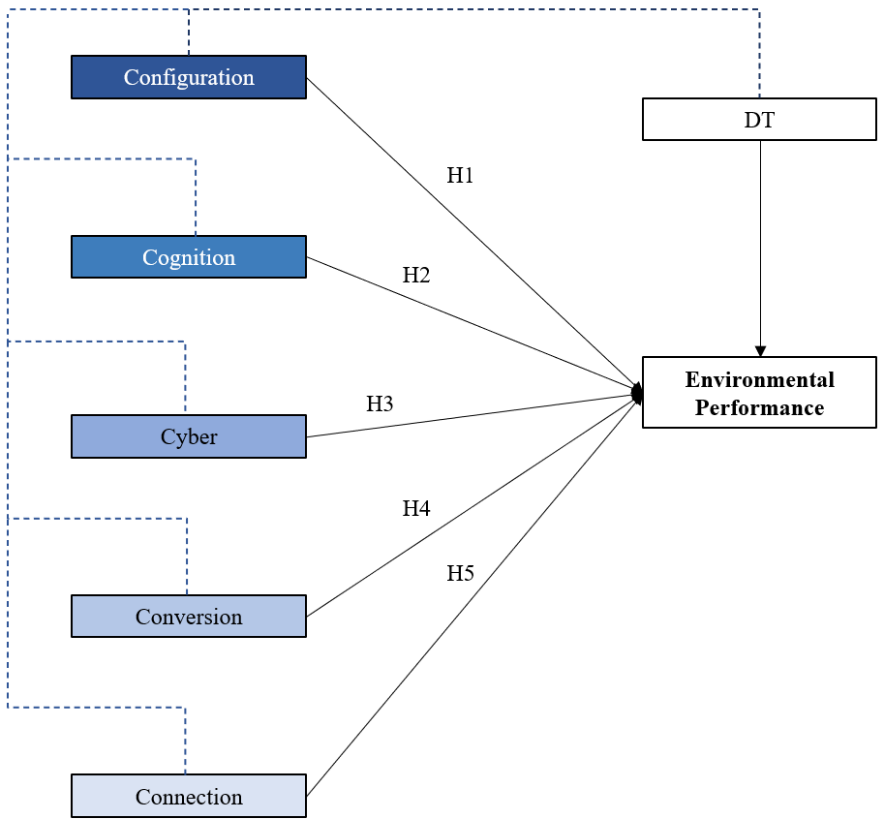

Fig. 5. Research model (Source: own depiction)

This thesis aims to define the relationship between a number of digital technologies and EP of Lithuanian manufacturing companies, as discussed in Chapter 1. In Chapter 2.1, the literature was reviewed to investigate the possibility of linear or curvilinear relationships. Given that these two forms of relationships theoretically exclude each other, and there appears to be a lack of research on the non-linear side, this thesis will focus on estimating curvilinear effects. To provide a more abstract understanding, the technologies were classified into five levels: smart connection, data-to-information conversion, cyber, cognition, and configuration. This classification was based on their implementation in manufacturing, as well as their level of complexity and independence (see Chapter 2.4). Throughout this study, the direct effects of these technology levels on EP will be measured, and the nature and strength of this relationship will be evaluated. These findings will then be used to provide managerial recommendations from a RBV.

2.6. Hypotheses Development

As described in Chapters 1.2.3 and 2.1, there is conflicting evidence concerning the impact of DT and digital technologies on the EP of manufacturing companies. While there are direct factors in production that help reduce energy consumption, waste, and other emissions, some researchers have also found a rebound effect that occurs once a certain level of DT is reached (Ahmadova et al., 2022; Chen et al., 2020; Hao, Wu, Wu, & Ren, 2020; Li, 2022). This thesis aims to further investigate this relationship.

As shown in Fig. 5, for this thesis the five technology categories are assumed to add up to create the overall DT level of a company. In turn, if DT has a non-linear relationship with EP, the same would be expected from the digital technologies that are combined in the categories. However, it is important to consider that the relationship might vary when considering different types of technologies due to their distinct environmental benefits and pollution patterns.

When it comes to smart connection technologies and data-to-information conversion technologies, the initial use is expected to have a strong positive influence on EP. For instance, these technologies can help predict and control water quality, air pollution, and contamination by hazardous waste, as they are capable of acquiring and managing a significant amount of information and data (Chen et al., 2020). Additionally, intelligent robots and AM can stabilize manufacturing quality, reducing rejects and waste, while enhancing production efficiency. However, it is important to acknowledge that the physical components of these technologies result in high energy consumption and diverse emissions throughout their life cycle, particularly during production and use (Ahmadova et al., 2022). Furthermore, at the end of their life cycle, the recycling rates of many of these components, especially sensors and microchips, are currently very low (Chen et al., 2020).

Considering technologies at the cyber level, the real-time control of inventory and manufacturing tracking can be beneficial for the implementation of EP initiatives, as companies can respond to observed outcomes and enable green manufacturing practices (Schöggl et al., 2023). However, it is important to note that the storage and processing of a large amount of data, of which only a small fraction is ultimately used, consumes a non-negligible amount of energy (Li, 2022). Hence, it can be expected that while there will be an initial positive effect, there is still an overall non-linear relationship.

At the configuration level, technologies such as fully automated/smart manufacturing, AI, and machine learning can be utilized to optimize resource allocation, including material, energy, and water use (Chen et al., 2020). Similarly, at the cognition level, simulation and AR solutions can reduce material and energy consumption by minimizing design errors and incorporating design for disassembly principles (Schöggl et al., 2023). These technologies also offer virtual testing opportunities and effective scenario generation, which ultimately reduces the need for physical prototypes and therefore decreases material and energy consumption. It can be assumed that these positive effects outweigh the energy consumption and pollution associated with the production and utilization of these technologies to a certain degree, so that the tipping point might be at a later level of implementation or the inverse-U shape might be more shallow.

Thus, the following hypotheses result:

H1: *There is an inverted U-shape relationship between configuration technologies and environmental performance.*

H2: *There is an inverted U-shape relationship between cognition technologies and environmental performance.*

H3: *There is an inverted U-shape relationship between cyber technologies and environmental performance.*

H4: *There is an inverted U-shape relationship between data-to-information conversion technologies and environmental performance.*

H5: *There is an inverted U-shape relationship between smart connection technologies and environmental performance.*

3. Methodological Solutions

The following chapter will present the research methodology, based on the research model described in Chapter 0. For the preparation of the analysis, the overall approach and data collection process will be explained. Afterwards, the measures and data analysis procedure will be discussed.

3.1. Overall Approach and Data Acquisition

To investigate the relationship between different types of digital technologies and EP in manufacturing companies, a bivariate regression analysis was conducted using the SPSS statistical software. The research approach adopted in this study is positivist, aiming to gather empirical evidence through a deductive reasoning process.

Secondary data were utilized, sourced from a survey conducted in 2022 by Ghobakhloo et al. (2023). The data is not publicly available and was collected through a survey conducted with 506 manufacturing companies in Lithuania. It employes a cross-sectional design. As this survey was created to find out about different dimensions of DT in Lithuanian manufacturing companies it does not reflect the research objectives specific to this thesis. Therefore, the technologies that can be examined were limited to the ones that were chosen for the survey

In terms of data collection, the survey was administered via telephone to ensure a wide coverage of participants. Stratified sampling was utilized, involving a total of 3,297 companies being contacted. The response rate obtained was 15.3%. The survey respondents consisted mainly of CEOs, accounting for 62.8% of the sample. Additionally, production managers, IT technical managers, technology/development managers, and other relevant individuals were also included in the sample.

3.2. Measures

The survey aimed to assess the technological and digital readiness of Lithuanian companies (Ghobakhloo et al., 2023). It consisted of questions related to change management, resources, products & services, operating systems, supply chain, investments in digitalization, and performance compared to competitors. The survey items were derived from existing literature on digital innovation (Lokuge et al., 2019) and the principles of industry 4.0 design (Annarelli, Battistella, Nonino, Parida, & Pessot, 2021). The levels of readiness were determined through an analysis of the implementation of specific technologies, such as CAD design and manufacturing employing CAD software, CNC machines, and AM. The questions were formulated as positive statements in the format of “We use..“, “We apply..“ and similar expressions (. Respondents were required to rate the items on a 5-point Likert scale, where 1 indicated strong disagreement, 5 indicated strong agreement, and there was an additional option for "Not applicable for our company." Unanswered questions will be treated as missing values and “not applicable“ will be represented as a value of zero.

Table 2. Construct composition

Construct (5C)	Technologies/Research Items	Questions
Configuration	AI/Machine learning	24.1
		24.2
		24.3
	Fully-automated / smart manufacturing	27.1
		27.2
		27.3
Cognition	Simulation	25.1
		25.2
		25.3
	Augmented reality solutions	26.1
		26.2
		26.3
Cyber	Real-time control of inventory	22.1
		22.2
		22.3
	Real-time control of manufacturing	23.1
		23.2
		23.3
Conversion	Industrial automation	19.1
		19.2
		19.3
	CAD manufacturing	20.1
		20.2
		20.3
Connection	ERP supported manufacturing	18.1
		18.2
		18.3
	Digitalization of production	21.1
		21.2
		21.3
DT	Overall Level of Digital Transformation	18.1-21.3
EP	Harmful Emission Prevention	32.4
	Industrial waste prevention	32.5
	Integrating (using) green resources	32.6

For this study, a two-stage hierarchical latent variable was employed, as presented in Table 2 (Becker, Klein, & Wetzels, 2012). The independent variables included general DT level (survey items 18-27), configuration (survey items 24 & 27), cognition (survey items 25 & 26), cyber (survey items 22 & 23), data-to-information conversion (survey items 19 & 20), and connection (survey items 18 & 21). The dependent variable was EP level (survey item 32b). Each item consisted of three questions, and the latent variables were calculated by summing up the values of the questions and dividing them by the number of values.

3.3. Data Analysis Procedure

A combination of descriptive and inferential statistics was used to address the research question. Initially, the data was analyzed using descriptive statistics to provide a comprehensive overview of the data and the respondents in terms of company size and industry.

To ensure internal consistency within the questions for each independent variable, a reliability analysis was conducted. This involved performing an exploratory factor analysis to confirm the structure of the selected latent variables created from the chosen items as shown in Chapter 2.4, as well as examining Cronbach's alpha to ensure internal reliability (Hair, Jr., Black, Babin, & Anderson, 2013). The outer loadings of indicators should ideally be >0.7. If they are lower but still over the acceptable level of 0.4, it will be investigated if the removal of said item would improve the internal reliability. The overall internal reliability measured by Cronbach’s alpha has to be a minimum of 0.7 for each construct. If the indicator loadings and reliability confirmed the appropriateness of the constructs, they were utilized as predictors for the subsequent analysis. To investigate the existence of a relationship between the predictors and the independent variable, a Spearman correlation analysis was conducted.

To address the hypotheses, inferential statistics, specifically bivariate regression analysis, were employed to examine the relationships between the variables. This included assessing the square and cubic polynomials of the independent variables to identify if non-linear relationships are given (Hair, Jr. et al., 2013). Afterwards, the robustness and stability of the relationships were tested to rule out spurious correlations. For this purpose, the control variables company size, number of IT staff and age of the company were introduced into a multivariate regression analysis. Using forward addition, a hierarchical linear regression with the predictors and their polynomials was performed. The construct had to be tested for multicollinearity issues, as these interrelations of independent variables could impose problems in the regression analysis. This was tested by assessing the tolerance and variance inflation factor (VIF), expecting a high tolerance level (close to 1) and VIF to be smaller than 3 (Hair, Jr. et al., 2013). The results will provide insights into the origin of the relationship between the five digital technology categories and EP.

4. Research Findings and Discussion

This chapter reports and reviews the empirical findings that resulted from conducting the analysis as described in Chapter 3.3. After creating a thorough understanding of the data and the relationships tested in this thesis, the results will be discussed and interpreted from a RBV. This finally leads to recommendations for organisations and managers and avenues for further academic research.

4.1. Descriptive Statistics

A thorough understanding of the sample composition provides valuable insights into the representativeness of the collected data. Moreover, it establishes a foundational framework for following analyses that explore the relationship between digital technologies and EP among manufacturing companies in Lithuania. The first section will present various characteristics of the sample and conduct a thorough examination of them. Afterwards, an overview of the data will be provided, including a detailed analysis of the dependent variable, "EP," and its predictors.

4.1.1. Sample and Population

The sample included 506 Lithuanian manufacturing companies. They represent a range of different sectors, sizes and business models from all over Lithuania. The survey respondents come from a range of companies in manufacturing subsectors. They were classified using the statistical classification of economic activities in the European Community (NACE) (European Commission, 2008). Since the focus was NACE cluster C, manufacturing, the NACE divisions 10 to 33 were taken into account. To receive a clearer overview they were grouped into six sectors. The sectors were diversely distributed, with 34.4% in metal and engineering (divisions C22, C24-C30, C33), 29.2% in wood and furniture (divisions C16-C18, C31), 11.2% in food and beverages (divisions C10-C11), 10.6% in textiles and apparel (C12-C15) 7.4% in chemical pharmacy (divisions C19-21, C23), and 7.2% in other sectors (division C32). This aligns closely with the current distribution of the population as shown in the comparison of sample and population in Table 3.

Table 3. Distribution industry sectors

	Sample		Population
Sector / Class	n	percent	percent
Metals and engineering	181	35.8	36.3
Wood and furniture	149	29.4	30.3
Food and beverages	54	10.7	10.9
Textiles and apparel	51	10.1	10.2
Chemical and Pharmacy	35	6.9	7.5
Other	36	7.1	4.9

Regarding company size, most of the participating companies had fewer than 250 employees. As can be seen in Table 4, around two-thirds of manufacturing companies in Lithuania are small businesses with less than ten employees. This could not be portrayed in the data, as this group only makes up

16.8% of the respondents, whereas companies with a workforce of 10 to less than 50 employees account for the greatest share of respondents.

Table 4. Distribution company size

	Sample		Population
Number of employees (2021)	n	percent	percent
250+	181	4.5	1.6
50-249	149	19.8	7.9
10-49	54	58.9	24.3
1-9	51	16.8	66.2

The companies were also asked about their year of foundation. The age distribution is spread over a range of 33 years, relatively evenly. All age groups are represented in this range with 0.6 to 4.7% (see **Fig. 6**).

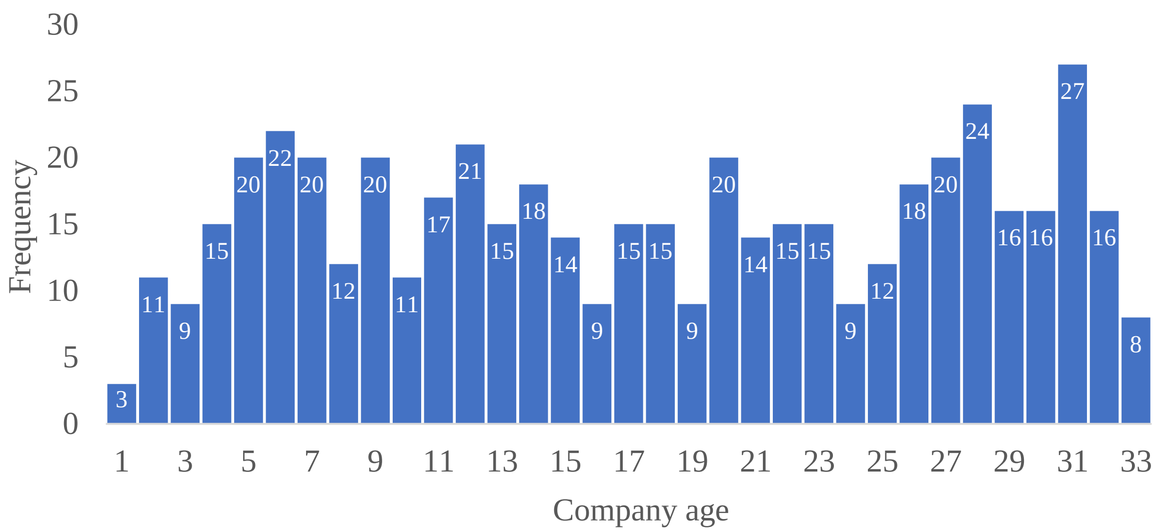

Fig. 6. Company age distribution (source: own depiction)

4.1.2. Digital Technology Levels and Environmental Performance Overview

The data findings suggest that the levels of digital technology implementation are relatively low across all sectors and technologies. In the survey, an answer of 1 or 2 indicates disagreement with the given statement. Thus, these results imply that digital technologies are not or hardly implemented in the responding companies. However, it is noteworthy that companies in the "metals and engineering" sector appear to have the highest overall level.

	Connection	Conversion	Cyber	Cognition	Configuration	DT total
Food and beverages (n=54)	2.4	1.37	2.5	1.3	1.75	1.86
Textiles and apparel (n=51)	2.2	1.36	2.2	1.12	1.4	1.65
Wood and furniture (n=149)	2.19	1.94	1.9	1.46	1.59	1.89
Chemicals and pharma (n=35)	2.05	1.64	1.63	1.21	1.41	1.66
Metals and engineering (n=181)	2.72	2.3	2.3	1.53	1.69	2.15
Others (n=36)	2.36	1.7	1.67	1.23	1.43	1.78

Fig. 7. Heatmap: Level of technology use by sector (source: own depiction)

When examining the different technology categories, it is observed that the highest overall levels are found in the "connection" and "cyber" categories. This suggests that these areas may be more advanced in terms of technology implementation compared to higher levels, such as cognition or configuration.

	Connection	Conversion	Cyber	Cognition	Configuration	DT total
1-9 (n=85)	2	1.61	1.85	1.31	1.6	1.6
10-49 (n=298)	2.17	1.88	2.17	1.29	1.8	1.8
50-249 (n=100)	3.24	2.17	3.13	1.76	2.1	2.47
250+ (n=23)	3.36	2.23	2.99	1.7	1.6	1.93

Fig. 8. Heatmap: Level of technology use by company size (source: own depiction)

Fig. 8 shows the technology implementation in companies with different-sized workforces. There's a tendency observable for larger companies to have a higher level of implementation in the examined technology categories. The lower implementation rate for small companies may be a result of high implementation costs or a lack of resources, such as skilled personnel and knowledge. This could indicate a correlation between the complexity of the technology and its level of implementation, which, however, will not be further discussed in this thesis.

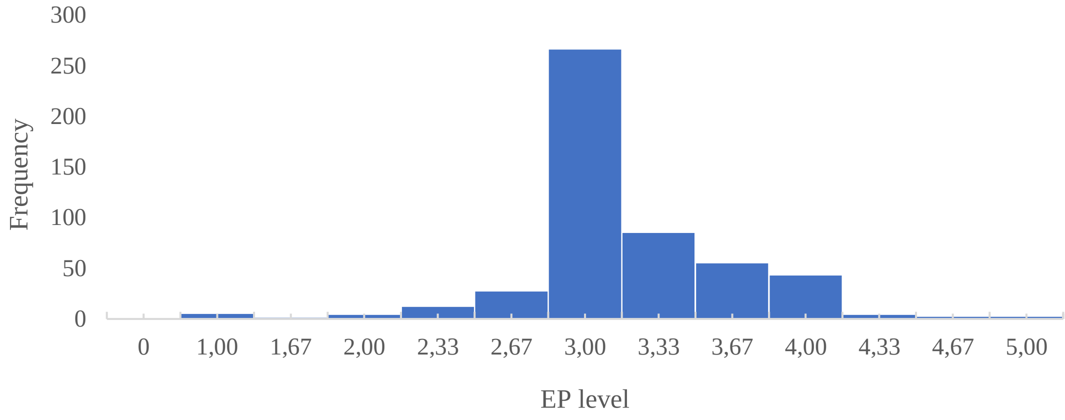

Fig. 9. Histogramm of EP

Regarding the EP level, the average level is 3.17, with no significant discrepancies between industries. The standard deviation is relatively small at 0.48. However, the data shows a high kurtosis of 4.365, indicating a relatively high peak in the distribution, as shown in Fig. 9. Based on these findings, most companies state that their EP level is equal to that of their competitors. The data also shows relatively low variance, which could be attributed to a slight central tendency bias. Central tendency bias occurs when respondents consistently select the midpoint option (e.g., "3" on a 5-point Likert scale) as default or due to uncertainty (Douven, 2018). Consequently, this leads to a clustering of responses around the centre of the scale. This phenomenon reduces the variability in the data, which may consequently obscure the true distribution of opinions or attitudes among respondents. As a result, it makes the data less informative and meaningful for analysis.

Table 5. Correlation matrix EP, digital technologies and DT total

	EP	Connection	Conversion	Cyber	Cognition	Configuration	DT total
EP							
Connection	0.163**						
Conversion	0.061	0.586**					
Cyber	0.143**	0.701**	0.517**				
Cognition	0.115**	0.505**	0.549**	0.562**			
Configuration	0.135**	0.597**	0.564**	0.702**	0.764**		
DT total	0.152**	0.831**	0.772**	0.842**	0.799**	0.867**	

Note: *p≤0.05, **p≤0.01, ***p≤0.001

When looking at the correlations between the constructs, it can be observed that almost all digital technologies except for the data-to-information conversion category exhibit weak but significant correlations with the EP. As to be expected, the technology categories show significant high correlations with each other. Moreover, DT total is calculated by using all the survey items that were used for the technology constructs, which is why there are correlations >0.07 visible.

4.2. Empirical Findings

In this chapter, the results from the analyses will be presented. It will examine the findings in detail, providing a thorough and comprehensive overview of the outcomes.

4.2.1. Reliability of Constructs

As described in Chapters 3.2 and 3.3, the first step is to investigate the appropriateness of constructs and explore the underlying dimensions by assessing the factor loadings of the survey items onto their respective constructs. Five constructs were examined: smart connection, data-to-information conversion, cyber, cognition, and configuration. Each of the constructs was based on theory and consisted of two technologies, with each technology represented by three survey items, resulting in a total of six items per construct (see Table 2).

Table 6. Factor analysis and Crohnbach's alpha results

Construct	Crohnbachs Alpha	Item	Factor loadings	Cronbachs Alpha without item
Configuration	0.862	24.1	0.841	0.834
		24.2	0.849	0.835
		24.3	0.852	0.835
		27.1	0.711	0.848
		27.2	0.738	0.839
		27.3	0.716	0.847
Cognition	0.877	25.1	0.754	0.860
		25.2	**0.651**	**0.883**
		25.3	0.810	0.848
		26.1	0.843	0.849
		26.2	0.834	0.852
		26.3	0.867	0.846
Cyber	0.806	22.1	0.694	0.827
		22.2	0.729	0.821
		22.3	0.747	0.816
		23.1	0.805	0.802
		23.2	0.731	0.821
		23.3	0.777	0.811
Conversion	0.739	19.1	0.739	0.692
		19.2	0.744	0.706
		19.3	0.751	0.683
		20.1	**0.540**	0.736
		20.2	**0.579**	0.701
		20.3	**0.688**	0.693
Connection	0.812	18.1	0.744	0.781
		18.2	0.815	0.759
		18.3	0.772	0.771
		21.1	0.774	0.766
		21.2	0.737	0.775
		21.3	**0.410**	**0.833**

The results, as shown in Table 6, revealed strong factor loadings (>0.7) for most items, indicating a clear coherence between the survey items and their intended constructs. However, for the smart connection and cognition constructs one item each, and for the data-to-information conversion construct three items showed factor loadings between 0.4 and 0.7. As this result is still acceptable, but not ideal, these items were further examined within the internal reliability analysis.

Following the factor analysis, internal reliability analysis was performed using Cronbach's alpha coefficient to assess the consistency and reliability of the measurement scales. It was found that

Cronbach's alpha coefficient for the three problematic items of the data-to-information conversion constructs improved with these items included. As a result, these items were retained in the data-to-information conversion construct, despite their factor loadings below the threshold of 0.7. However, the two items of the smart connection and cognition constructs were removed, as their removal improved the internal consistency and therefore the informative value of these constructs.

Overall, Cronbach's alpha values for all constructs exceeded the threshold of 0.7, indicating satisfactory internal consistency among the survey items within each construct. Specifically, the alpha values were as follows: smart connection ($\alpha = 0.833$), data-to-information conversion ($\alpha = 0.739$), cyber ($\alpha = 0.806$), cognition ($\alpha = 0.883$), and configuration ($\alpha = 0.862$).

This process of examining both factor loadings and Cronbach's alpha coefficients ensured that the final measurement scales accurately captured the intended dimensions of the underlying constructs while maintaining satisfactory levels of internal consistency.

4.2.2. Regression Analysis

The regression analysis aimed to investigate the relationship between the five technology categories, smart connection, data-to-information conversion, cyber, cognition, configuration, and EP in Lithuanian manufacturing companies. First of all, a bivariate regression with one technology category as independent and environmental performance as the dependent variable was performed. This was repeated for all categories and the polynomials of each variable, to find any linear, quadratic or cubic relationships. The results can be seen in **Fehler! Verweisquelle konnte nicht gefunden werden.** Table 7, and indicate a significant and positive relationship of some form for all categories except for data-to-information conversion.

Table 7. Bivariate regressions with technology categories and EP

Category		stand. Beta	R^2
Configuratioı	linear	0.136**	0.019
	quadratic	0.13**	0.017
	cubic	0.017*	0.012
Cognition	linear	0.021*	0.008
	quadratic	0.059	0.003
	cubic	0.010	0.000
Cyber	linear	0.152***	0.023
	quadratic	0.173**	0.019
	cubic	0.118**	0.014
Conversion	linear	0.730	0.005
	quadratic	0.046	0.011
	cubic	0.027	0.011
Connection	linear	0.171***	0.029
	quadratic	0.168***	0.028
	cubic	0.162***	0.026

Note: *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$

The strength of these relationships can be compared by looking at the standardized β coefficient and the R square value. Both of these indicators show that although most of the tested relationships are significant, they tend to be weak (stand. β < 0.3). The coefficients for smart connection, linear (β = 0.171, p < 0.001) and cyber, linear (β = 0.152, p < 0.001) show a profoundly high significance level. Except for data-to-information conversion, where no significant relationship to EP was proven, and cognition, all tests showed significant results for the linear, quadratic and cubic predictors. Hence, further testing is required to find the models that provide the best fit for the relationship.

Thus, to validate the revealed relationships and examine their stability, multiple regression analyses were conducted. Control variables, namely company size based on the headcount in 2021, company age and number of IT staff, were introduced in the equations, performing a hierarchical linear regression. The control variables were chosen since they reflect objective indices and information on the respondents and do not use subjective ratings. In addition to that studies show that these kinds of corporate key figures can affect the overall company performance (Rahman & Yilun, 2021; Rossi, 2016; Yadav et al., 2017).

Table 8. Regression analysis smart-connection

Connection	Model 1	Model 2	Model 3	Model 4
Company size	0,157***	0.122**	0.120**	0.120*
IT staff	-0.053	-0.054	-0.056	-0.055
Company age	-0.002	-0.002	-0.002	-0.005
Connection		0.142**	0.101	0.301
Connection ^2			0.044	-0.502
Connection ^3				0.362
R^2	0.164	0.046	0.046	0.047

Note: *p≤0.05, **p≤0.01, ***p≤0.001

Table 9. Regression analysis data-to-information conversion

Conversion	Model 1	Model 2	Model 3	Model 4
Company size	0,157***	0,151***	0,151***	0,152***
IT staff	-0.053	-0.054	-0.045	-0.046
Company age	-0.002	0	0.001	0.002
Conversion		0.061	0.264	0.225
Conversion ^2			-0.214	-0.119
Conversion ^3				-0.061
R^2	0.164	0.03	0.035	0.035

Note: *p≤0.05, **p≤0.01, ***p≤0.001

In Table 8**Fehler! Verweisquelle konnte nicht gefunden werden.**, it can be seen that in the regression model with only the control variables, exclusively the company size has a significant relationship to EP, while IT staff and company age do not reach the critical significance level to be considered beneficial to the model. Since the intention of adding them is solely the testing of the digital technologies, the non-significance is not an issue for the procedure. When inserting the linear smart connection variable in the equation, there is a significant and positive but weak relationship visible. The R square value, however, is lower than in the first model. Continuing with the polynomials, neither they nor the linear variable have a significant effect anymore. This indicates that the relationship between digital technologies that fall into the category “smart connection“ and EP is rather unstable. Nevertheless, there is a slight linear relationship.

As expected, the data-to-information conversion category variable shows no significant influence when introducing control variables to the regression. This is the case for the linear, quadratic and cubic variables, similar to the bivariate regression shown in Table 9. Therefore, no relationship between the data-to-information conversion technologies and EP could be determined.

Table 10. Regression analysis cyber

Cyber	Model 1	Model 2	Model 3	Model 4
Company size	0,157***	0,136**	0,138**	0,139**
IT staff	-0.053	-0.052	-0.05	-0.047
Company age	-0.002	-0.013	-0.012	-0.014
Cyber		0,129**	0.218	0.225
Cyber ^2			-0.094	-0.085
Cyber ^3				-0.038
R^2	0.164	0.043	0.044	0.045

Note: *p≤0.05, **p≤0.01, ***p≤0.001

Table 11. Regression analysis cognition

Cognition	Model 1	Model 2	Model 3	Model 4
Company size	0,157***	0.150***	0.156***	0.158***
IT staff	-0.053	-0.048	-0.046	-0.047
Company age	-0.002	-0.003	-0.005	-0.006
Cognition		0.072	0.235	0.135
Cognition ^2			-0.177	0.000
Cognition ^3				-0.098
R^2	0.164	0.032	0.037	0.037

Note: *p≤0.05, **p≤0.01, ***p≤0.001

Table 12. Regression analysis configuration

Configuration	Model 1	Model 2	Model 3	Model 4
Company size	0,157***	0,140**	0,141**	0,144**
IT staff	-0.053	-0.051	0.05	0.051
Company age	-0.002	-0.007	-0.007	-0.007
Configuration		0,114*	0.126	-0.151
Configuration ^2			-0.013	0.648
Configuration ^3				-0.421
R^2	0.164	0.039	0.039	0.043

Note: *p≤0.05, **p≤0.01, ***p≤0.001

The cyber (see Table 10) and configuration (see Table 12) variables show the same pattern as the smart connection and thus establish a weak but significant relationship between these digital technologies and EP. Concurrently, cognition (see Table 11) as a predictor does not show a reliable significance level as soon as control variables are introduced in the equation. This proves that the relationship is not stable enough to be considered confirmed.

The strength of the effect, measured by the standardized Beta value, is considerably similar for all three significant relationships with values between β=0.114 and β=0.142. This indicates that the improvement of the DT level always has a similar effect on the EP, regardless of the digital technology used, given that it stems from the smart-connection, cyber or configuration category.

To ensure the quality and meaningfulness of this regression analysis, it is important to test for multicollinearity issues, since this could also have an influence on the tested relationships. For all models, the tolerance for each predictor is close to one and the VIF is below the threshold of three (Hair, Jr. et al., 2013), which would indicate minor multicollinearity issues. Additionally, a potential correlation between the technology category variables and company size was checked. Although there is a weak correlation between these variables, as shown in Table 13, there is no correlation over the critical value of 0.7 (Hair, Jr. et al., 2013), which would indicate severe multicollinearity issues.

Table 13. Correlation analysis technology categories and control variables

	Company size	Company age	IT staff
Connection	0.406**	0.053	0.316**
Conversion	0.168**	-0.016	0.188**
Cyber	0.382**	0.126**	0.219**
Cognition	0.106*	0.031	0.086
Configuration	0.262**	0.151**	0.072
Company size	-	0.334**	0.288**
Company Age		-	0.091*
IT staff			-

Note: *p≤0.05, **p≤0.01, ***p≤0.001

Finally, the hypotheses H1 and H3 were confirmed, while H2, H4 and H5 were rejected. In addition to that it was found that there is a stable, significant relationship between company size and EP, indicating that larger companies tend to exhibit higher levels of environmental performance.

The empirical results have to be set into perspective of the environment in that they were developed as well as some executive decisions that were made for the analysis and which can have an impact on the outcome. First of all, the categorization of digital technologies was created theoretically. As explained in chapter 2.3 there are many ways to categorize digital technologies. Those other categorizations might have led to a different outcome with more or less significance. However, the linearity or non-linearity is most likely unchanged by that. It is probable that any categorization would have led to the conclusion that there is a linear relationship between the regarded technologies and the corporate environmental performance of manufacturing companies. Another possibility might have been to perform an exploratory factor analysis and use the created factors as predictors, but this solution lacks meaningful predictors and is therefore difficult to interpret.

Secondly, the results in the regression analysis can be influenced by a central tendency bias in the dependent variable, EP. With a variance of 0.2304, indicating limited variability among responses, and a majority of respondents, approximately 52.6%, consistently selecting the midpoint score of 3 on a 5-point Likert scale, there is a risk of reduced accuracy in the data. This clustering of responses around the neutral option may disguise differences in EP that exist in reality. This might reduce the ability of the regression model to accurately capture the relationships between predictors and the dependent variable. Therefore, the regression coefficients may lack precision, confidence intervals may widen, and statistical significance may be lower, leading to inconclusive findings regarding the impact of predictor variables on EP, like in this case with data-to-information conversion and cognition.

4.3. Discussion

This investigation sought to clarify the relationship between digital technologies and EP. The previous chapter served as a foundation for the theoretical analysis examined the secondary data and presented empirical results from the regression analysis. The purpose of this chapter is to discuss the theoretical implications derived from these findings, provide recommendations based on the RBV theory, and outline the limitations and potential directions for future research in this area.

4.3.1. Theoretical Implications

The results of the regression analysis indicate a weak yet statistically significant positive linear relationship between smart connection technologies and EP (H1), cyber technologies and EP (H3), and configuration technologies and EP (H5). This contradicts the assumption that there is a non-linear relationship between digital technologies and EP, suggesting instead a linear relationship. Given that digital technologies are a central component of DT (see Chapter 1.1.1), this study also proposes a positive relationship between DT and EP. As a result, this thesis aligns with the research conducted by Chen and Hao (2022), Wu et al. (2019), Feroz et al. (2021), Sarfraz et al. (2022), and Bendig et al. (2023), who all proposed a positive link between DT and EP. Consequently, the EP of manufacturing companies improves as they implement digital technologies of various levels of complexity and independence into their production systems. Hence, the increasing use of digital technologies leads to improved EP.

Consequently, this study disagrees with the findings of Ahmadova et al. (2022), Chen et al. (2020), and Hao et al. (2020), who suggested a more complex relationship, such as an inverse U-shaped relationship. The differences in findings may be due to several reasons, On the one hand, different measurement models for EP were applied. While some studies measured energy or material consumption in absolute values, the data from the survey evaluated in this thesis was conducted using a comparative approach (Wen et al., 2021). On the other hand, the results can differ based on local circumstantial differences due to geographical location, political climate and social dynamic, being factors that affect the common level of environmental sustainability or development stage of digital technologies (Yang et al., 2022).

Furthermore, the negative effects of digital technologies on EP can have long-lasting implications. These effects may not be immediately apparent but rather appear at a later stage in the lifecycle or after a few years of implementation. While digital technologies may initially facilitate change and improvements that positively influence EP, it is important to consider the potential negative consequences that may arise over time.

These negative effects can encompass a range of issues, such as maintenance, energy consumption, data landfill, and end-of-life disposal. It is worth considering that these detrimental environmental effects may not be accurately reflected in the EP measurements of companies using these technologies. For instance, the primary environmental impact of microchips, which serve as the foundation for many digital technologies, stems from the production of semiconductors and their disposal at the end of their lifespan (Ruberti, 2023). Kuo et al. (2022) suggest that 85% of the climate change impact of integrated circuits originated in the production stage, while the highest impact on water resources was measured in the raw-material stage. Therefore, it is evident that the negative consequences of digital technologies on EP extend beyond what can be measured solely through the EP metrics of companies.

An additional finding that emerged from this study is that the size of the company has a positive impact on EP. It is worth noting, however, that due to the limitations of this thesis, a more comprehensive investigation into this specific aspect will not be conducted.

In summary, technological advancement has been found to play an important role in enhancing the EP of manufacturing companies. By adopting technologies that enable the digitalization of production processes, real-time monitoring of inventory and manufacturing activities, or fully automated and smart manufacturing systems, a demonstrable improvement in the EP of Lithuanian manufacturing companies has been proven. This improvement is primarily attributed to the enhancement of production efficiency and more effective distribution of resources, thereby reducing waste generation as well as water and energy consumption (Le Ha et al., 2022). The results from this analysis contribute additional insights from Europe to the existing body of research, further strengthening the evidence supporting a positive linear relationship between DT and EP.

4.3.2. Managerial Perspective and Recommendations

From a RBV perspective, the main findings of this thesis suggest that companies should expand their digital technology resources in order to enhance their EP. This means that companies need to invest in acquiring and developing more digital technology resources, such as advanced software and hardware, that can be utilized to improve their EP. By doing so, companies can optimize their environmental practices and processes within the scope of their EMS, leading to more sustainable and eco-friendly operations. Furthermore, they should effectively leverage their existing digital technology applications to capitalize on opportunities that can significantly reduce their environmental footprints. They should identify and explore opportunities within these applications that can support environmental sustainability initiatives.

Enhancing EP is attractive for companies as it not only contributes to their competitive advantage but also enhances their reputation in the market. By improving EP, companies can achieve increased efficiency, leading to significant cost savings. This cost advantage can give companies an edge by increasing their profits or allowing them to offer lower prices, depending on their strategic goals.

Concurrently, enhancing EP can make a company more appealing to potential employees. In today's world, many employees prioritize working for environmentally responsible companies. By demonstrating a commitment to environmental sustainability, companies can attract top talent and improve their recruitment efforts.

Based on the findings of this thesis, it is recommended that companies focus on three key areas: smart connection, cyber technologies, and configuration technologies. This involves leveraging advanced technologies such as ERP-supported manufacturing and the digitization of production processes. By embracing these technologies, companies can streamline their operations, improve efficiency, and enhance overall productivity. By adopting technologies that empower real-time inventory control and manufacturing companies can gain valuable insights into their inventory levels and production progress, allowing for better planning and allocation of resources, such as material, parts and human resources. Configuration technologies, involving machine learning, AI, and fully-automated / smart production, enhance efficiency, minimize errors, and reduce production costs. These technologies also have the potential to enable customization and personalization of products, allowing companies to cater to individual customer preferences and gain a competitive edge.

Furthermore, better EP can help companies minimize the expenses associated with regulatory compliance. For instance, reducing CO_2 emissions can result in reduced costs spent on ETS carbon emission allowances. By actively improving their EP, companies can also become eligible for subsidies offered for achieving good EP in various areas.

Nevertheless, the literature evaluated for the problem analysis still shows that there are environmental impacts caused by digital technologies that need to be addressed. The results from this thesis open up the possibility that the negative environmental effects of digital technologies do not primarily affect the sustainability performance of the analyzed companies. Since they only use the technologies, and the majority of the footprint is generated during production and disposal, the EP does not fully reflect these influences.

The European Parliament recently approved the Corporate Sustainability Due Diligence Directive (CSDDD) (European Parliament, 2024). This directive aims to enforce corporate due diligence, with a particular focus on environmental impact and human rights compliance. According to Human Rights Watch (2024), this means that companies will be held accountable for thoroughly examining their value chains. As a result, environmental factors related to the production of digital technologies will also be affected. The semi-conductor production industry has previously faced criticism for its environmentally and socially problematic practices (Ruberti, 2023). With the responsibility now partly shifting to manufacturing businesses, this might become an additional metric for their corporate

EP and thus develop pressure to mitigate the environmental effects of this part of the digital technologies‘ lifecycle.

In conclusion, based on the findings of this thesis, the RBV suggests that investing in digital technologies is advisable for companies aiming to improve their EP. By capitalizing on already implemented digital technologies and investing in smart connection, cyber, and configuration technologies, companies can reduce their environmental footprints, gain a competitive advantage, reduce costs, comply with regulations, and become more attractive to various stakeholder groups such as investors, customers and potential employees. However, managers should be careful about the selection of the technologies and their impact outside of the operational stage, since the impact on the production and end-of-life disposal of these technologies can be greater and should be considered when measuring the internal EP, especially to comply with future regulation based on the CSDDD.

4.3.3. Limitations and Directions for Further Research

The study conducted has certain limitations that should be taken into account when examining the results. One limitation is that the study was solely conducted in Lithuania, which means that there may be certain local factors or peculiarities that have influenced the outcome. While this geographical focus allowed for a comprehensive analysis within a specific context, it also restricts the generalizability of the findings to broader contexts. Additionally, the study only included respondents from the manufacturing industry sectors, specifically NACE cluster C. This provided insights into the manufacturing industry as a whole, although it was not possible to evaluate potential differences between smaller sectors due to the small sample sizes. To gain a more comprehensive understanding, further research could be conducted on more specific industries, allowing for an exploration of the variations between them. Moreover, there is potential for future research to expand the scope of the study. One suggestion is to include multinational comparisons or cross-cultural analyses to enhance the external validity of the findings. This would allow for a more robust understanding of the topic by considering different cultural contexts and exploring potential variations in the outcomes.

Other constraints relate to the way the data was gathered. The survey format allowed different levels of understanding of digital technologies among survey respondents. This variance could have introduced bias or inconsistency in the collected data. To address this issue, future research could consider conducting interviews to ensure a comprehensive understanding of how exactly these technologies are being employed within the companies. Additionally, the subjective assessment of EP by managers in higher-level positions, as well as production managers, IT technical managers, and technology/development managers instead of sustainability managers, may have implications for the accuracy and comprehensiveness of the data collected. To gain a more grounded insight into the various aspects that contribute to EP within manufacturing companies, future research could explore the perspectives of sustainability managers. Another option could be evaluating EP based on measurable indicators such as greenhouse gas emissions, energy and water consumption, or waste per unit of time or unit of production.

Considering the long-term nature of EP, it would be beneficial to conduct a follow-up survey after a period of two to five years. This follow-up survey would provide valuable insights into the long-term effects of adopting digital technology on the environment. By conducting such a survey, a more comprehensive evaluation of how digital technologies influence environmental outcomes over time would be possible. This would facilitate a deeper understanding of the impact of digital technology on the environment and informed decision-making regarding its implementation.

In addition, the study revealed a heterogeneous distribution of the digital technologies being considered and their respective categories. This can potentially affect the measurable impact on EP, given that it appears as if the categories with no significant relationship to EP had very low implementation levels across all industries. Since these technologies have not been widely implemented, it is difficult to determine how a higher level of implementation would affect EP. Future studies could further explore this discrepancy and investigate the contribution of different types of technologies to environmental sustainability in manufacturing companies.

Moving forward, several directions for further research emerge. Firstly, further investigation of moderating and mediating factors could be performed to deepen the understanding of the relationship between digital technologies and EP. This could involve investigating contextual factors that influence the effectiveness of technology interventions in driving sustainability outcomes.

Secondly, qualitative research provides an opportunity to explore the nuances of how companies employ technologies to improve environmental sustainability. Through the identification of best practices and the examination of real-world case studies, qualitative research can provide valuable insights into the strategies and mechanisms by which digital technologies can be leveraged to accomplish environmental objectives.

In conclusion, while this study has highlighted the positive relationship between digital technologies and EP in manufacturing companies, it also opens up areas for further investigation and refinement. By addressing the constraints encountered and investigating new research directions, future studies can contribute to advancing knowledge in this research field.

Conclusion

1. **Although research agrees that DT and digital technologies provide opportunities for improving the EP, there is conflicting evidence as to whether a broad and higher-level use of digital technologies can lead to negative effects that outweigh the positive ones or not.**

DT has several ways of impacting the EP of manufacturing companies, which can be positive and negative.

On the one hand, the positive effects are primarily direct in nature. They help reduce environmental issues such as greenhouse gas emissions, water and energy consumption, and waste by improving production efficiency. Technologies, such as IoT, real-time control of production and stock, or simulations help create efficient workflows, optimise material distribution, and manage tasks. Machine learning and AI applications can also learn from existing data collected by machines and tools and improve maintenance and logistics operations or independently adapt the production based on orders. Additionally, technologies can support the design stage of new eco-friendly products that are made for a more circular economy and are created with eco-efficiency in mind.

On the other hand, the production of digital technologies can also cause significant environmental damage. In particular, the production of micro-chips and the required semi-conductor extraction were shown to have a detrimental effect on the environment. In addition to that, the technology lifecycles become increasingly shorter as technological progress becomes more rapid. Together with low recycling rates at the end of life, this facilitates an increasing amount of technological waste. This phenomenon is known as the rebound effect, which occurs when the usage of digital technologies for environmental purposes escalates to a point where it becomes destructive

In summary, the technological advancement and use of digital technologies for production purposes present opportunities for improvement and eco-efficiency. However, they also carry risks, such as the potential for a rebound effect that could harm the environment more than it protects it.

2. **The proposed framework to sensibly categorize digital technologies is the 5C architecture of CPS. It allows categorizing digital technologies according to their complexity and independence of human input.**

The 5C architecture of CPS, developed by Lee et al. in 2020, offers a practical and effective method for classifying digital technologies. Originally designed to streamline the implementation of CPS in companies, this framework also serves as a valuable categorization model for digital technologies that are part of CPS.

The framework comprises five distinct categories: smart-connection, data-to-information conversion, cyber, cognition, and configuration. Each category includes unique core activities and specific areas of focus for CPS implementation. The technologies encompassed within these categories span a wide range of complexity and reliance on human input. For instance, the smart-connection category includes technologies such as sensors that have low complexity and thus high dependency on human input. On the other hand, the configuration category includes technologies such as AI, which are characterized by high complexity and low dependency on human input.

Due to the detailed characterization of these categories, the framework permits a seamless allocation of digital technologies into their appropriate categories. Some technologies may be eligible for inclusion in multiple categories, as they can sometimes have varying levels of complexity within different application areas. However, for the purposes of this study, a single category was selected for each technology to avoid redundancy.

To validate the selection of categories utilized in this thesis, an internal consistency analysis was conducted using Crohnbach's Alpha and factor analysis. This analysis confirmed that the chosen categories were internally consistent and reliable. Each category was treated as a construct consisting of a 3-stage latent variable, which was derived from two technologies using three survey items each.

3. **Based on empirical research, three out of five digital technology categories were found to have a statistically significant and positive relationship with EP. This suggests a positive relationship between DT and EP as well. Next to these key outcomes, the analysis in this thesis revealed that there is a significant positive relationship between the firm size and EP.**

The empirical research conducted in this thesis involved performing a regression analysis with control variables to examine the relationship between each of the five technology categories and EP. The problem analysis revealed an area that so far received limited research attention, specifically, the potential non-linear relationship between DT and EP. To investigate this relationship, the 5C constructs and their quadratic and cubic polynomials were tested. Within this analysis, no issues of multicollinearity were discovered.

The quantitative analysis revealed a statistically significant but weak linear relationship between the smart-connection, cyber, and configuration technologies with EP. The strength of the relationships is very similar, indicating that all technologies from the smar-connection, cyber or configuration categories have a comparable effect on EP and none of them should be specifically prioritized when it comes to implementation. As a result, the hypotheses proposing a curvilinear effect of these technologies on EP were disproven. However, since digital technologies are a fundamental aspect of DT, it can be assumed that a linear relationship exists between DT and EP, which is consistent with much of the recent research in this field.

Additionally, one of the control variables, the size of the company, demonstrated a significant impact on EP. The firm size was measured by the number of employees in 2021 and consistently exhibited a measurable effect across all regression models. However, due to the scope of this thesis, the underlying reasons for this relationship were not further investigated.

4. **The resource-based view methodology shows how companies should invest in implementing and further developing their digital resources to create a competitive advantage through EP. A better EP can lead to improvements in cost and reputation in various ways.**

The implementation and utilization of digital technologies in manufacturing companies have numerous benefits from an RBV perspective. Despite being digital in nature, these technologies are considered physical capital resources. By enhancing efficiency and enabling new manufacturing methods, they can support cost reductions and, subsequently, profit maximization. Mass customization capabilities, facilitated by new production technologies such as AM, can create a competitive advantage, particularly appealing to new and existing customers. Moreover, technology leadership can attract various stakeholders.

When companies focus on how DT can positively impact their EP, they can simultaneously benefit from the advantages that EP as an intangible resource offers. One of the most significant benefits is an improved reputation. As society and governments exert pressure on industries to become more environmentally friendly, making efforts towards environmental sustainability can increase popularity among stakeholders such as customers, investors, and potential employees. A positive EP can also ensure compliance with regulatory reforms, such as those outlined in the EU Green Deal. Additionally, companies can save costs that would otherwise function as sanctions for having a detrimental environmental footprint, such as ETS carbon emission allowances.

In summary, from an RBV standpoint, it is logical for companies to invest in the implementation and expansion of digital technologies across smart-connection, cyber, and configuration categories. By doing so, they can leverage the benefits that these technologies and an improved EP bring to gain a competitive advantage.

5. **Although in principle there is a positive influence, the negative environmental effects of digital technologies have to be kept in mind and counteracted actively. They oftentimes occur outside of the operational use in the production and end-of-life disposal of digital technologies and can, therefore, not be reflected properly in the EP of manufacturing companies that simply employ them.**

This study provides evidence of a positive linear relationship between certain digital technologies and EP. This finding is consistent with the conclusions drawn from various studies mentioned in this thesis. However, there is also research suggesting a more complex relationship, highlighting the negative effects associated with the production and disposal of these technologies. Therefore, the results of this study can be interpreted as an indication that these adverse impacts occur during stages other than the actual use of the technology. This is supported by lifecycle assessments conducted with semi-conductors and technology-related materials.

Although this may not be an immediate concern for the companies examined in this thesis that employ the digital technologies under investigation, it could become relevant in the future, particularly with the introduction of the EU's CSDDD and CSRD. Therefore, it is advised that companies start investigating these effects, even though it does not directly impact their EP at the moment.

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Appendices

Appendix 1. Excerpts from survey Questionnaire (Ghobakhloo et al., 2023).

COVID-19 Aukšto lygio MTEP (SMART) projektas: : Dirbtinio intelekto generuojami realaus laiko skaitmenizacijos scenarijai mažoms ir vidutinėms gamybos įmonėms

Digitalization roadmaping survey

The aim of the questionnaire to gather representative data on digitalization practices of manufacturing companies. The anonymised data will be used for automated generation of individualized digitalization roadmaps. The questionnaire is anonymous, we don't ask to provide title of the company, if you don't want to. The survey will take about 18 minutes of your time!

The survey is organized by a Kauno university of technology.
If you have any further questions, please do not hesitate to contact us: Mantas Vilkas E-email: mantas.vilkas@ktu.lt, Tel: +37068792345

Your answers in this questionnaire **should refer to the manufacturing site** where you are based, not to the whole company.

Please indicate your industry and the main (line of) product(s) produced at your factory.

Industry (e.g. textile industry, chemical industry, machinery etc.): *enter*	
Main line of products (e.g., furniture, beverages) *enter*	

Indicate how well the statements characterize **operating system** of your company X Fill example	Strongly disagree	Disagree	Neither agree or disagree	Agree	Strongly agree	Not aplicable for our company
18. ERP supported manufacturing						
18.1 We use software (e.g., ERP, MES) for production planning and control 18.1.1. Pradėta taikyti (metai)'						
18.2 We can identify the order delivery progress of each order batch in our software (e.g., ERP, MES) system . 18.2.1. Pradėta taikyti (metai)'						
18.3 Our sales, manufacturing planning, warehouse and accounting processes are integrated using software (e.g., ERP, MES) . **18.3.1** Pradėta taikyti (metai)'						
19. Industrial automation (robots)						
19.1 We use industrial robots for manufacturing processes (e.g. welding, painting, cutting). 19.1.1 Pradėta taikyti (metai)'						
19.2 We use collaborating robots (Cobots) . **19.2.1.** Pradėta taikyti (metai)'						
19.3 We automate routines activities using robotic process automation (RPA) solutions or manufacturing aplications. 19.3.1. Pradėta taikyti (metai)'						
20. Computer-aided design and manufacturing						

Indicate how well the statements characterize **operating system** of your company Fill example	Strongly disagree	Disagree	Neither agree or disagree	Agree	Strongly agree	Not aplicable for our company
20.1 We use computer-aided design solutions (e.g., CAD software) across manufacturing operations.. 20.1.1 Pradėta taikyti (metai)'						
20.2 We use programable CNC manufacturing equipment/lines in our production. 20.2.1. Pradėta taikyti (metai)'						
20.3 We use additive manufacturing (e.g., 3D printers) for prototyping new products, parts, or tools. 20.3.1. Pradėta taikyti (metai)'						
21. Digitization of production documentation/ paperless						
21.1 We use electronic interactive procedures and instructions on the shop floor. 21.1.1. Pradėta taikyti (metai)'						
21.2 The production workers receive tasks and report performance using computers or tablets 21.2.1 Pradėta taikyti (metai)'						
21.3 No paper-based production order documentation is moving along production operations with a particular batch or order. 21.3.1 Pradėta taikyti (metai)'						
22. Real-time control of inventory						
22.1 We have precise, real-time information on our raw material inventory levels 22.1.1 Pradėta taikyti (metai)'						
22.2 We use solutions for generation of automatic orders for stockouts of materials or components 22.2.1. Pradėta taikyti (metai)'						
22.3 We have precise, real-time information on our finished goods inventory levels 22.3.1. Pradėta taikyti (metai)'						
23. Real-time control of manufacturing						
23.1 We use automatically collected data on performance of each work center or production lines with minutes or hours precision						
23.2 The work-in-process inventory is equipped with bar codes, RFIDs allowing automatic tracking of stages of production						
23.3 We use automatically collect data on downtime, setup times, run times of the manufacturing equipment/ lines with minutes precision						
24. Machine learning/AI solutions in manufacturing						
24.1 We use machine learning/AI predictions for product demand forecasting. 24.1.1. Pradėta taikyti (metai)'						
24.2 We use machine learning/AI for automatic control of quality through image recognition or other means. 24.2.1 Pradėta taikyti (metai)'						
24.3 We use machine learning/AI for predictive maintenance through real-time anomaly detection. 24.3.1. Pradėta taikyti (metai)'						
25. Simulation						
25.1 We use simulation to identify causes of technical problems involved in the production process and develop necessary solutions. 25.1.1. Pradėta taikyti (metai)'						
25.2 We use process mining for identification of process botlenects, other problems and propose imrovements . 25.2.1. Pradėta taikyti (metai)'						

Indicate how well the statements characterize **operating system** of your company Fill example X	Strongly disagree	Disagree	Neither agree or disagree	Agree	Strongly agree	Not aplicable for our company
25.3 We use simulation to predict plant performance and test the effectiveness of the production schedule. 25.3.1. Pradėta taikyti (metai)'						
26. Augmented reality solutions						
26.1 We use augmented/virtual reality for employee training purposes. 26.1.1. Pradėta taikyti (metai)'						
26.2We use augmented reality for asset identification across various functions (e.g., warehousing) 26.2.1. Pradėta taikyti (metai)'						
26.3 We use augmented reality to streamline maintenance management operations 26.3.1. Pradėta taikyti (metai)'						
27. Fully-automated/smart manufacturing						
27.1 All our manufacturing processes are integrated into continuous automated production lines. **27.1.1.** Pradėta taikyti (metai)'						
27.2 Real-time data generated across production processes are used for autonomous production control. 27.2.1. Pradėta taikyti (metai)'						
27.3 We autonomously analyze the historical data and patterns collected across production processes to make informed decisions. 27.3.1. Pradėta taikyti (metai)'						

Indicate how well your factory **performed compared to its competitors** within your industry **over the last 3 years** along the following performance dimensions Fill example X	A lot of worse	Worse	Equal	Better	A lot of better
32a. Business performance					
32.1 Sales growth					
32.2 Market share					
32.3 Overall competitive position					
32b. Environmental performance					
32.4 Harmful emission prevention					
32.5 Industrial waste prevention					
32.6 Integrating (using) green resources					
~~32.7 Product durability~~					
32c. Symbolic performance					
32.8 Number of positive endorsements of company in media					
32.9 Students‘ and other companies comapnies represenattives learning visits in the company					
32.10 Contracts with nationally and inetrnationally known customers					