Breaking Barriers

Identifying Human Resource Barriers to the Adoption of Industry 4.0 Technologies in Dutch Manufacturing firms.

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Abstract

This research sought to uncover human resource related barriers to the adoption of Industry 4.0 technologies among Dutch manufacturing firms. Empirical methods were used through employing data from the European Manufacturing Survey to test a series of hypotheses connected to barriers previously identified in different national contexts. A secondary goal was to contextualize any barriers supported and offer alternatives on how to tackle these barriers. The main findings support two barriers, one related to the lack of competency recording, and another related to the lack of annually pre-determined days for training. The barrier stemming from a lack of competency recording inhibits Dutch manufacturing firms from achieving an overview of acquired competences, and thus consequently disallow the change in organizational behavior through hiring and training. The barrier stemming from the lack of annually pre-determined days for training inhibit Dutch manufacturing firms from creating a culture in which change, and personal development, are central and the need for theoretical and practical training is addressed. Moreover, a lack in pre-determined training days inhibits employees from remaining competitive in their field, and thus diminishes the firm's competitive advantage. Through discussion these barriers were contextualized, and an attempt was made to 'break' the barriers.

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1. Introduction

Problem Description

The fourth industrial revolution, Industry 4.0, is a burgeoning topic in academia (Raj et al., 2020) and firm environment practice (Helmond et al., 2018). Industry 4.0 refers to the change in industrial manufacturing through the use of digital solutions, including the use of artificial intelligence (AI), Big Data, Cyber Physical Systems (CPS), and more (Kamble et al., 2018). The potential contributions to firm performance through increased digitalization include the amelioration of value chains, novel business models, and innovative participation in business circles (Huizinga et al., 2014). An under researched aspect of Industry 4.0 is which barriers firms face when attempting to adopt Industry 4.0 technologies (Raj et al., 2020). These Industry 4.0 technologies fuse both traditional practices in manufacturing and innovations in the fields of information and communication, resulting in the creation of CPS (Zheng et al., 2018). Therefore, a major factor in adopting Industry 4.0 technologies is the ability of the personnel file of a firm to accept, understand, and work together with a computer or AI counterpart (Geissbauer et al., 2014; Kamar, 2016). The distinct challenge managers face here is threefold. Firstly, an appropriate (new) personnel file needs to be attained through hiring and practices that are in line with the needs of the firm to innovate. Secondly, current personnel need to be brought up to date with developments through training and education facilitated by the firm. Thirdly, the organizational culture needs to be supportive of the technological innovations, and aid personnel in accepting, understanding, and acquiring the necessary skills to successfully comply. If managers fail in addressing these challenges, the firm is likely to struggle with the adoption of contemporary technologies. Factually, lacking the appropriate human resource (HR) conditions is the second largest barrier to the adoption of Industry 4.0 technologies (Geissbauer et al., 2014).

Contemporary studies on HR barriers to Industry 4.0 technology adoption examine different firms and (national) contexts, with research on Industry 4.0 technologies being especially prevalent in manufacturing and logistical spheres due to considerable practical potential (Hofmann & Rüsch, 2017). Therefore, different HR conditions resulting in barriers have been identified in different national contexts. Raj et al. (2020), examined barriers in France and India, Vuksanović Herceg et al. (2020) identified challenges in Serbia, Türkeș et al. (2019) in Romania, and Lin et al. (2019) sought barriers in China. The common denominator among these countries is their manufacturing value added, both absolute and relative to their size and population. The practical potential of Industry 4.0 technologies in manufacturing contexts as outlined by Hofmann & Rüsch (2017), is therefore similarly visible in the academic contributions, with high-ranking manufacturing countries having contemporary research to their name when it comes to inhibiting forces, challenges, and barriers to the adoption of Industry 4.0 technologies. In the Netherlands, research on barriers to technology adoption is lacking, specifically so in the context of HR conditions internal to firms. This, despite the Netherlands ranking highly in absolute manufacturing value added, being 22nd worldwide, outranking countries as Australia, Argentina and Bangladesh (The World Bank, 2019). Moreover, the Dutch manufacturing industry does struggle with adopting Industry 4.0 technologies, with only a small amount of technologies currently present in most manufacturing firms (Helmond et al., 2018). The insight into which HR barriers identified in other national contexts similarly affect Dutch manufacturing firms will elevate the Dutch manufacturing industry at large beyond international competitors and advance the competitive position of the country, as managers can direct HR departments more effectively in being a driving force in the transition towards an Industry 4.0 firm.

Research Purpose

The purpose of this research is twofold. Firstly, potential HR related barriers present in Dutch manufacturing firms that inhibit them from adopting Industry 4.0 technologies are investigated through an analysis based on previously identified barriers in literature, in different countries. Secondly, breaking the barriers found. Barriers are not only investigated, but also contextualized, and advice is formulated for managers to deal with and overcome these barriers. To achieve the former part of the research purpose, empirical data from the European Manufacturing Survey (EMS) is employed. The EMS is a European initiative with the aim of attaining a deeper insight into the modernization of the manufacturing industries within the European Union (Ligthart et al., 2008). The latter research purpose is consequently achieved through a discussion of relevant literature proposing solutions. Both purposes are encompassed in the following research question aiding the direction of research in this thesis:

Which HR related factors internal to Dutch manufacturing firms inhibit the adoption of Industry 4.0 technologies?

Academic & Managerial Relevance

Research on barriers of Industry 4.0 technology adoption is scarce (Raj et al., 2020) and often in disagreement (Kamble et al., 2018). The lack of consensus stems from studies using dissimilar contexts around their units of analysis, thus concluding upon different barriers (Horváth & Szabó, 2019; Kamble et al., 2018). However, this is not necessarily an issue. It is valuable to identify different barriers in different contexts, as an exhaustive overview might be created in future research. Herein, the academic value of this research is nestled. This research and its results offer an enrichment of current literature and are of additive next to comparative value. Past and present literature plays a role through hypothesis development and establish a confirmatory nature in the research. The additive value is thus derived from the non-use of exploratory research, of which considerably more is available. Instead, this research builds upon past exploratory research and enriches thereby. Enrichment occurs through the consideration of social, labor, and HR factors in organizations. The enrichment of HR literature regarding the role in firm-level technology adoption is important as Industry 4.0 technologies are set to be an important change for human capital in the near future, which will comprise both positive and negative consequences (Flores et al., 2020; Haddud et al., 2017; Kovacs, 2018). The confirmation of HR factors forming barriers towards Dutch manufacturing firms therefore shed light on how HR policy and management input need to develop to prepare for the future of novel technologies.

Most industrialized countries around the world have major manufacturers that have implemented, or are working on implementing, some Industry 4.0 technologies, such as digital production planning, real time production surveyance systems, and automated management of internal logistics (Helmond et al., 2018). Moreover, the importance of the transition towards Industry 4.0 is internationally recognized (McKinsey Digital, 2016), as the advantages are considered to outweigh the disadvantages when certain challenges are overcome. Manufacturing firms should thus strive to adopt and implement these when and where appropriate. Uncertainty, however, is prevalent. High levels of investment and an unfit personnel file are primary reasons for manufacturing firms to stagnate in adopting new technologies (Geissbauer et al., 2014; Schrauf & Berttram, 2014). Workforces often lack adequate skills and competences to effectively cope with Industry 4.0 technologies, and thus create ambiguity on whether these systems should be implemented at all (Kamble et al., 2018). This ambiguity leads to an organizational culture that resists this type of change regardless of the opportunities posed. A similarly slow adoption process is found among Dutch manufacturing firms (Helmond et al., 2018), indicating a series of HR barriers and challenges preventing firms from implementing more Industry 4.0 technologies. Therefore, a confirmatory study on the HR barriers that the Dutch manufacturing firms face is essential in overcoming said barriers. Practical relevance is thereby achieved, as identifying barriers, and consequently suggesting how to overcome them, makes Dutch manufacturing firms better prepared for the inevitable future of manufacturing in the era of Industry 4.0.

Scope

The research examines HR factors leading to barriers to adoption of Industry 4.0 technologies. Within the concept of barriers, obstacles leading to active non-adoption are considered. Specifically, barriers internal to the firm. Consequently, external barriers are not considered. However, it is possible that determined barriers have antecedents in socioeconomic or institutional factors. A key insight is thus that the practical relevance of the proposed research is not solely limited to the firm environment and can be applicable to policymakers and (educational) institutions, which are in control of those socioeconomic factors.

Outline

The subsequent chapters go in depth on the specific facets of this research. Firstly, a literature overview in which concepts are defined, theories considered for hypothesis creation, and the research grounded in the academic fields it interacts with. Secondly, a methodological elaboration on the design choices, data considerations, and practical or theoretical concerns. Moreover, the approaches and assumptions taken are carefully delineated to conform to strict methodological standards, assuring the internal validity. Thirdly, a results chapter which briefly displays the results from the methodological analyses delineated in the methods section. Fourthly, a discussion section, which contextualizes the supported barriers and elaborately describes their specificities in the Dutch manufacturing industry, whereafter strategies are proposed for breaking the barriers. Lastly, a conclusion follows with a reflection on the limitations of the research, and the potential directions for future research.

2. Theoretical Framework

This chapter addresses prominent literature on Industry 4.0 and technology adoption barriers. Before exploring Industry 4.0, however, literature on the adoption of innovation is briefly considered, as it plays a crucial part in the transition from old methods to new. Thereafter, technological developments through Industry 4.0 are considered, and distinctions in definitions are made. Moreover, HR literature is briefly considered as to what impact HR has and can make into the adoption process of new technologies. Finally, all described theories are considered, resulting in the formulation of hypotheses.

Adoption of Innovation

An important part of dealing with innovation is understanding how to adopt and implement new technological developments, especially so when these developments are 'high-tech' solutions and require considerable knowledge, skill, and competence to utilize to their potential. Understanding adoption starts with understanding innovation. Rogers (1995) defined innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (p. 11). Within this definition, it does not matter whether this idea, practice or object is verifiably and objectively new, as long as it is new to the unit of adoption (Straub, 2009). The unit of adoption, either an individual or other decision-making unit (e.g., a firm or an AI), then must make a choice on whether to adopt this innovation or not. Rogers mainly concerned his theory with individual adoption of innovation, but the theory can be applied elsewhere too, such as in the context of a firm (Frambach & Schillewaert, 2002). This is because the basic premise of organizational adoption entails two stages; initiation and implementation (Frambach & Schillewaert, 2002; Zaltman et al., 1973). As these two important stages are encompassed in the adoption theory of Rogers, Rogers' theory of adoption is fit to be used in this context. Rogers (1995) defines adoption as the product of five distinct stages, in which the unit slowly concurs with the full adoption of the innovation; (1) the unit becomes aware of the innovation, (2) the unit is persuaded when plentiful knowledge on the innovation's salience is attained, (3) the unit makes a decision on accepting or rejecting the innovation, (4) the unit acts upon a decision and implementation follows, (5) the unit confirms and reflects on the decision and implementation process. An important addition is that within organizations, the fourth stage, implementation, is twofold. Firstly, the organization must choose to implement an innovation by committing the necessary resources to internalize the new development, as follows Rogers. Secondly, however, the acceptance and assimilation become important beyond the reflection on the decision and implementation process by higher management (Frambach & Schillewaert, 2002). It is important here that the personnel file is both able and willing to demonstrate commitment to the innovation by using it over a period of time (Bhattacherjee, 1998). Herein, the importance of HR policies and characteristics in organizations is emphasized.

The above delineation of innovation adoption following Rogers' adoption theory with the added consideration of Frambach & Schillewaert is most suitable for the proposed research and is therefore the accepted definition when referring to adoption of innovation. Adoption thus includes all processes from initiation of awareness, through the reflection upon the implementation. Key is that implementation is included in the definition of adoption, and not a separate process that should follow suit after an adoption (initiation) process is completed.

Industry 4.0

The first industrial revolution entailed the use of mechanical production methods aided by steam, and during the second industrial revolution mass production was established due to the availability of electrical energy. The third industrial revolution is closer to modern times and encompassed the first use of computers and information systems to guide manufacturing processes. Industry 4.0, or the fourth industrial revolution, consequently, follows this development and takes the integration of computers and information systems to a new level. The term "Industry 4.0" was first used in Germany in 2011, at the Hannover Fair, where it was meant as a strategic initiative to revolutionize manufacturing industries (Li, 2018; Raj et al., 2020; Xu et al., 2018). The intention behind the term was to instigate a paradigm shift in manufacturing that went far beyond a simple advancement. New technologies would be used to change the industry in every facet, as the implementation of more advanced computer guided systems would change the organization from digitization processes (Li, 2018), through employment relationships (Hüther, 2016; Kovacs, 2018; Vacek, 2017). It symbolized the fourth industrial revolution, hence Industry 4.0 (Xu et al., 2018).

The awareness of the conception of Industry 4.0 was not exclusive to German academics though. Industry 4.0 was coined in China as "Made-in-China 2025" (Li, 2018) in the same time period, which intends to accomplish the same, by revolutionizing manufacturing processes with information technology (IT) and CPS. Other terms identifying Industry 4.0 are; *smart factory*, *smart manufacturing*, and *smart industry*. These terms focus on the application of Industry 4.0 in manufacturing practice, and comprise the concept of a decentralized production system, in which humans, machines and other assets communicate with each other over an information network supported by CPS (Kagermann et al., 2013; Kamble et al., 2018). These terms are part of Industry 4.0 but focus on different levels of segregation on which Industry 4.0 has an impact. The terms represent the 'crux' of Industry 4.0 and jointly define it. The term thus revolves around the emergence of the digitization and computerization of all areas of production (Kamble et al., 2018; Schröder, 2017). This is the adopted definition for Industry 4.0, as it represents the area of impact of the fourth industrial revolution. Furthermore, *Industrial Internet*, *the Internet of (Every) Thing*, and *the Big Shift*, are all terms that represent Industry 4.0, and embody the previous definition (Vuksanović Herceg et al., 2020). These are focused on the technological capabilities of the developments and innovations. Technologies included are those as the Industrial

Internet of Things (IIoT), which integrates the possibilities of the internet into the value creation at firm level (Lin et al., 2019; Müller et al., 2018), and CPS that combine virtual and physical realities to create synergistic infrastructures and advantages (Lolli et al., 2019). Furthermore, cloud-based manufacturing and the use of big data are upcoming technologies in Industry 4.0 and are often compiled under *The Big Shift*.

Future of Industry 4.0

The future and impact of Industry 4.0 have not fully been established. Like any other technological advancement, Industry 4.0 comes with a certain set of challenges, both when it comes to the adoption of technologies which fall under the umbrella concept, and with further research on the topic. Before Industry 4.0 can become the widespread standard in manufacturing around the world, challenges such as preparing IT infrastructures (e.g. bandwidth capacity) around the world, scalability of expensive technologies, and inefficiencies in the analysis of large amounts of (personal) data, need to be addressed and solved (Xu et al., 2018). Although these issues do not currently pose challenges to the adoption of Industry 4.0 technologies for manufacturing firms around the world, they do inhibit the development of better, more effective and efficient systems. To overcome the issues, standardization and uniformity in technology needs to be pursued, next to better information security and privacy protection (Xu et al., 2018). To accomplish this, research trends to further Industry 4.0 mainly focus on a selective set of issues. One of which is creating integration processes for heterogeneous CPS tools and methods, which will help increase the uniformity in Industry 4.0 technologies (Zhou et al., 2015). Another important research direction is the potential of blockchain technology in manufacturing, which can be used for data resilience, scalability and using blockchain to timestamp sensor data to increase the security of autonomous CPS (Joshi, 2017). Industry 4.0 will increase in overall quality of solutions over time, with the essence of Industry 4.0 being achieved through interdisciplinary integration and collaboration, to embrace the cutting edge technology and techniques that prepare organizations for the manufacturing requirements for decades to come (Xu et al., 2018).

Barriers to Adopting Industry 4.0

Research into the barriers and challenges of adopting Industry 4.0 technology is becoming more widespread and popular now that the advantages and transformative potential is starting to become clear for practitioners and academics alike (Hofmann & Rüsch, 2017). However, compared to the advantages of Industry 4.0 technology, few researchers have conducted scientific research on specific barriers (Raj et al., 2020). Prominent contemporary studies on Industry 4.0 barriers related to the labor characteristics of a firm examine different firms, contexts, economies, and countries. The main reasons for uncertainties lie in the high investment levels required to adopt and use the technologies, and the unclear cost-benefit structure of most of the technologies (Kamble et al., 2018). It is simply hard to assess what precisely the financial impact will be of implementing a new technology, and especially the rewards to be expected. Aside from financial and technological challenges however, social barriers are one of the major factors inhibiting the adoption of certain technologies (Geissbauer et al., 2014). Social barriers are those that include the organizational culture, the type of management in a firm, and employees. An example includes the lack of a sufficiently open organizational culture that would help foster change among employees. The employee and HR factors are of special interest in this study and form the research objective when it comes to confirming the presence of such barriers in the Dutch manufacturing industry.

Some additional noteworthy barriers identified by research include legal and contractual uncertainty derived from issues with data protection (Christians & Liepin, 2017). Depending on the national and legislative context of firms attempting to adopt certain technologies, these contexts can be detrimental to that effort. This is an example of a barrier external to an organization and is not in the direct sphere of influence of it. This is valid for most security and privacy issues, as manufacturing firms often lack the power and knowhow to influence the developers of novel technologies towards more sustainable data practices (Kamble et al., 2018). A lack of standardization and uniformity in technologies does not help in this regard, as it complicates the adoption of both sustainable technologies data-wise, and technologies that seamlessly function complementary without the need for additional resource commitment (Mueller et al., 2017; Xu et al., 2018).

Role of HR in Technology Adoption and Industry 4.0

Industry 4.0 is not entirely new to the field of human resource management (HRM), and HRM departments in companies around the world have a significant part to play in the transition towards more digitalized work. Initially, HR should seek to provide employees with training in data-skills and create a data driven work culture (Rana & Sharma, 2019), but this is not all. Research has shown that different HR and management styles will need to be developed to cope with the changing nature of work. In fact, HR can be a positive force in developing an organization towards being nimble and able to adopt new technologies by designing HR practices accordingly (Shamim et al., 2016, p. 5312). The inverse, however, also occurs and HR practices can be great inhibitors of innovation and organizational technology adoption (Geissbauer et al., 2014), as researched here.

There are five specific areas in which HR can make a difference in organizations wanting to adopt more novel technologies: (1) Training, (2) Staffing, (3) Compensation, (4) Performance Appraisal, and (5) Job Design (Shamim et al., 2016). Two of these areas are central to this research and are later used in hypothesis development: training and staffing. Employee training should mostly be focused on the development of skills that complement the current job of an employee and develop them into skills not necessarily relevant to their current job (Chang et al., 2011; Shamim et al., 2016). Multidisciplinary competences and a larger variety of skills are key here. Staffing relates to the hiring of new employees and the distribution of labor within an organization. Staffing needs of the future should be strongly focused on finding employees that fit the attributes, characteristics and competences that organizations would like to possess (Shamim et al., 2016). An employee with a learning orientation should herein be preferred over one without a learning orientation. There are suggestions in literature (Haddud et al., 2017; Lorenz et al., 2015; Raj et al., 2020; Schwab, 2017) that hiring new employees should mostly be done for jobs in R&D and IT positions, or other theoretical jobs. This is because shift is expected to happen from low skills/low pay jobs towards high skills/high pay job. This shift is not only an outcome of the transition to Industry 4.0 technologies, but to a certain extent also a prerequisite, as most skills and competences required are captured within what are currently known as high skilled jobs.

Evidently, training and staffing of employees, and more generally the role that HR can play in the ability of firms to adopt novel technologies, greatly depends on a firm's self-knowledge and their ability to understand the competences required. Firms can no longer solely rely on technology to create competitive advantages but require the added value of people able to leverage these technologies. Herein, employees are shifting towards becoming long-term success factors (Meyer et al., 2015). Through this development, an increased focus on employees their competences exist within firms (Sengupta et al., 2013). Competences are the combination of attributes, abilities, skills, and knowledge, that help an individual in performing some type of task, either in life or a work related role (Flores et al., 2020; Meyer et al., 2015). Leveraging employee competences is becoming more relevant for management of organizations, but this, however, comes with certain challenges. One of these challenges includes identifying which competences are important for the transition towards new technologies, next to the tracking and recording of (current) worker competences (Meyer et al., 2015).

For HR departments to successfully face change it is vital to understand that Industry 4.0 poses disruptive challenges at many different levels of organizations, governments and even at a human scale. For employees of organizations that choose to adopt Industry 4.0 technologies, different expectations are brought onto the work floor. It will be necessary to 'upgrade' the employees in technical, psychological and social aspects to meet the changes and complexities of Industry 4.0 (Flores et al., 2020, p. 698). Human Capital 4.0 is thereby proposed as a term that explains and guides the change that Industry 4.0 brings from a human side. Prerequisite elements herein are the need to be highly adaptable, resourceful, resilient and able to work in interdisciplinary positions (Flores et al., 2020, p. 698). The notion of Human Capital 4.0 is a construct that HR departments may use to further their organizations through the training of employees. Other terms coined by research include 'Smart-HRM', which also proposes that organizations align their HR practices with the ever changing field of technology (Verma et al., 2020), and thus adopt similar practices seen in the innovation of technology: making employees more malleable, versatile and adaptable. Research cannot stress enough that HR departments will make all the difference in the future of employees, as work will be radically overhauled by Industry 4.0 (Flores et al., 2020; Verma et al., 2020).

Hypotheses Formulation

To determine the relevant barriers to the adoption of Industry 4.0 technologies the literature described was used and expanded upon. Additionally, a review was performed of relevant articles that considered barriers to the adoption of Industry 4.0 technologies in general (e.g. Kamble et al., 2018; Raj et al., 2020), and articles focusing more specifically on HR factors that form barriers to adoption of technologies (Breunig et al., 2016; Hung, 2016; Hüther, 2016). Therefrom, four categories were derived: employee competency recording, employee training, employee education, and distribution of labor. These barriers are discussed in the following paragraphs after which the accompanying hypothesis is formulated. Additionally, the hypotheses are displayed in Table 1, and the resulting conceptual model in Figure 1.

Employee Competences

In the adoption of Industry 4.0, employees are key. Specifically, those with the required knowledge and skills to usefully leverage the technologies introduced by Industry 4.0 (Hung, 2016; Raj et al., 2020). However, many firms are aware of their lack of necessary expertise and skills to use new technologies (Breunig et al., 2016), and thus understand that they need to invest in training and competence management to ultimately further their competitive advantage and avoid stagnation due to a resistant culture (Lee & Lee, 2015; Schröder, 2017). Moreover, one of the major inhibitors of realizing Industry 4.0, is having many under-qualified employees, or not being aware of the qualifications of employees (Geissbauer et al., 2014). Competence recording therefore plays a vital role in the training of employees, and furthering Industry 4.0 technology adoption. And thus, as follows, the following hypothesis is formulated on employee competences recording:

> H1: *The non-awareness of worker competences inhibits the adoption of Industry 4.0 technologies.*

Employee Training

Being aware of worker competences is only a first step in being able to adopt Industry 4.0 technologies, as possible discrepancies in competences, skills and expertise also need to be mediated. It is vitally important for firms to keep ‘updating’ their workforce on what new developments are out there, and what the firm could profit from (Breunig et al., 2016). Thus, firms need to train their employees and keep them up to date with current developments in their field. If they fail to do so, the adoption and effective use of Industry 4.0 technologies becomes significantly more challenging (Breunig et al., 2016). Moreover, in an organizations in which employee training is not standardized, an organizational culture can foster that is naturally resistant to change, making implementing new technologies even more challenging (Haddud et al., 2017). And thus, as follows, the following hypotheses are formulated on employee training:

H2a: *A lack of training programs for production personnel inhibits the adoption of Industry 4.0 technologies.*

H2b: *A lack of pre-determined annually recurring days for training or development inhibits the adoption of Industry 4.0 technologies.*

Employee Education

Tension in the labor market is unavoidable with the uprising of Industry 4.0 (Raj et al., 2020). This is partially due to the shift in the type of work needed, from practical towards theoretical work. In the context of the Dutch manufacturing industry this means a shift from production and assembly towards data management and controlling. The consequent effect of this could be either positive or negative, dependent on the a-priori perspective. However, it will segregate the market into categories of low skills/low pay and high skills/high pay (Schwab, 2017). Inequality and social tension are in that regard an unavoidable consequence of Industry 4.0, and are considered one of the dark corners of Industry 4.0 (Kovacs, 2018). To a certain extent, the adoption of Industry 4.0 technologies therefore relies on workers being able to transition towards more theoretical jobs, requiring more than basic and practical education. And thus, as follows, the following hypothesis is formulated on the employee education level:

H3: *A workforce with a larger reliance on practical education inhibits the adoption of Industry 4.0 technologies.*

Employee Distribution of Labor

On the other side of an increase in inequality and social tension, however, findings suggest that technologies of Industry 4.0 will eventually help people remain and return to the workforce, albeit in different positions and less so in the assembly and production oriented fields (Haddud et al., 2017; Lorenz et al., 2015). Effectively, a transition towards Industry 4.0 technologies requires significantly different skills than manufacturing firms traditionally possess, theoretical and IT related skills are at the core of this, putting practically educated workers at a distinct disadvantage (Lorenz et al., 2015; Ryan & Watson, 2017; Schwab, 2017). Moreover, to foster an organizational culture that is both open for innovation, and able to work with innovations, requires people within the organization to be attentive of external developments. This is mostly achieved through R&D and IT positions. As follows, the following hypothesis is formulated on the organizational distribution of labor:

H4: *Fewer employees in R&D positions inhibit the adoption of Industry 4.0 technologies.*

H#	Topic	Hypothesis
H1	Competences	The non-awareness of worker competences inhibits the adoption of Industry 4.0 technologies.
H2a	Training	A lack of training programs for production personnel inhibits the adoption of Industry 4.0 technologies.
H2b	Training	A lack of pre-determined annually recurring days for training or development inhibits the adoption of Industry 4.0 technologies.
H3	Education	A workforce with a larger reliance on practical education inhibits the adoption of Industry 4.0 technologies.
H4	Distribution of Labor	Fewer employees in R&D positions inhibit the adoption of Industry 4.0 technologies.

Table 1. Hypotheses Overview

HR Factors		
Competences Training Education Distribution of Labor	——>	Barriers in adoption of Industry 4.0 technologies

Figure 1. Conceptual Model

3. Research Method

In this chapter, methodological choices and considerations are outlined and elaborated upon. The used and applied methods are explained, and the data collection and analysis strategy justified. The European Manufacturing Survey (EMS) played a central role within this research. It comprised the primary data source, and all analysis was carried out with data extracted therefrom. The formulated hypotheses are matched with measures to perform statistical tests.

The research in this thesis was of quantitative deductive nature and followed a nomothetic approach to knowledge creation. The deductive approach was derived from establishing literary significant barriers related to HR factors in the previous chapter. A quantitative method was used to analyze and use the data. The objective was confirming or refuting a series of hypotheses, which had already been established from literature and assessed in different (geographical) contexts. Although a qualitative approach would have been valuable when identifying wholly new barriers, the confirmatory instead of exploratory nature of the research implied that the research purpose was not to seek new barriers through HR factors in firms, but to confirm pre-specified ones.

The EMS is carried out biennially and is answered by a varying sample of the whole Dutch manufacturing industry. The EMS database contains data on different categories of variables of Dutch manufacturing industry firms. A subset of variables was used to carry out the research, specifically those related to HR factors. In this research, the choice was made to use pre-collected data because of the fit and the sample size. Firstly, the fit of the data was appropriate to the goal of the research as Dutch manufacturing firms are addressed. Moreover, the necessary data to test the hypotheses was found in the EMS database. This includes, labor distribution, education and training of employees, and the adoption of Industry 4.0 technologies. Collecting new empirical data would therefore have been redundant to the research purpose. Secondly, the sample size of the EMS posed an advantage to the validity of the research, and thus aided in generating more valuable results and practical implications. The sample size would have been challenging to replicate provided the timespan of the research, and this option was therefore deemed unrealistic.

Sample

The units of analysis were the firms within the Dutch manufacturing industry. These firms included manufacturers of (raw-)metals, wood, furniture, food, and more. The Dutch Central Bureau for the Statistics (CBS) categorizes these firms as category C: *Industry* (firm-code 10 through 33, SBI 2008). Collectively, these firms encompass the Dutch manufacturing industry. In 2015, the Netherlands possessed more than 7.000 firms that were active in a dimension of the manufacturing industry, and employed more than 10 persons (Centraal Bureau voor de Statistiek, 2021). The EMS survey of 2015 determined a population of 8195, which represented the manufacturing firms falling into the aforementioned categories, the firms that were economically active, and had an employee count of 10 or higher. From this population, 6146 firms were successfully addressed by a letter, and consequently two reminders. The total response rate to the EMS was 5%, making 178 response cases. The EMS database sample was deemed representative to the population it represented by the original researchers who constructed the survey. The representativeness was therefore assumed as the populations of the EMS and this research were identical.

A missing value analysis was performed, as described later, which somewhat reduced the sample size, but greatly increased the validity of the sample towards the research purpose. The total valid sample size was 156 cases, which were used for further analysis. The sample represented a variety of industries, within which different firms were active in many different sub-industries. The metal and machinery industry were the most represented industries in the sample, accounting for 19.2% of the cases. Next was the electronic industry with 17.9% of the cases. The textile and chemical industry both accounted for 12.8%, whereafter the food industry measured 10.3%. The smallest industry represented in the sample was the construction industry with 7.7%.

Questionnaire

The EMS contained a broad spectrum of questions for the intended population, ranging from financial data through ownership structure, to technology use. For this research, only specific data was relevant, and a (data) subset of the EMS was used. In the paragraphs below and Table 2, these specific measures and accompanying EMS variables are described. The questions for these variables can be found in Appendix A. As the EMS targets the Dutch manufacturing industry, the survey itself is entirely in Dutch. The questions and variables, however, were translated and throughout the research specific measures, variables, or items stemming from the EMS are all referred to in English.

Measures

Two categories of measures were used in this research. First, the *main variables*, which were those directly connected to the testing of the specified hypotheses. Secondly, the *control variables*, which served as descriptive variables of the sample. All measures are found in Table 2, which also lists the variable that is used in statistical tests. The variables accompanying their respective measures are underscored, such as <u>Policy for Training</u>. Some variables are directly sourced from the EMS, while others use different items from the EMS to be computed. When different items were used to compute one variable, the items are italicized: for example: *Technical Qualifications*. Further, a column was added that indicated the specific variable or item name from the EMS in the statistical processing software. The EMS variables were named similar to the constructed variables but have a ‘v’ added in front of them, such as: v_Policy_Training. The EMS items were listed with their EMS question number displayed, such as: *i15.1_2*. Throughout the following paragraphs, the measures were constructed and explicated. These measures comprise the information presented in Table 2, but specifically describe data alterations made, or differences in computing as opposed to the recording done through the survey in Appendix A. Through the column EMS Question in Table 2, the variables in Table 2 can be derived back to the questions in Appendix A.

<table>
<tr><th></th><th>Measure</th><th>Variable</th><th>EMS Name</th><th>EMS Question</th><th>Measurement</th><th>Response Categories</th><th>Literature / Comment</th></tr>
<tr><td rowspan="29">Main Variables</td><td rowspan="4">Competences</td><td><u>Competence Recording</u></td><td>v_Competence_Recording</td><td></td><td>Ratio</td><td>Open</td><td>Computed as sum of i4.1 items.</td></tr>
<tr><td>Systematic Competence Recording</td><td>i4.1_1</td><td rowspan="3">4.1</td><td rowspan="3">Nominal</td><td rowspan="3">Yes / No</td><td rowspan="3">Breunig et al., 2016; Geissbauer et al., 2014; Hung, 2016; Lee & Lee, 2015; Raj et al., 2020; Schröder, 2017.</td></tr>
<tr><td>Job Specification Development</td><td>i4.1_2</td></tr>
<tr><td>Competence Programs Presence</td><td>i4.1_3</td></tr>
<tr><td rowspan="2">Training</td><td><u>Policy for Training</u></td><td>v_Training_Policy / i4.3_1</td><td>4.3</td><td rowspan="2">Nominal</td><td rowspan="2">Yes / No</td><td rowspan="2">Breunig et al., 2016; Geissbauer et al., 2014; Haddud et al., 2017; Hung, 2016; Raj et al., 2020.</td></tr>
<tr><td><u>Pre-determined Days for Training</u></td><td>v_Days_for_Training / i5.1_1</td><td>5.1</td></tr>
<tr><td rowspan="4">Education Level</td><td><u>Practical Education</u></td><td>v_Practical_Education</td><td></td><td rowspan="4">Ratio</td><td rowspan="4">Open</td><td>Computed as sum of i15.1 items.</td></tr>
<tr><td>Technical Qualification</td><td>i15.1_2</td><td rowspan="3">15.1</td><td rowspan="3">Breunig et al., 2016; Hung, 2016; Kovacs, 2018; McKinsey Digital, 2016; Raj et al., 2020; Schwab, 2017.</td></tr>
<tr><td>Commercial Technical Qualification</td><td>i15.1_3</td></tr>
<tr><td>Semiskilled and Unskilled</td><td>i15.1_4</td></tr>
<tr><td rowspan="5">Distribution of Labor</td><td><u>Non-R&D Jobs</u></td><td>v_Non_RnD</td><td></td><td rowspan="5">Ratio</td><td rowspan="5">Open</td><td>Computed as sum of i15.2 items.</td></tr>
<tr><td>Ideation and Design</td><td>i15.2_2</td><td rowspan="4">15.2</td><td rowspan="4">Buer et al., 2018; Haddud et al., 2017; Kamble et al., 2018; Lorenz et al., 2015; Raj et al., 2020; Ryan & Watson, 2017; Schwab, 2017.</td></tr>
<tr><td>Fabrication and Assembly</td><td>i15.2_3</td></tr>
<tr><td>Customer Care</td><td>i15.2_4</td></tr>
<tr><td>Other</td><td>i15.2_5</td></tr>
<tr><td rowspan="7">Adoption of Technologies</td><td><u>Number of Technologies Adopted</u></td><td>v_Adopted_Technologies</td><td></td><td>Ratio</td><td>Open</td><td>Computed as sum of i8 items.</td></tr>
<tr><td>Additive Manufacturing for Prototyping</td><td>i8_1</td><td rowspan="6">8.1</td><td rowspan="6">Nominal</td><td rowspan="6">Yes / No</td><td rowspan="6">In accordance with Helmond et al., 2018.</td></tr>
<tr><td>Production with Additive Techniques</td><td>i8_2</td></tr>
<tr><td>Multi Agent Systems</td><td>i8_3</td></tr>
<tr><td>CPS</td><td>i8_4</td></tr>
<tr><td>Digital Production Planning</td><td>i8_5</td></tr>
<tr><td>Real-time Production Control System</td><td>i8_6</td></tr>
</table>

		Production Planning Information Exchange	*i8_7*				
		Automated Management Internal Logistics	*i8_8*				
		Mobile Devices	*i8_9*				
		PLM	*i8_10*				
		Safe Human-Machine Interaction	*i8_11*				
		Digital Solutions for Drawings and Schemes	*i8_12*				
Control Variables		Metal Industry	v_Metal	1.2	Ratio	Open	
		Food Industry	v_Food				
		Textile Industry	v_Textile				
		Construction Industry	v_Construction				
		Chemical Industry	v_Chemical				
		Machinery Industry	v_Machinery				
		Electronics Industry	v_Electronic				
		Turnover	v_Turnover / *i21.1*	21			
		COGS	v_COGS / *i21.3*				
		Investments	v_Investment / *i21.4*				

Table 2. *Measures Table*

Adoption of Technologies

The dependent variable was the adoption of Industry 4.0 technologies, which in the hypotheses was formulated as the inability to adopt these technologies. Within the confounds of the EMS, and the literature discussed, twelve specific technologies were identified as constituting 'Industry 4.0 technologies'. In Table 2, these technologies are listed under the appropriate measure and have been italicized. Within EMS question 8.1, multiple aspects of these technologies were measured next to their adoption. This included whether there were plans to adopt the technology if not currently adopted, and an estimation of the potential of the technology to be impactful. Within this research, however, only the adoption / non-adoption data is used, as further data on adoption intention and potential impact were outside of the scope. Adoption of technologies was therefore operationalized as an outcome rather than a process. In operationalization, the specific technologies were used collectively, and an encompassing variable computed, summing the individual adoptions / non-adoptions of technologies into one ratio variable with answer categories between 0, not having adopted a single Industry 4.0 technology, and 12, having adopted all Industry 4.0 technologies. This changed the measurement level of the data, to allow for more types of analysis. The computed independent variable is therefore: v_Adopted_Technologies, as found in Table 2.

Competences

The hypothesis encompassing competences argued for the inability to adopt Industry 4.0 technologies when competences were not recorded and tracked. The EMS measured this through three different items, whether systematic competency recording occurs, whether job specifications are developed, and whether competence programs exist for the personnel file. These three items defined the operationalized measure competences, and specifically applied to the production personnel. The items were measured as nominal variables with simple yes / no response categories. In operationalization, the three items were computed into one variable, v_Competence_Recording. In the hypothesis, however, the measure intended to measure the lack of competence recording in a firm, instead of the level of competence recording. Therefore, the data from the items from question 4.1 from the EMS was reversed, so that 'No' became the reference category, represented by a score of 1. Afterwards, the three items were summated, and thus represent a score between 0 and 3, indicating the lack of competence recording that occurs at a firm. Herein, 0 indicated no lack whatsoever, and 3 indicates a full lack i.e., no competence recording occurred.

Training

Two hypotheses were formulated for training of employees. These hypotheses were similar in their assumption of training and development of personnel as a necessary activity for the adoption of Industry 4.0 technologies. The first hypothesis (H2a) solely dealt with whether training activities existed and were carried out, while the second hypothesis (H2b) specified whether pre-allocated days for personnel training and development were set in the firm. In the EMS, these hypotheses were operationalized through one variable each. First, hypothesis 2a, was measured through a nominal variable prompting whether policy is present for the training of personnel with a response category of yes / no. This variable was measured in the EMS through question 4.3. Second, hypothesis 2b, was measured through a nominal variable prompting whether a pre-allocated number of days is set for training and development of personnel, with a response category of yes / no. This variable was measured through EMS question 5.1. In operationalization, the constructed variables became v_Training_Policy, and v_Days_for_Training. As in the operationalization of the competences measure, the scores of the questions were reversed in computation to match the polarity of the hypothesis. Therefore, 'No' became the reference category, representing a score of 1. The variables therefore measured whether a lack in training policy, or a lack of annually pre-determined days for training was present in firms.

Education

A paradoxical aspect of Industry 4.0 technologies is that it requires highly skilled workers to leverage the advantages in efficiency, in an industry traditionally reliant on low skilled laborers specialized in practical functions. Hypothesis 3 encompassed this through presuming a firm largely reliant on a practically educated workforce will struggle with adopting Industry 4.0 technologies. The key measure here was thus the education level of the workforce of a manufacturing firm. Through EMS question 15.1, the distribution of education levels was measured. These education levels ranged from highly educated to apprenticeship workers. To operationalize the intended measure, practical education needed to be represented. Therefore, of the education variables in the EMS, three were summed in operationalization to represent a 'practical education level'. These were (1) semi and unskilled laborers, (2) laborers with a technical qualification, and (3) laborers with a commercial technical qualification. The operationalized variable, v_Practical_Education, is therefore computed as the sum of the three education levels and could theoretically represent a score between 0 and 100, with 0 being no practically educated laborers in the firm, and 100 being solely practically educated laborers in the firm.

Distribution of Labor

The fourth hypothesis dealt with the disturbance of current labor distributions, and the transition in distribution towards R&D jobs both consequent to and a prerequisite for Industry 4.0 technology adoption. The relevant measure to this hypothesis, distribution of labor, was measured through EMS question 15.2 similarly to the measure of *Education*. Different variables were present indicating the prevalence of employees in specific job areas. These job areas were represented through items ranging from R&D through assembly work to customer care. To operationalize the measure, fewer employees in R&D needed to be measured. Therefore, all non-R&D items were summed into variable v_Non_RnD, which can effectively measure the effect of having fewer employees in R&D positions, as the EMS requires the total distribution of labor to be 100%. Table 2 specifies the items used in the non-R&D variable.

Control Variables

Firstly, the industry that a firm was active in was determined through question 1.2 in the EMS. The responses to this were categorized according to the Dutch categorization of industries. Afterwards, the results of this were used to construct several dummy variables for each industry segment. Therefore, the control variables, v_Metal, v_Food, v_Textile, v_Construction, v_Chemical, v_Machinery, and v_Electronic, all represent their industry with v_Metal being the reference category and thus being excluded in statistical analyses. These control variables were selected to be present in the data analysis, as the type of industry could theoretically make a difference in the adoption of technologies. Especially technologies like additive manufacturing could reasonably be assumed to be more present in the construction industry than in the food industry, which makes having the different industries represented through dummy variables important for the quality of the statistical tests.

Three additional control variables were enlisted based on their theoretical applicability to the research. As presented in Table 2, the turnover, costs of goods sold (COGS), and investments in new machinery, were selected as control variables. The turnover and cost of goods sold variables were included to establish the size of the organization and consider whether this size had an impact on the adoption of technologies. The investment in new machinery variable was included as it contains information of spending on machinery in a firm, which could potentially indicate a spending towards technologically innovative machinery. These latter control variables were derived from EMS question 21 and can therefore be found in the survey in Appendix A.

Missing Value Analysis

After having determined the measures, variables, and items that were to be used in analysis, a missing value analysis was carried out to determine the number of valid cases per variable, which allowed for a cleaner and more rigorous statistical tests. Frequency tables were used to visually inspect missing values, after which a missing value analysis (MVA) was performed. This was solely done with the items that were later used or constructed into the variables as discussed above and outlined in Table 2. The objective of the MVA was to determine the missing values, and whether the missing value were at random (MAR) or completely at random (MCAR).

Table 3 displays all items used to construct the variables in Table2 and shows the missing values per item. The MVA showed several noteworthy missing cases. Two items used for the construction of control variables stood out. This were i21.3 and i21.4, which were used to construct variables COGS and Investment respectively. These two items showed a missing count far exceeding a somewhat acceptable threshold of around 10%. Additionally, item i21.1, which was used to construct the variable Turnover, yielded a missing value around 10%. A full output of the performed MVA is found in Appendix B.

Variable	**N**	**Missing #**	**Missing %**
i4.1_1	178	0	.0
i4.1_2	178	0	.0
i4.1_3	178	0	.0
i4.3_1	178	0	.0
i5.1_1	178	0	.0
i8_1	178	0	.0
i8_2	178	0	.0
i8_3	178	0	.0
i8_4	178	0	.0
i8_5	178	0	.0
i8_6	178	0	.0
i8_7	178	0	.0
i8_8	178	0	.0
i8_9	178	0	.0
i8_10	178	0	.0
i8_11	178	0	.0
i8_12	178	0	.0
i15.1_1	178	0	.0
i15.1_2	178	0	.0
i15.1_3	178	0	.0
i15.1_4	178	0	.0
i15.1_5	178	0	.0
i15.2_1	178	0	.0
i15.2_2	178	0	.0
i15.2_3	178	0	.0
i15.2_4	177	1	.6
i15.2_5	178	0	.0
i21.1	157	21	11.8
i21.3	121	57	32.0
i21.4	130	48	27.0

Table 3. *Missing Values*

To remedy the three variables that showed many missing cases, two separate decisions were made. The variables COGS and Investment were deemed to be too missing-prone and excluded from further analysis. This was deemed to be the most appropriate decision as the validity and potential for variance explanation further statistical tests would increase. Although the variables COGS, Investment were determined to be MCAR, it was clear that they did pose significant alterations to the means of other variables when in- or excluded, almost pattern-like. A remedy through case wise exclusion was therefore refrained from, as a certain quality, and large quantity, would be lost in the recorded sample.

However, the missing values that were recorded for the variable Turnover were deemed to be acceptable and fit for remedy through case wise deletion. Therefore, after applying the remedies, a total of 21 cases were excluded, bringing the total responses from 178 to a total of valid responses to 156.

Construct Validity

Before a data analysis method was applied, and statistical tests were carried out, the constructed measures were tested on construct reliability and validity through a reliability analysis. The measure tested was *Competences*. The measures *Education*, and *Distribution of Labor*, were not tested due to theoretical considerations. These measures were operationalized through the computation and summation of different items representing different categories and factors. It would be redundant to test these through reliability analysis as there is no theoretical justification for the variance between education levels or the distribution of labor to be similar. However, computed as one construct they do function properly, as they do represent an overarching, immeasurable construct, practical education or non-R&D jobs.

Table 4 represents the reliability test performed on the construct *Competences*, which yielded an acceptable Cronbach's Alpha, and did not allow for further improvement through item deletion.

Construct / Variable	**Original Items**	**Cronbach's Alpha**	**Items Deleted**	**Cronbach's Alpha**
Competences	3	.712	0	-

Table 4. *Construct Reliability Analysis*

Data Analysis Method

The data analysis method chosen was multiple regression analysis (MRA). MRA lends itself towards two specific purposes: prediction, and explanation. Prediction with MRA is focused on the regression coefficients (including their magnitude, polarity, and statistical significance) for each independent variable and attempts to develop a theoretical explanation for the effects of the independent variables (Hair et al., 2019, p. 273). These purposes are not mutually exclusive however, and both could be addressed and achieved. Within regression analysis, a relationship between independent variable(s) and a dependent variable is estimated, in the context of this research the dependent variable was the *Adoption of Technology*, while the independent variables were encompassed by the measures *Competences*, *Training*, *Education*, and *Distribution of Labor*. Due to the formulated hypotheses, and the operationalization of the methods, a directional MRA was performed, which means that a one-tailed significance test was carried out with an alpha level of 5%. Therefore, as explained in the result section, the interpretation of significance changed from regular MRA to directional MRA.

Justification & Alternative Strategies

The first reason why MRA was chosen as the analysis method was because of the purpose that MRA lends itself towards. As aforementioned, explanation through focusing on regression coefficients for each independent variable to develop a theoretical explanation for the effect, is one of these purposes. This purpose matched well with the overall purpose of the study as described in the introduction, namely (1) confirming which HR barriers were present among Dutch manufacturing firms, and (2) developing explanations for the barriers and recommendations as to how they can be broken. This was in line with the range of achievable results of MRA with an explanatory purpose. Another valuable feature of MRA was that the relative importance of independent variables can be assessed, unlike in univariate measures (Hair et al., 2019, p. 274). A measure of relative variable importance allowed for practical insight into which independent variables, and thus which hypotheses, were of greater importance in the (inhibition of) adoption of Industry 4.0 technologies. Finally, MRA allowed for the transformation of non-metric variables, which was important due to the nominal character of some relevant measures.

Different analysis methods were considered, but ultimately rejected. Logistical regression could have been a suitable method as it is somewhat more suitable in dealing with nominal variables. However, the dependent variables should be a nominal, dichotomous, variable. A dichotomous dependent variable would in this case mean that the 'Adoption of Technology' measure was computed into two categories: adoption of technology, and non-adoption of technology. Theoretically this could have been achieved, but a significant issue arises when an adopter and a non-adopter should be defined within the confound of the measure. It would have had to rely on an arbitrary split-off point, or one through a mean split. In all scenarios this would have meant that the generalizability and reliability of the results would have suffered, as the general replicability would have been dependent upon the similarity of datasets. Another issue was the purpose of Logistical regression, as logistical regression attempts to establish the likelihood of the dependent variable in the event of the independent variable. This meant that the result would not be able to tell the relative impact of independent variables through the regression coefficients, significantly straying from the intention of the research purpose.

Discriminant analysis was also considered as analysis method, but a similar issue surfaced where the dependent variable had to be dichotomous. This analysis technique could have been possible through identifying the '*Industry4.0-ness'* of technologies and consequently, somewhat arbitrarily form dichotomies of strong adopters, and non or weak adopters. However, similarly to logistical regression, the purpose of the research would not have fully been achieved, as it would not have been able to measure the relevant importance of independent variables towards the effect on the dependent variable. Therefore, the MRA method was deemed the best fit to the research purpose and was chosen as the data analysis method.

Assumption Tests for Linear Regression Analysis

To assure MRA was a fit analysis technique, multiple prerequisites and assumption tests were performed. The first requirement to be met was that of general method-research fit. As aforementioned, explanation of relationships through MRA can be a purpose of the method, and thus was deemed to fit well with the general purpose of the research. An important prerequisite for MRA is the measurement level of the independent variables and the dependent variable, both should be of either interval of ratio measurement level, and thus of continuous or metric nature. To incorporate non-metric data in the MRA method, however, dummy variables can be used, and were used in this research. A final general prerequisite was an adequate sample size, where 50 would be the minimum sample size, and 100 the preferable one (Hair et al., 2019, p. 280). A total valid response of 156 was recorded and used in the analysis and was thus satisfactory for this requirement. Additionally, the preferable observation to independent variable ratio should be as high as possible and at least above 5:1 (Hair et al., 2019, p. 279). In this case solely accounting for the main variables, the ratio was 31:1, which is well within the desired level. Accounting for the main variables and control variables the ratio was 13:1, which is similarly acceptable.

The assumptions that had to be examined were four distinct areas: (1) linearity of the phenomenon measured, (2) constant variance of the error terms, (3) normality of the error term distribution, and (4) independence of the error terms. To test the assumptions, the statistical output of the MRA performed and explained in Chapter 4 were examined.

Linearity

First, the linearity of the relationship between the dependent and independent variables represents the degree to which a shift in the dependent variable is explained by the independent variable. The regression coefficient should therefore be true across the range of values of the independent variable. To examine whether the variables conformed to this linearity, a residual scatterplot was formed. Within the scatterplot no clear sign of a break of linearity was present (see Figure 2), which would be indicated by curving or rainbow-like patterns in the residuals plot. One outlier was determined that scored different than other residuals. However, upon investigation of the connected case, no reason was found to remove or exclude the case. This case had a much larger than average number of turnover, which is possible and also occurs within the natural variation of population of Dutch firms in the manufacturing industry with organizations such as Philips or ASML being much larger than most. Moreover, it increases the variability of the data and thus reduces the chance of Type 1 (Alpha) error (Frost, 2019).

Homoscedasticity

Second, the assumption of constant variance of error terms, also known as homoscedasticity. This serves to assure that all error terms are constant across the range of the independent variables. Similarly to the linearity assumption, this assumption was tested using a residual scatterplot. Within Figure 2 no cone-shaping, or other obvious pattern is present to assume heteroscedasticity, and therefore the assumption is met, and homoscedasticity assumed.

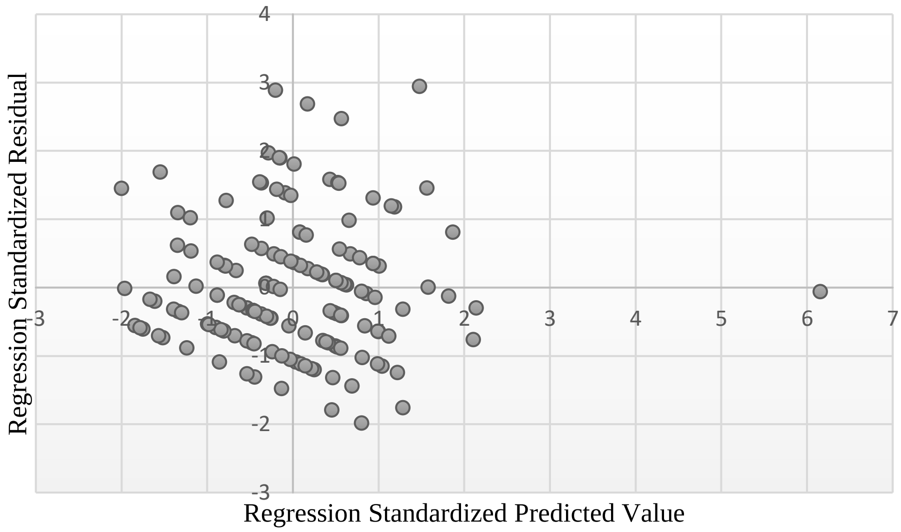


Figure 2. *Residuals Scatter Plot*

Multivariate Normality

Third, the normality of the error was examined. This test attempts to establish whether the residuals are normally distributed, and if not the normality of the dependent and independent variables needs to be assessed. This assumption test is achieved through visual inspection of a normal probability plot as presented in Figure 3. The Normal Probability Plot showed no large deviations from the expected line and did not show excessive S-like shapes or other issues. Multivariate normality was therefore assumed to be present. In Figure 3, some deviation was found from the trendline, albeit small. Possible reasons for the break of normality stem from the manner in which data was collected for the EMS, and the companies that responded. Other reasons could include the use of multiple distributions, as there is a group of cases that adopted more technologies than another other group or even multiple groups. This could give the impression of a bimodal or multimodal distribution.

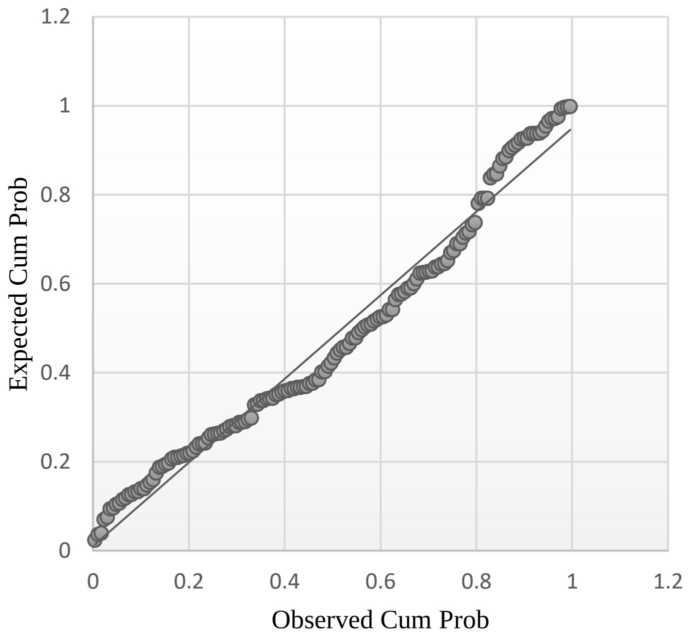


Figure 3. *Normal Probability Plot*

Independence of Error Terms

Fourth and final was the test of independence of the error terms. Herein, the assumption that a predicted value is not related to any other prediction is assessed. Grouping and sequencing can be signs of violation of this assumption and indicate the absence of independence. This assumption test was likewise performed with the residual scatterplot in Figure 2 and did not seem problematic. The interdependence of the error terms could be broken when time dependent or group dependent patterns such as highly sloped residuals were present. However, this did not seem to be the case and the independence of the error terms was therefore assumed.

Having tested all assumptions, MRA was moved forward as the data analysis technique of choice and used to obtain the results presented in the following chapter.

4. Results

A descriptive analysis was carried out to inspect the characteristics of variables, and to assess the inter-correlations. Table 5 displays this correlation matrix of main and control variables, next to the mean and standard deviation of each main and control variable. The control variables representing the industry segment were all dummies and did not pose a meaningful mean, therefore the distributions were displayed. Calculation of the correlation coefficients was done through Pearson's Correlation, as it assesses the linear relationship between two continuous variables, and thus appropriate in this research. Several significant correlations were identified. Firstly, the control dummy variables for the different industries had several significant correlations between them. All observed significant correlations between dummy control variables were varying degrees of negative correlations, which was to be expected. Due to the discriminatory nature of operating in one industry and not in another, the presence in a given industry will have a negative effect on the presence in another.

The control variable Turnover showed a somewhat weak positive correlation with the machinery industry (.164, $p < .05$). Turnover did not have other significant correlations with industry dummy variables. A possible cause for this significant correlation is the outlier mentioned in the previous chapter. Turnover did show a moderate negative correlation with the lack of annually pre-determined days for training (-.206, $p < .05$). The correlation indicated that the higher the turnover of a firm, the lesser firms lack annually pre-determined days for training, and thus have more training days.

Within the main variables three significant correlations were found. The lack of competence recording is positively correlated with the lack of training policy (.314, $p < .01$), and showed a moderately strong positive correlation. This suggests that the presence of either goes accompanied with the presence of the other. Theoretically, one could expect a company that does not record the competences of its employees to also not have training policies in place. This is further strengthened by the significant correlation between the lack of competence recording and the lack of annually pre-determined days for training (.171, $p < .05$), which indicates that companies that fail to record competences also fail to preselect days for training. This shows that three main variables, Competence Recording, Training Policy, and Days for Training, are somewhat closely related and measure similarly.

A different significant correlation was found between the lack of R&D jobs and having a highly practically educated workforce (.221, $p < .01$). This correlation showed a moderate effect in the positive sense. It suggests that having a large amount of people in jobs other than R&D often goes paired with a more practical workforce. This could be explained through R&D jobs generally being more advanced positions requiring theoretical knowledge obtained through higher and theoretical education.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Metal Industry													
2. Food Industry	-.165*												
3. Textile Industry	-.187*	-.130											
4. Construction Industry	-.141	-.098	-.111										
5. Chemical Industry	-.187*	-.130	-.147	-.111									
6. Machinery Industry	-.238*	-.165*	-.187*	-.141	-.187*								
7. Electronic Industry	-.228**	-.158*	-.179*	-.135	-.179*	-.228**							
8. Turnover Industry	-.042	-.015	-.032	-.024	-.032	.164*	-.041						
9. Competence Recording	0.55	.006	.002	-.057	-.087	.010	.043	-.008					
10. Training Policy	.034	-.149	.052	-.019	-.025	.001	.070	-.091	.314**				
11. Days for Training	.104	-.227**	.100	.048	-.120	.058	-.002	-.206*	.171*	.100			
12. Practical Education	.190*	.080	.004	.061	.095	-.286**	-.094	.052	.006	-.125	-.092		
13. Non-R&D Jobs	.078	.056	.057	.051	.011	.020	-.239**	-.005	-.069	-.019	.127	.221**	
Mean								124.73	1.04	0.53	0.86	80.24	94.38
Percent (Only for Dummies)	19.2%	10.3%	12.8%	7.7%	12.8%	19.2%	17.9%						
SD								1336.43	1.08	0.5	0.35	15.16	5.88

n = 156; **p < .01 , *p < .05 (2-tailed results).

Table 5. Correlation Matrix Independent Variables

Multiple Regression Analysis Results

The MRA was performed successfully. It is important to note that the MRA is interpreted as a one-tailed test, and thus all *p*-values of the statistical output as found in Appendix C are divided by two to account for this. The (one-tailed) MRA was ran in two stages, with the first model being made up of solely the control variables, while the second model containing the control variables and the main variables. A control model was ran first, to establish a baseline in explained variance and significance. This allowed testing whether the main variables added a significant explanation of variance and overall statistical significance. The full statistical output of the performed MRA is reported in Appendix C, while Table 6 summarizes the key results found. In the MRA, the control variable for the metal industry was not included in the regression, as it was the reference category of the other industry dummy variables.

	Model 1 Control Variables			**Model 2** Control and Main Variables		
Variables	β	SE	p	β	SE	p
Food Industry	-.032	.680	.364	-.097	.667	.139
Textile Industry	-.061	.634	.256	-.072	.601	.209
Construction Industry	.121	.750	.086	.092	.708	.135
Chemical Industry	-.062	.634	.256	-.126	.606	.081
Machinery Industry	.136	.572	.087	.108	.569	.139
Electronic Industry	.102	.577	.148	.076	.562	.212
Turnover	.226	.000	.003**	.185	.000	.009**
Competence Recording				-.263	.167	.001***
Training Policy				-.096	.359	.114
Days for Training				-.154	.525	.029*
Practical Education				-.043	.012	.299
Non-R&D Jobs				-.016	.030	.420
R^2(Adjusted R^2)	.113* (.071)			.241*** (.178)		
ΔR^2				.128***		
F (df; p-value 1-tailed)	2.693 (7, 148; .006**)			3.790 (12, 143; .001***)		

n = 156; ***p < .001, **p < .01, *p < .05 (1-tailed results); β = Standardized Regression Coefficient, SE = Standard Error, *p* = p-value, F = F-value, R^2 = Coefficient of Determination; all dummies use Steel as reference category.

Table 6. Effect on Adoption of Technology

The MRA was used to test if the measures *Competence*, *Training*, *Education*, and *Distribution of Labor* significantly explained the adoption of Industry 4.0 technologies. The results of the regression indicated that the model including the control and main variables (Model 2) explained a significant proportion of the variance (R^2 = .241, F (12,143) = 3.790, p < .001), which is a significant 113.27% higher than the model containing solely the control variables (Model 1), (R^2 = .113, F (7,148) = 2.693, p = .006).

Main Effects

Two main effects were found in the performed MRA. The variables Competence Recording and Days for Training both reported significant (negative) effects. Firstly, Competence Recording measured the lack of competence recording as a predictor for the adoption of Industry 4.0 technologies, which yielded a statistically significant effect (β = -.263, $p < .001$). Herein, the lack of competence recording is a negative predictor for the adoption of technology, meaning the less competence recording was done by firms (the larger the lack of competency recording), the fewer Industry 4.0 technologies were adopted. The measure of competence recording was connected to Hypothesis 1, and the obtained result supports the hypothesis.

Days for Training measured whether there was an absence of annually pre-determined days for employee training, and its relationship as a predictor towards the adoption of Industry 4.0 technologies was tested. The yielded result was statistically significant (β = -.154, $p = .029$) and showed a negative effect, indicating that when there was an absence of annually pre-determined training days, fewer Industry 4.0 technologies were recorded. The measure of days for training was connected to Hypothesis 2b, and the obtained result supports the hypothesis.

The other variables, Training Policy, Practical Education, and Non-R&D Jobs all showed no significant effect as a predictor of Adoption of Technologies. These variables and their respective measures were connected to hypotheses 2a, 3, and 4 respectively. No support was found for these hypotheses through the MRA. Reasons for the lack of these hypotheses are further explored in the Discussion chapter.

Control Effects

One significant control effect was found in the MRA (Model 2). The different industries proved not to be significant predictors of technology adoption, but the variable measuring a firm's turnover did. Turnover yielded a statistically significant effect (β = .185, $p = .009$) as a predictor for the adoption of technology and displayed a small to medium sized positive effect. As follows, an increase in turnover yields an increase in the number of Industry 4.0 technologies adopted, suggesting that firms with larger turnover were better fit to adopt Industry 4.0 technologies.

5. Discussion

In this chapter an overview is provided of the significant and insignificant effects, whereafter the effects are contextualized as barriers. The hypotheses connected to the main variables are discussed when support for the barriers was found, and literature is used to 'break' barriers or avoid them altogether. Moreover, the value of breaking such barriers is discussed, as the adoption of Industry 4.0 technologies is considered to carry great advantages over refraining from doing so. The statistical values used in the discussion on main and control variables are derived from Table 6 from the previous chapter, which displayed the MRA outcome scores.

Main Effects

Two main effects were found in the performed MRA. Both the lack of competence recording and the lack of annually pre-determined days for training reported significant effects, both in negative direction. These variables resulted from operationalization of the measures used in the hypotheses. Competence recording is connected to Hypothesis 1, and the days for training is connected to Hypothesis 2b. From the statistical tests, both effects found support for their connected hypothesis, and both indicated that when the lack of competence recording or annually pre-determined training days increased, the adoption of Industry 4.0 technologies would lessen. The effect of competence recording proved to have a standardized beta of -.263, while the effect of days for training had an effect size of -.154. The former effect is considered to be of moderate size as $0.2 < \beta < 0.5$, while the latter is a weak effect with $\beta < 0.2$ (Acock, 2014, p. 293). In this case, the strengths of both effects are appropriately far removed from zero to be considered real effects. The fact that the effects are not categorized as strong ($\beta > 0.5$) indicates that there are more factors that explain the adoption of technology within manufacturing firms and that these HR factors are not the sole determinants. This, however, is conform to literature in the field, suggesting that HR factors are one of the main factors causing barriers in adoption (Geissbauer et al., 2014), but are not the sole factors. Financial concerns, data privacy issues and low degrees of technology standardization also play important roles (Kiel et al., 2017; Raj et al., 2020). It is therefore acceptable that the effect sizes are moderate at best.

Support derived from the performed statistical analyses therefore acknowledges that similar challenges exist in the Dutch manufacturing industry. Firstly, firms struggle with recording competences of employees, or choose not to, and thereby intensify the challenge of adopting innovative technologies. Skilled workforces are after all one of the driving factors of technology adoption (Kiel et al., 2017), and attaining sufficiently skilled workforces requires understanding the current competences of a workforce. The barrier hypothesized through the lack of competence recording thus actively prevents organizations from realizing the workforce required, to be ready for adopting the Industry 4.0 technologies. Secondly, firms that do not have annually pre-determined days for training will struggle with adopting technologies. In the Dutch manufacturing industry this could contribute to not having a proper workforce ready to brace the challenges of innovation, which requires re-training and employee development (Koleva & Andreev, 2018).

Non-Significant Main Effects

Other main variables were examined in the MRA, but no significant effects were found next to the ones described above. These insignificant variables measured whether a lack of training policy existed, the degree to which a firm's employees were practically educated and the degree to which employees fulfilled jobs other than R&D related. These variables were operationalized to test hypotheses 2a, 3 and 4 respectively, and all returned insignificant effects in the MRA. The shown (insignificant) effects were all considerably small and the standardized beta was close to zero, indicating that they had little influence as a predictor towards the adoption of Industry 4.0 technologies. These barriers were derived from literature on adoption barriers to Industry 4.0 and have therefore found support in different contexts. In this case, however, no supported can be extended to the barriers based on the empirical results of this study.

Several reasons could be fundamental to why these barriers remain unsupported by the analysis in this research. Theoretical, methodological, and contextual reasons could underly this phenomenon and are thus explored. A theoretical reason includes the fact that the two measures used to operationalize the three variables to test hypotheses 1, 2a, and 2b respectively are relatively close in theoretical meaning. Especially variables Training Policy (insignificant effect) and Days for Training (significant effect). These two variables are part of the same measure, and both operationalized the measurement of training practices of firms in the Dutch manufacturing industry. Therefore, the concept of training is present in both variables, and thereby represented twice to some degree. The theoretical closeness of the concepts may have led to an insignificant result for Training Policy in favor of Days for Training, while the underlying measure of both, employee training, is in itself a significant factor. Moreover, the variable Competence Recording is also connected to the training of employees and is in a theoretical sense an antecedent and prerequisite of the training of employees. As established, competences need to be recorded and mapped to conduct effective employee training. This means that the inclusion of all three variables might have been unfavorable to the variable Policy Training, as the concept measured was ultimately similar and contained an amount of overlap.

The variables measuring the degree to which a firm's employees are practically educated, or work in fields other than R&D also tested insignificant and showed no real value in predicting the adoption of technologies. This could be because literary they are slightly less important and prominent than the training of employees and the management of employee competences. While education does provide some form of competence development, most competences required for the transition towards Industry 4.0 have only recently surfaced and therefore cannot have been taught in schools (Flores et al., 2020). This means that the practical education status of workers does not necessarily inhibit the adoption of new technologies, as what really counts is the content of this education and the competences required herein. For the variable representing the degree to which employees fulfill R&D jobs, other methodological reasons might be at the cause of insignificance. The questions and data from the EMS might not have been fit enough to adequately measure the concepts intended to represent, or researcher decisions might have led to (unintended) insignificant results.

A final explanation includes a contextual scenario, in which the barriers measured by the three main variables that tested insignificant are simply not present in the Dutch manufacturing industry. This could speculatively be due to different structures in Dutch manufacturing firms, different cultures, management styles, culture values or other national differences.

Control Effects

One significant effect was found among the control variables predicting the adoption of Industry 4.0 technologies. This control variable was Turnover and indicated a positively significant correlation with the dependent variable. The effect size displayed a standardized beta of .185 and thus constituted a relatively weak effect. Nonetheless, an increase in turnover yields an increase in the number of Industry 4.0 technologies adopted, suggesting that firms with larger turnover were better fit to adopt Industry 4.0 technologies. This aligns with observations during the third industrial revolution in which companies just started using the internet in their practices, wherein the adoption of internet based tools was heavily dependent on the financial size of a firm (Del Aguila-Obra & Padilla-Meléndez, 2006). Reasons include the capital-intensive nature often accompanied with adopting new technologies, but additionally, high turnover organizations tend to have larger business networks and are thus better able to detect new innovations.

Non-Significant Control Effects

The non-significant control variable included all dummy variables used to represent the different industries in which the manufacturing firms operate. Some industry variables had effect sizes larger than others, for example the chemical industry (β = -.124, p = .081), but none showed significant predictive value for the adoption of Industry 4.0 technologies. This result suggests that no industry is comparatively more suit as a predictor towards the adoption of the Industry 4.0 technologies. A lack of literature on this topic might indicate the prevalence of this result.

Barriers to Technology Adoption

As support for Hypothesis 1 was found, the lack of competence recording is deemed a barrier to the adoption of Industry 4.0 technologies in the Dutch manufacturing industry. This barrier stems from the different foundation in skill and competency that Industry 4.0 requires a firm to have compared to more traditional manufacturing relying on simple actions and movements in Taylor-istic fashion.

Organizations cannot effectively adopt new technologies when employees are unable to leverage these, but a workforce unable to deal with innovation can also flourish a cultural resistance to new technology (Kiel et al., 2017). Competences are thus vital to not only change the ability of employees to use new technologies, but also to change organizational cultures to being more receptive towards innovation (Geissbauer et al., 2014). The ability to determine the ‘acquired’ competences in organizations through employees thus enables the establishment of an overview and change practices or policy accordingly. The barrier described has found support in multiple national and industrial contexts (Geissbauer et al., 2014; Kamble et al., 2018; Kiel et al., 2017; Raj et al., 2020), and poses one of the more significant challenges to overcome for organizations. However, organizations are not solely responsible for not having the proper tools in place to record competences, or not having the required competences in the firm. Industry 4.0 is a relatively recent development and has developed quickly, which creates uncertainty. Yet, Industry 4.0 and the technological advancements it represents face some challenges regarding being applicable and accessible to all firms. Concerns include the lack of standardization, and thus the differing competences required to effectively leverage the systems (Xu et al., 2018). The novelty and uncertainty of Industry 4.0 technologies has had the effect that educational institutions around the world have not had the ability to implement the new skills and competences required in their programs, and oftentimes, these competences are rather tacit and non-transferable (Flores et al., 2020). Some changes have been made in educational institutions and initiatives towards the importance of the more theoretical and methodological sides of practical competences (Pfeiffer, 2015). The challenges of Industry 4.0 thereby increase the complexity of the barrier. Dealing with this barrier, and solving it, is therefore vital for Dutch manufacturing firms when it comes to preparing themselves for the future of manufacturing.

Next to Hypothesis 1, support for Hypothesis 2b was found which stated that the lack of annually pre-determined days for training are a barrier to the adoption of Industry 4.0 technologies. This barrier is connected to the bigger topic of training, and how training is important for firms to enable competitive advantages through new technologies and employees. In fact, the lack of training or personnel incompetence is a major reason why manufacturing firms choose not to adopt new technologies, or fail in attempting to (Geissbauer et al., 2014). This barrier thus prevents firms from acquiring the correct set of competences required to successfully adopt innovations. Herein, the inhibiting factor resides in not having an organizational culture open for, or interested in, the training of employees. This closed organizational culture can (in part) be caused by not valuing the effect of employee training through regular training days. Moreover, when employees do not receive regular training, they might be less receptive to training in the future as a larger competence gap exists, which in the fast-moving world of Industry 4.0 technology development, happens rapidly.

Breaking Barriers

Three distinct steps may aid a manufacturing firm in overcoming the barrier of competence recording, and attain an organizational environment that is more open, able, and fit to adopt and leverage new Industry 4.0 technologies. The first step is understanding which competences matter in a transition towards a more digitalized workforce and the use of advanced technologies. It is important that both present and future competence requirements are accounted for, and that the changing image of work is captured. Concepts such as Society 4.0 (Vacek, 2017) and Human Capital 4.0 (Flores et al., 2020) thereby aid in shaping the direction these competences should be sought in. The second step in overcoming the barrier is through the use of tools and programs that allow organizations to assess their employees in a manner that is beneficial for both parties. Industry 4.0 will bring disturbances to the labor market, and especially so to jobs that traditionally qualify as low skill / low pay jobs. Therefore, employee skill assessment should not become a dreaded event connected to job insecurity for employees, but rather an opportunity for growth. The third and final step involves changing hiring needs and procedures based on an acquired 'inventory' of competences. This step comes in when competence recording is in place and is therefore an example of the advantages of breaking the barrier, as effective hiring practices should rely on competence demand and supply in the era of Industry 4.0. However, to acquire an overview of the inner-organizational demand and supply, effective competency recording is required, thus making it a prerequisite for effective hiring.

Following step 1, identifying and understanding valuable and required competences is crucially important in the transition towards Industry 4.0. Different types of competences exist, and different types are required. The debate of social competences versus technical competences takes center stage herein (Popkova & Zmiyak, 2019). Overall though, firms should seek nimbleness (Shamim et al., 2016), adaptability (Flores et al., 2020), and polyvalence (Cimini et al., 2020, p. 710) in employees. Concretely, four competences were identified by Meyer (2015) in the pursuit of key manufacturing competences for employees: (1) flawless execution, (2) quality awareness, (3) analytical abilities, and (4) openness to change (p. 1009). These key competences are explicitly relevant both for current manufacturing needs, and what is expected of future manufacturing needs. They reflect the adaptability and nimbleness through analytical abilities and openness to change, while the increased need for high quality, durable products is reflected through flawless execution and eye for quality awareness. The latter are arguably the most important competences employees need to be fit for a manufacturing industry reliant on Industry 4.0 technologies, as the relevance of flawless execution and quality awareness is only expected to increase as technology develops further (Meyer et al., 2015, p. 1011). Adding onto these competences, however, is a different need that further expands on the need for employee mobility. Being interdisciplinary, and able to work in a team of people with diverse jobs and tasks, or being able to fulfill a range of tasks, is a quality employers should actively seek and value within employees (Cimini et al., 2020, p. 713).

Having determined essential competences, firms need to start tackling step 2, the actual recording of competences. The tracking of competences is essential in understanding the competence 'inventory' of an organization and creates vital insights into lacking areas. The recording and development of employee competences thereby falls within the range of HR activities, and should be picked up by HR professionals in organizations (Leinweber, 2013). Over the years, various tools have been developed for HR departments to obtain information about their employees and assess their capabilities. Tools as work configurations, mentoring, or 360 degree feedback can all be used to understand the competences of employees and their shortcomings (Kock & Ellström, 2011). Recording of competences should be done periodically (Leinweber, 2013; Meyer et al., 2015), as Industry 4.0 will bring continuous, mostly incremental, change to organizations instead of rapid change at one point in time that further remains stable.

Consequently, organizational behavior can be altered to complement the competences present in the organization and acquire a wider palette. Industry 4.0 hiring practices should thus focus on acquiring a variety of heterogenous competences, that complement the organization next to what it readily has available in employee competences (Shamim et al., 2016, p. 5312). Thereby, selecting personnel with competences relevant to the organization for future manufacturing will not only help short-term, but also prepare for greater future competitiveness with employees becoming long term success factors (Meyer et al., 2015, p. 2014).

Overcoming Training Barriers

Competence recording is thus required to understand the variety of competences in an organization, after which hiring can be used to change the composition of competences in a firm. However, hiring is not the sole practice able to accomplish this, as training of current employees can greatly ameliorate firm competences at an improved cost efficiency (Blatter et al., 2016). A barrier was found here, however, as support for Hypothesis 2b was found. The lack of annually pre-determined days for training of employees will have a significant negative effect on the ability to adopt Industry 4.0 technologies. This barrier further delineates literature claiming the importance of correct training practices in manufacturing firms to prepare their workforce for more digitalization and changing labor conditions.

To achieve an organization in which training is a central component, multiple approaches can be taken. The need for both social training and technical training is high in Industry 4.0 (Popkova & Zmiyak, 2019), but the methods used in training either competence category are rather different. To overcome this difference, organizations can make use of a so called 'learning factory approach' (Schallock et al., 2018). Schallock et al. (2018) developed the approach specifically towards Industry 4.0 technology adoption and empirically tested it. This learning approach encompasses the duality of Industry 4.0 and thus includes both theoretical and practical competences, and the goals include preparing staff for change management, decision making and the use of technological innovation

(Schallock et al., 2018, p. 27). There is thus a focus on developing competences that aim at understanding how to choose technologies and approach novel innovation (Baena et al., 2017). This connects well with the required competences for Industry 4.0 that include variability, adaptability and, to a certain extent, autonomy (Shamim et al., 2016). The learning factory approach uses an action learning approach and allows practical learning and training through training days filled with tasks and challenges revolving around Industry 4.0 technologies (Schallock et al., 2018, p. 32). This approach therefore captures the essence of why training is vital in Industry 4.0. The consequences of the barrier of not having annually pre-determined training days are prevalent here. The breaking of this barrier is required for implementing training approaches such as the learning factory, training games, business games, and learning on the job (Meyer et al., 2015), but breaking the barrier once also helps in overcoming the barrier in the long term. An organizational culture is created in which training and competence development is central, and the use of pre-planned training days are appreciated as employees experience the added value for personal development (Flores et al., 2020; Kiel et al., 2017).

6. Conclusion

This research aimed at using literature to establish known HR related barriers to the adoption of Industry 4.0 technologies, and consequently use empirical methods to test these methods in the context of the Dutch manufacturing industry. The leading research question guiding the research was therefore: which HR related factors internal to Dutch manufacturing firms inhibit the adoption of Industry 4.0 technologies? A secondary goal was to contextualize any barriers that were supported through statistical analysis, and offer variation in solving, avoiding, or dealing with the barriers. To answer the research question EMS data was used in an MRA, through which hypothesis were tested.

The main findings of the research confirm that two barriers exist, one related to the lack of competency recording, and another related to the lack of annually pre-determined days for training. The barrier stemming from a lack of competency recording inhibits Dutch manufacturing firms from achieving an overview of acquired competences within the firm, and thus consequently disallow the change in organizational behavior through hiring and training required to develop the current employee competences to be on par with the future of manufacturing through Industry 4.0 technologies. The barrier stemming from the lack of annually pre-determined days for training inhibit Dutch manufacturing firms from creating a culture in which change, and personal development is central, and the need for theoretical and practical training is addressed. Moreover, a lack in pre-determined training days inhibits employees from remaining competitive in their field, and thus effectively diminishes the competitive advantage that an organization can develop. Both barriers significantly inhibit the adoption of Industry 4.0 technologies through the lack of prerequisite HR conditions, which are a vital part of the transition towards more digitalized manufacturing. This transition therefore poses an opportunity for manufacturing firms to turn their employees into long term success factors, unlike ever before.

The discussion examined different options in how the barriers could be broken and addressed. The lack of competence recording should be overcome through employing tools such as work configurations, mentoring, or 360-degree feedback, and competence recording should be a regular activity for firms. This allows an up-to-date inventory of competences to be established and organizational hiring and training to be changed accordingly. The specific competences vital in Industry 4.0, and this in the practice of competence recording, are (1) flawless execution, (2) quality awareness, (3) analytical abilities, and (4) openness to change. Moreover, being interdisciplinary, and able to work in a team of people with diverse jobs and tasks is a quality firms should actively pursue in the recording of competences and establishing an inventory of competences. The barrier of annually pre-determined days for training should be tackled by employing a learning factory approach and change the organizational culture to be open towards annual training accordingly. This approach allows for firms to timely plan training activities, and thereby keep up with the steep demand of development from Industry 4.0 technologies. The learning factory approach should focus on a combination of both theoretical and practical competences and can be achieved through an active learning stance. These solutions, as described in this research. will help Dutch manufacturing firms in overcoming the barriers they face through current HR practices and characteristics, and help preparing them for the future of Industry 4.0 technologies and achieving competitive advantages through the leverage of innovation by employees.

Theoretical Contributions

Research on Industry 4.0 adoption barrier is relatively scarce compared to research on the use and advantages of Industry 4.0. Nonetheless, adoption barriers are an important aspect of manufacturing transitioning towards Industry 4.0 technologies. Different studies have examined adoption barriers and provided insight into these barriers from different perspectives and (national) contexts. It is valuable to identify barriers in different contexts, as these all add to the knowledge generated on Industry 4.0 adoption and work towards an exhaustive overview. This research enriched the literature on adoption barriers through the examination of barriers readily identified in literature and empirically testing these in the context of the Dutch manufacturing industry. The results are of additive next to comparative value as they allow the comparison of barriers across national borders, and thus add to an exhaustive overview of barriers present in a given context. The theoretical contributions include the identified barrier of competence recording and the training related barrier of annually pre-determined days for training. These barriers enrich literature through being supported in a different context and thus expand the theoretical foundations therein. HR literature is therefore enriched through identifying situations in which HR tools or practices are useful, and the value of HR practices in manufacturing firms overall. Finally, research directions were found in which current literature is subpar or non-existent, such as in the case of the influence of different sub-industries in manufacturing. The theoretical contributions therefore also included an expansion of the field of adoption barriers to Industry 4.0, and potential new research directions.

Managerial Implications

This research identified a set of important managerial implications, which arguably span beyond being solely relevant to (HR) managers but provide insights into how (Dutch) educational institutions could leverage the knowledge generated. Key HR functions were identified to be potentially problematic in the adoption of Industry 4.0 technologies when not approached effectively. By contextualizing the barriers identified, managers understand the importance of the barriers, what specifically is causing them, and what these barriers are preventing from achieving, may it be acquiring an inventory of competences the firm possesses, or creating an organizational culture fit towards the training and development practices needed to leverage Industry 4.0 advantages. Moreover, for the identified barriers in the Dutch manufacturing industry, solutions were offered to help managers deal with the barrier, and explain the effects and organizational behaviors that could be changed after solving them to better prepare for the inevitable future of Industry 4.0. Key competences were identified that should be focused on in developing the competences a firm possesses through employees after breaking the barrier of competence recording. Next to that, a learning factory approach was specified which uses action learning to aid practical and theoretical training of employees when the barrier of days for training was broken. In conclusion, HR professionals and other stakeholders to Industry 4.0 manufacturing have attained insight into the practices that can be problematic for the adoption of innovative technology, why this is problematic, how these practices should be changed, and the advantages of doing so.

Limitations and Future Directions

This research encountered several limitations due to the theoretical scope of the research, and methodological considerations. These limitations, however, do not take away from the research itself, and offer new opportunities for future directions of research. Firstly, a theoretical limitation of this research included that only HR factors were examined. The Dutch manufacturing industry is relatively large, especially compared to the population of the Netherlands. It does, however, not have any research to its manufacturing industry when it comes to the barriers associated with Industry 4.0. This research investigated some of the barriers previously identified in literature but limited itself to HR related practices and barriers. This means that only a small portion of barriers is explored, and the scope of the study limits the value of the results when it comes to understanding all barrier for adopting Industry 4.0 in the Dutch manufacturing industry. Secondly, a methodological limitation of this research might have led to not all HR barriers identified in literature being represented. This research used the EMS database to access relevant data to perform statistical tests for hypothesis testing. A limitation of this method was that the constructed hypotheses had to be measurable through the EMS database, as no other data collection methods were used. This led to barriers such as hiring processes and compensation concerns not being included in the analysis. Moreover, the EMS database from 2015 was used, which was early in the process of Industry 4.0 taking over the manufacturing industry and is therefore not the best option for Industry 4.0 technology adoption research.

From the limitations, a recommendation for future research can be made. The main recommendation involves research into adoption barriers of Industry 4.0 technologies for Dutch manufacturing firms other than HR barriers. Research should investigate all areas where barriers might form, and how these barriers could be addressed. Moreover, working together with stakeholders (i.e., governments, educational institutions) regarding the further digitalization of manufacturing should be sought in future research, as it will help understand how competitive advantages can be achieved through Industry 4.0 on a larger than firm level scale. Qualitative approaches could be used to further enrich the understanding of barriers Dutch manufacturing firms have to tackle, through the use of in-depth process analyses.

Bibliography

Acock, A. C. 1944-. (2014). *A gentle introduction to Stata* (Fourth edition.). A Stata Press Publication, StataCorp LP; WorldCat.org. http://catdir.loc.gov/catdir/enhancements/fy1412/2014935652-b.html

Baena, F., Guarin, A., Mora, J., Sauza, J., & Retat, S. (2017). Learning Factory: The Path to Industry 4.0. *Procedia Manufacturing*, *9*, 73–80. https://doi.org/10.1016/j.promfg.2017.04.022

Bhattacherjee, A. (1998). Managerial Influences on Intraorganizational Information Technology Use: A Principal-Agent Model. *Decision Sciences*, *29*(1), 139–162. https://doi.org/10.1111/j.1540-5915.1998.tb01347.x

Blatter, M., Muehlemann, S., Schenker, S., & Wolter, S. C. (2016). Hiring costs for skilled workers and the supply of firm-provided training. *Oxford Economic Papers*, *68*(1), 238–257. https://doi.org/10.1093/oep/gpv050

Breunig, M., Kelly, R., Mathis, R., & Wee, D. (2016). *Getting the most out of Industry 4.0 | McKinsey*. https://www.mckinsey.com/business-functions/operations/our-insights/industry-40-looking-beyond-the-initial-hype#

Buer, S.-V., Strandhagen, J. O., & Chan, F. T. S. (2018). The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda. *International Journal of Production Research*, *56*(8), 2924–2940. https://doi.org/10.1080/00207543.2018.1442945

Centraal Bureau voor de Statistiek, C. B. voor de. (2021). *Bedrijven; bedrijfstak* [Webpagina]. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/cijfers/detail/81589NED

Chang, S., Gong, Y., & Shum, C. (2011). Promoting Innovation in Hospitality Companies through Human Resource Management Practices. *International Journal of Hospitality Management*, *30*(4), 812–818.

Christians, A., & Liepin, M. (2017). The consequences of digitalization for German civial law from the national legislator’s point of view. *Intellectual Property Journal*, *9*(3), 331–339.

Cimini, C., Boffelli, A., Lagorio, A., Kalchschmidt, M., & Pinto, R. (2020). How do industry 4.0 technologies influence organisational change? An empirical analysis of Italian SMEs. *Journal* *of Manufacturing Technology Management*, *32*(3), 695–721. https://doi.org/10.1108/JMTM-04-2019-0135

Del Aguila-Obra, A. R., & Padilla-Meléndez, A. (2006). Organizational factors affecting Internet technology adoption. *Internet Research*, *16*(1), 94–110. https://doi.org/10.1108/10662240610642569

Flores, E., Xu, X., & Lu, Y. (2020). Human Capital 4.0: A workforce competence typology for Industry 4.0. *Journal of Manufacturing Technology Management*, *31*(4), 687–703. https://doi.org/10.1108/JMTM-08-2019-0309

Frambach, R. T., & Schillewaert, N. (2002). Organizational innovation adoption: A multi-level framework of determinants and opportunities for future research. *Journal of Business Research*, *55*(2), 163–176. https://doi.org/10.1016/S0148-2963(00)00152-1

Frost, J. (2019, October 23). Guidelines for Removing and Handling Outliers in Data. *Statistics By Jim*. https://statisticsbyjim.com/basics/remove-outliers/

Geissbauer, R., Schrauf, S., & Koch, V. (2014). *Industry 4.0: Opportunities and Challenges of Industrial Internet*. PWC. https://www.pwc.nl/en/assets/documents/pwc-industrie-4-0.pdf

Haddud, A., DeSouza, A., Khare, A., & Lee, H. (2017). Examining potential benefits and challenges associated with the Internet of Things integration in supply chains. *Journal of Manufacturing Technology Management*, *28*(8), 1055–1085. Scopus. https://doi.org/10.1108/JMTM-05-2017-0094

Hair, J., Black, W., Babin, B., & Anderson, R. (2019). *Multivariate Data Analysis* (8th ed.). Cengage UK.

Helmond, C. G. C. van, Kok, R. A. W., Ligthart, P. E. M., & Vaessen, P. (2018). Veel ruimte voor meer digitalisering Nederlandse maakbedrijven. *Economisch Statische Berichten*, 2–3.

Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, *89*, 23–34. https://doi.org/10.1016/j.compind.2017.04.002

Horváth, D., & Szabó, R. Zs. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, *146*, 119–132. https://doi.org/10.1016/j.techfore.2019.05.021

Huizinga, G., Walison, P., Bouws, T., & Kramer, F. (2014). *Smart Industry: Dutch Industry fit for the Future.* (p. 64). www.rijksoverheid.nl

Hung, M. (2016). *IoT Implementation and Management—From the Edge to the Cloud [WWW Document]*. Gartner. https://www.gartner.com/technology/research /internet-of-things/report/

Hüther, M. (2016). *Digitalisation: An engine for structural change - A challenge for economic policy* (Working Paper 15/2016E). IW Policy Paper. https://www.econstor.eu/handle/10419/148408

Joshi, N. (2017, September 5). *Blockchain meets industry 4.0—What happened next?* [Software Solution]. Allerin. https://www.allerin.com/blog/5659-2

Kagermann, H., Wahlster, W., & Helbig, J. (2013). *Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0—Securing the Future of German Manufacturing Industry | BibSonomy*. National Academy of Science and Engineering, Munchen. https://www.bibsonomy.org/bibtex/25c352acf1857c1c1839c1a11fe9b7e6c/flint63

Kamar, E. (2016). *Directions in Hybrid Intelligence: Complementing AI Systems with Human Intelligence*. 4.

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry. *Computers in Industry*, *101*, 107–119. https://doi.org/10.1016/j.compind.2018.06.004

Kiel, D., Arnold, C., & Voigt, K.-I. (2017). The influence of the Industrial Internet of Things on business models of established manufacturing companies – A business level perspective. *Technovation*, *68*, 4–19. https://doi.org/10.1016/j.technovation.2017.09.003

Kock, H., & Ellström, P. (2011). Formal and integrated strategies for competence development in SMEs. *Journal of European Industrial Training*, *35*(1), 71–88. https://doi.org/10.1108/03090591111095745

Koleva, N., & Andreev, O. (2018). Aspects of Training in the Field of Operations Management with Respect to Industry 4.0. *2018 International Conference on High Technology for Sustainable Development (HiTech)*, 1–3. https://doi.org/10.1109/HiTech.2018.8566581

Kovacs, O. (2018). The dark corners of industry 4.0 – Grounding economic governance 2.0. *Technology in Society*, *55*, 140–145. https://doi.org/10.1016/j.techsoc.2018.07.009

Lee, I., & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons*, *58*(4), 431–440. https://doi.org/10.1016/j.bushor.2015.03.008

Leinweber, S. (2013). Stage 3: Competence Managementcompetence management. In M. T. Meifert (Ed.), *Strategic Human Resource Development: A Journey in Eight Stages* (pp. 109–133). Springer. https://doi.org/10.1007/978-3-642-31473-5_7

Li, L. (2018). China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0". *Technological Forecasting and Social Change*, *135*, 66–74. https://doi.org/10.1016/j.techfore.2017.05.028

Ligthart, P. E. M., Vaessen, P., & Dankbaar, B. (2008). *Innovatie van Productie: Onderzoeksrapportage van de European Manufacturing Survey (EMS) in de Nederlandse Maakindustrie.* https://repository.ubn.ru.nl/bitstream/handle/2066/68734/68734.pdf?sequence=1/handle/2066/98390

Lin, B., Wu, W., & Song, M. (2019). Industry 4.0: Driving factors and impacts on firm's performance: an empirical study on China's manufacturing industry. *Annals of Operations Research*. https://doi.org/10.1007/s10479-019-03433-6

Lolli, F., Balugani, E., Ishizaka, A., Gamberini, R., Rimini, B., & Regattieri, A. (2019). Machine learning for multi-criteria inventory classification applied to intermittent demand. *Production Planning & Control*, *30*(1), 76–89. https://doi.org/10.1080/09537287.2018.1525506

Lorenz, M., Ruessmann, M., Strack, R., Lueth, K., & Bolle, M. (2015). *Man and machine in Industry 4.0: How will technology transform the industrial workforce through 2025?* (p. 18 p.). Boston Consulting Group. http://www.bcg.it/documents/file197250.pdf

McKinsey Digital. (2016). *Industry 4.0 after the Initial Hype. Where Manufacturers Are Finding Value and How They Can Best Capture it.* McKinsey & Company. https://www.mckinsey.com/~/media/mckinsey/business%20functions/mckinsey%20digital/our%20insights/getting%20the%20most%20out%20of%20industry%204%200/mckinsey_industry_40_2016.ashx

Meyer, G., Brünig, B., & Nyhuis, P. (2015). Employee competences in manufacturing companies – an expert survey. *Journal of Management Development*, *34*(8), 1004–1018. https://doi.org/10.1108/JMD-06-2014-0056

Mueller, E., Chen, X.-L., & Riedel, R. (2017). Challenges and Requirements for the Application of Industry 4.0: A Special Insight with the Usage of Cyber-Physical System. *Chinese Journal of Mechanical Engineering*, *30*(5), 1050–1057. https://doi.org/10.1007/s10033-017-0164-7

Müller, J. M., Buliga, O., & Voigt, K.-I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, *132*, 2–17. https://doi.org/10.1016/j.techfore.2017.12.019

Pfeiffer, S. (2015). Effects of Industry 4.0 on vocational education and training | VOCEDplus, the international tertiary education and research database. *Institute of Technology Assessment*, 47.

Popkova, E. G., & Zmiyak, K. V. (2019). Priorities of training of digital personnel for industry 4.0: Social competencies vs technical competencies. *On the Horizon*, *27*(3/4), 138–144. https://doi.org/10.1108/OTH-08-2019-0058

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics*, *224*, 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Rana, G., & Sharma, R. (2019). Emerging human resource management practices in Industry 4.0. *Strategic HR Review*, *18*(4), 176–181. https://doi.org/10.1108/SHR-01-2019-0003

Rogers, E. M. (1995). *Diffusion of innovations*. Free Press.

Ryan, P. J., & Watson, R. B. (2017). Research Challenges for the Internet of Things: What Role Can OR Play? *Systems*, *5*(1), 24. https://doi.org/10.3390/systems5010024

Schallock, B., Rybski, C., Jochem, R., & Kohl, H. (2018). Learning Factory for Industry 4.0 to provide future skills beyond technical training. *Procedia Manufacturing*, *23*, 27–32. https://doi.org/10.1016/j.promfg.2018.03.156

Schrauf, S., & Berttram, P. (2014). *Industry 4.0: Opportunities and Challenges of the industrial internet.* Strategy & PwC. https://www.strategyand.pwc.com/gx/en/insights/2015/industry-4-opportunities-and-challenges/industry-4-0.pdf

Schröder, C. (2017). *The challenges of industry 4.0 for small and medium-sized enterprises* (p. 28). Friedrich Ebert Stiftung. https://www.researchgate.net/profile/Christian-Schroeder-24/publication/305789672_The_Challenges_of_Industry_40_for_Small_and_Medium-sized_Enterprises/links/57a1dfe808ae5f8b258a5e69/The-Challenges-of-Industry-40-for-Small-and-Medium-sized-Enterprises.pdf

Schwab, K. (2017). *The Fourth Industrial Revolution*. Crown.

Sengupta, A., Venkatesh, D. N., & K. Sinha, A. (2013). Developing performance-linked competency model: A tool for competitive advantage. *International Journal of Organizational Analysis*, *21*(4), 504–527. https://doi.org/10.1108/IJOA-05-2011-0488

Shamim, S., Cang, S., Yu, H., & Li, Y. (2016). Management approaches for Industry 4.0: A human resource management perspective. *2016 IEEE Congress on Evolutionary Computation (CEC)*, 5309–5316. https://doi.org/10.1109/CEC.2016.7748365

Straub, E. T. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research*, *79*(2), 625–649.

The World Bank. (2019). *Manufacturing, value added (current US$)*. https://data.worldbank.org/indicator/NV.IND.MANF.CD?most_recent_value_desc=true&view=map

Türkeş, M. C., Oncioiu, I., Aslam, H. D., Marin-Pantelescu, A., Topor, D. I., & Căpuşneanu, S. (2019). Drivers and Barriers in Using Industry 4.0: A Perspective of SMEs in Romania. *Processes*, *7*(3), 153. https://doi.org/10.3390/pr7030153

Vacek, J. (2017). On the road: From industry 4.0 to society 4.0. *Trendy v Podnikani*, *7*, 43–49.

Verma, A., Bansal, M., & Verma, J. (2020). Industry 4.0: Reshaping the future of HR. *Strategic Direction*, *36*(5), 9–11. https://doi.org/10.1108/SD-12-2019-0235

Vuksanović Herceg, I., Kuč, V., Mijušković, V. M., & Herceg, T. (2020). Challenges and Driving Forces for Industry 4.0 Implementation. *Sustainability*, *12*(10), 4208. https://doi.org/10.3390/su12104208

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. *International Journal of Production Research*, *56*(8), 2941–2962. https://doi.org/10.1080/00207543.2018.1444806

Zaltman, G., Duncan, R., & Holbeck, J. (1973). *Innovation and Organizations*. John Wiley.

Zheng, P., wang, H., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., Yu, S., & Xu, X. (2018). Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering*, *13*(2), 137–150. https://doi.org/10.1007/s11465-018-0499-5

Zhou, K., Liu, T., & Zhou, L. (2015). *Industry 4.0: Towards future industrial opportunities and challenges*. 2147–2152. https://doi.org/10.1109/FSKD.2015.7382284

Appendix A: EMS Questions

1.2 Bedrijfstak (bijv. textiel, chemische industrie, machinebouw, enz.): | hoofdproductgroep | aandeel van hoofd-product (groep) in omzet ca. %

4.1 **Welke van de volgende activiteiten worden uitgevoerd voor uw productiepersoneel in uw bedrijfsvestiging?**

Aanwezige competenties van productiewerknemers worden systematisch vastgelegd?	☐ nee	☐ ja
Functiebeschrijvingen zijn ontwikkeld voor specifieke functiegebieden in de productie?	☐ nee	☐ ja
Er bestaan specifieke competentieprogramma's for bepaalde functies	☐ nee	☐ ja

4.3 **Bestaat er afzonderlijk beleid voor competentie-ontwikkeling en training van productiepersoneel?**

☐ nee ☐ ja → Is er in uw bedrijf voor dit beleid een vast jaarlijks budget beschikbaar? ☐ nee ☐ ja

5.1 **Is er een vastgesteld aantal dagen per jaar voor verdere kwalificatie, training en ontwikkeling van het productiepersoneel?**

☐ **nee** ☐ **ja** → **Hoeveel dagen per jaar is er per persoon vastgesteld?** ca. dagen per jaar

8.1 **Welke van de volgende technologieën worden momenteel in uw bedrijfsvestiging toegepast?**

Toepassing gepland voor 2018	Nee	Technologieën	Ja	Voor het eerst gebruikt (Jaar)[1]	upgrade sinds 2012 Ja	upgrade sinds 2012 Nee	Omvang van het toegepaste potentieel[2]
		Additieve productietechnologieën					
☐	←☐	Additive productietechnologie voor maken van prototypes (bijv. 3D printing, rapid prototyping; Selective Laser Sintering; Stereolithografie, Laser Beam Melting)	☐→	19/20	☐	☐	g m h
☐	←☐	Productie met additieve productietechnologie (incl. enkelstuksproductie; kleine productieseries; reserveonderdelen)	☐→	19/20	☐	☐	g m h
☐	←☐	Systemen voor Machine2Machine communicatie, Multi-agent systemen	☐→	19/20	☐	☐	g m h
☐	←☐	Systemen voor Cyber-Physical systems, cloud-computing	☐→	19/20	☐	☐	g m h
		Digitale fabriek / IT netwerken					
☐	←☐	Digitale productieplanning en roostering (bijv. ERP-systeem)	☐→	19/20	☐	☐	g m h
☐	←☐	Bijna real-time productiebeheersingssystemen (bijv. systemen voor gecentraliseerde aansturing en machinegegevensverwerking	☐→	19/20	☐	☐	g m h
☐	←☐	Digitale uitwisseling van productieplanningsgegevens met toeleveranciers en/of klanten (supply chain management)	☐→	19/20	☐	☐	g m h
☐	←☐	Systemen voor geautomatiseerd management van interne logistiek en orderverzameling (e.g. RFID, warehouse management system)	☐→	19/20	☐	☐	g m h
☐	←☐	Mobiele/draadloze apparaten voor programmering en bediening van installaties en machines (e.g. tablets)	☐→	19/20	☐	☐	g m h
☐	←☐	Product Lifecycle Management (PLM) systemen of Product/Productieproces datamanagement	☐→	19/20	☐	☐	g m h
☐	←☐	Technologieën voor veilige mens-machine interactie (bijv. coöperatieve robots, open werkstations e.d.)	☐→	19/20	☐	☐	g m h
☐	←☐	Digitale oplossingen voor het direct beschikbaar maken van tekeningen, werkschemas en -instructies op de werkvloer (e.g. tablets, smartphones)	☐→	19/20	☐	☐	g m h

Toelichting:

1 Het jaar waarin deze technologie voor het eerst werd toegepast in uw bedrijfsvestiging (maak een schatting indien u onzeker bent over het exacte jaar)

2 Daadwerkelijke toepassing ten opzichte van maximaal zinvolle toepassingsmogelijkheden: omvang van het gebruikte potentieel is "gering" bij eerste aanzetten, "midden" bij gedeeltelijke toepassing en "hoog" bij omvangrijke toepassing

15.1 **Wat is het opleidingsniveau van het personeel van uw bedrijfsvestiging?**

Hoger onderwijs (HBO+WO)	ca.		%	=100%
MBO technische opleiding	ca.		%	
MBO adminstratieve en commerciële opleiding	ca.		%	
LBO of ongeschoold	ca.		%	
Personeel in opleiding (leerlingen, stagiaires)	ca.		%	

15.2 **Hoe is het personeel in uw bedrijfsvestiging verdeeld over de volgende werkterreinen:**

Onderzoek en ontwikkeling	ca.		%	=100%
Ideevorming, ontwerp en vormgeving	ca.		%	
Fabricage en montage	ca.		%	
Klantenservice	ca.		%	
Overige (administratie, inkoop, logistiek/distributie, onderhoud, productieplanning enz.)	ca.		%	

21 **Hier worden enkele gegevens over uw bedrijfsvestiging gevraagd:**

Jaaromzet 2014 ☐ miljoen € 2012 ☐ miljoen €

Aantal werknemers (excl. uitzendkrachten) 2014 ☐ aantal

Aantal werknemers dat is afgevloeid in 2014 2014 ☐ aantal

Had uw bedrijfsvestiging uitzendkrachten in dienst in 2014? ☐ nee ☐ ja → Hoeveel uitzendkrachten waren in 2014 gemiddeld in dienst bij uw bedrijfsvestiging? ca. ☐ aantal

Inkoop 2014 (ingekochte onderdelen, materialen en diensten) ☐ , ☐ miljoen €

Afschrijvingen op machines en installaties 2014 (zonder grond en gebouwen) ☐ , ☐ miljoen €

Investeringen in machines en installaties 2014 ☐ , ☐ miljoen €

Personeelskosten als percentage van de omzet in 2014 (incl. loonnevenkosten) ☐ %

Graad van capaciteitsbenutting (gemiddeld in 2014) ☐ %

Totale energiekosten als percentage omzet 2014 ☐ %

Rendement op de omzet (vóór belasting in 2014) ☐ negatief ☐ 0 tot 2% ☐ > 2 tot 5% ☐ > 5 tot 10% ☐ > 10%

Jaar van oprichting, c.q. inschrijving bij de Kamer van Koophandel jaar: ☐

Heeft uw bedrijfsvestiging een ondernemingsraad? ☐ nee ☐ ja

Appendix B: Missing Value Analysis

Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
i4.1_1	178	.7191	.45071	0	.0	0	0
i4.1_2	178	.7921	.40692	0	.0	.	.
i4.1_3	178	.4663	.50027	0	.0	0	0
i4.3_1	178	.4551	.49938	0	.0	0	0
i5.1_1	178	.1404	.34843	0	.0	.	.
i8_1	178	.1966	.39857	0	.0	.	.
i8_2	178	.2303	.42224	0	.0	.	.
i8_3	178	.1573	.36511	0	.0	.	.
i8_4	178	.1348	.34251	0	.0	.	.
i8_5	178	.7416	.43900	0	.0	0	0
i8_6	178	.3483	.47778	0	.0	0	0
i8_7	178	.3258	.47001	0	.0	0	0
i8_8	178	.2697	.44504	0	.0	0	0
i8_9	178	.1517	.35973	0	.0	.	.
i8_10	178	.1517	.35973	0	.0	.	.
i8_11	178	.1124	.31670	0	.0	.	.
i8_12	178	.3539	.47954	0	.0	0	0
i15.1_1	178	16.0281	14.62311	0	.0	0	16
i15.1_2	178	31.8876	25.61137	0	.0	0	0
i15.1_3	178	10.4326	10.16355	0	.0	0	4
i15.1_4	178	38.2360	27.85293	0	.0	0	0
i15.1_5	178	3.4157	6.26588	0	.0	0	3
i15.2_1	178	5.5815	5.80258	0	.0	0	1
i15.2_2	178	5.9888	7.66291	0	.0	0	8
i15.2_3	178	61.9250	19.38512	0	.0	1	0
i15.2_4	177	8.2797	10.91272	1	.6	0	11
i15.2_5	178	18.2716	13.53369	0	.0	0	10
i21.1	157	123.9521	1332.17477	21	11.8	0	19
i21.3	121	7.1938	14.36312	57	32.0	0	14
i21.4	130	.3723	.52783	48	27.0	0	8

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

Appendix C: MRA Statistical Output

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	v_Turnover, v_Food, v_Construction, v_Chemical, v_Textile, v_Electronic, v_Machinery[b]	.	Enter
2	v_Competence_Recording, v_Non_RnD, v_Training_Policy, v_Days_for_Training, v_Practical_Education[b]	.	Enter

a. Dependent Variable: v_Adopted_Technologies

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.336[a]	.113	.071	2.19596	.113	2.693	7	148	.012	
2	.491[b]	.241	.178	2.06612	.128	4.837	5	143	.000	1.816

a. Predictors: (Constant), v_Turnover, v_Food, v_Construction, v_Chemical, v_Textile, v_Electronic, v_Machinery

b. Predictors: (Constant), v_Turnover, v_Food, v_Construction, v_Chemical, v_Textile, v_Electronic, v_Machinery, v_Competence_Recording, v_Non_RnD, v_Training_Policy, v_Days_for_Training, v_Practical_Education

c. Dependent Variable: v_Adopted_Technologies

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90.897	7	12.985	2.693	.012[b]
	Residual	713.693	148	4.822		
	Total	804.590	155			
2	Regression	194.143	12	16.179	3.790	.000[c]
	Residual	610.446	143	4.269		
	Total	804.590	155			

a. Dependent Variable: v_Adopted_Technologies

b. Predictors: (Constant), v_Turnover, v_Food, v_Construction, v_Chemical, v_Textile, v_Electronic, v_Machinery

c. Predictors: (Constant), v_Turnover, v_Food, v_Construction, v_Chemical, v_Textile, v_Electronic, v_Machinery, v_Competence_Recording, v_Non_RnD, v_Training_Policy, v_Days_for_Training, v_Practical_Education

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	2.963	.401		7.390	.000		
	v_Food	-.238	.680	-.032	-.350	.727	.727	1.376
	v_Textile	-.417	.634	-.061	-.658	.511	.688	1.453
	v_Construction	1.032	.750	.121	1.376	.171	.774	1.292
	v_Chemical	-.418	.634	-.062	-.659	.511	.688	1.453
	v_Machinery	.783	.572	.136	1.370	.173	.608	1.644
	v_Electronic	.605	.577	.102	1.049	.296	.630	1.586
	v_Turnover	.000	.000	.226	2.880	.005	.973	1.028
2	(Constant)	5.938	2.862		2.075	.040		
	v_Food	-.727	.667	-.097	-1.091	.277	.669	1.495
	v_Textile	-.488	.601	-.072	-.812	.418	.679	1.474
	v_Construction	.785	.708	.092	1.108	.270	.768	1.302
	v_Chemical	-.853	.606	-.126	-1.408	.161	.667	1.500
	v_Machinery	.620	.569	.108	1.090	.277	.545	1.835
	v_Electronic	.451	.562	.076	.803	.423	.589	1.699
	v_Turnover	.000	.000	.185	2.425	.017	.909	1.100
	v_Competence_Recording	-.555	.167	-.263	-3.334	.001	.851	1.175
	v_Training_Policy	-.435	.359	-.096	-1.213	.227	.853	1.172

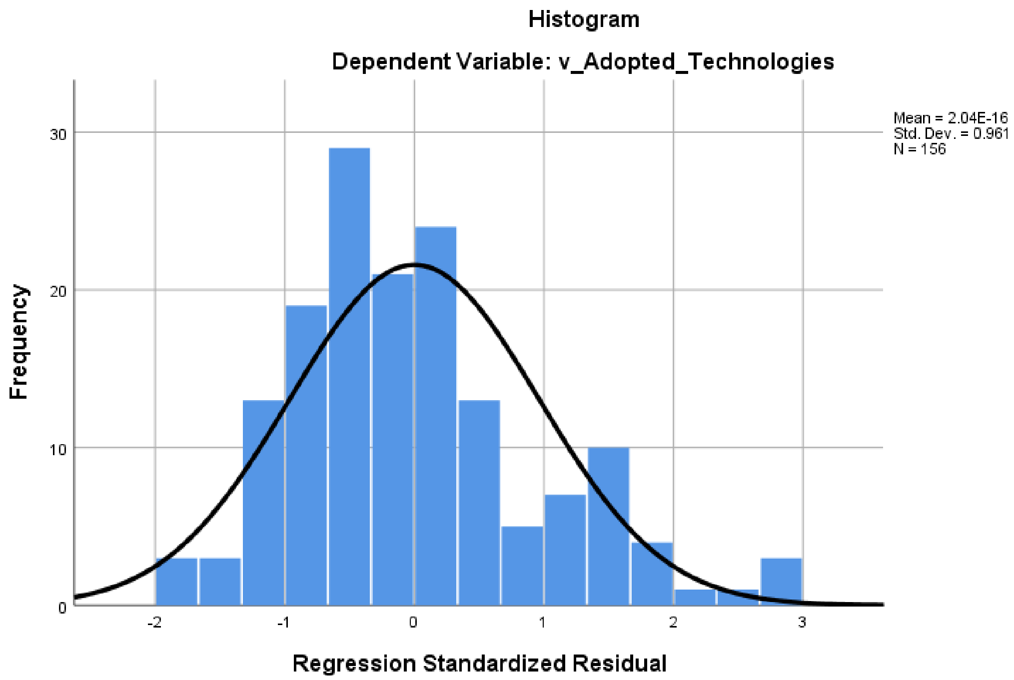
	v_Days_for_Training	-1.005	.525	-.154	-1.916	.057	.820	1.219
	v_Practical_Education	-.006	.012	-.043	-.529	.598	.810	1.234
	v_Non_RnD	-.006	.030	-.016	-.203	.839	.868	1.151

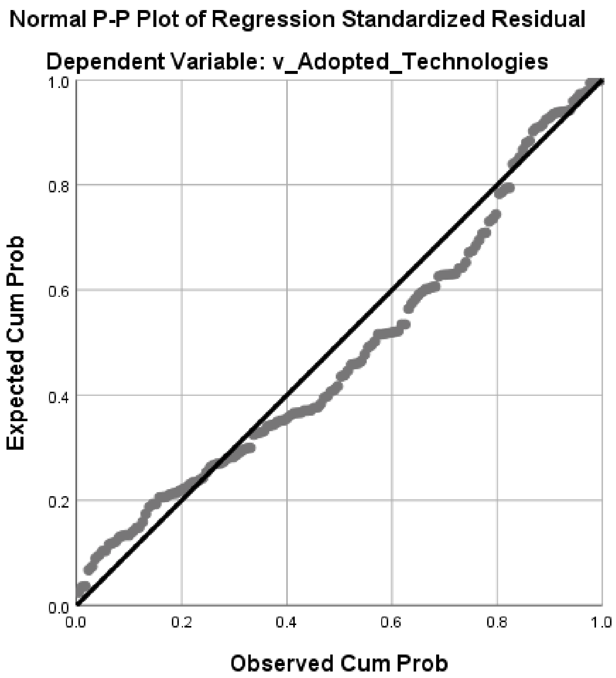
a. Dependent Variable: v_Adopted_Technologies

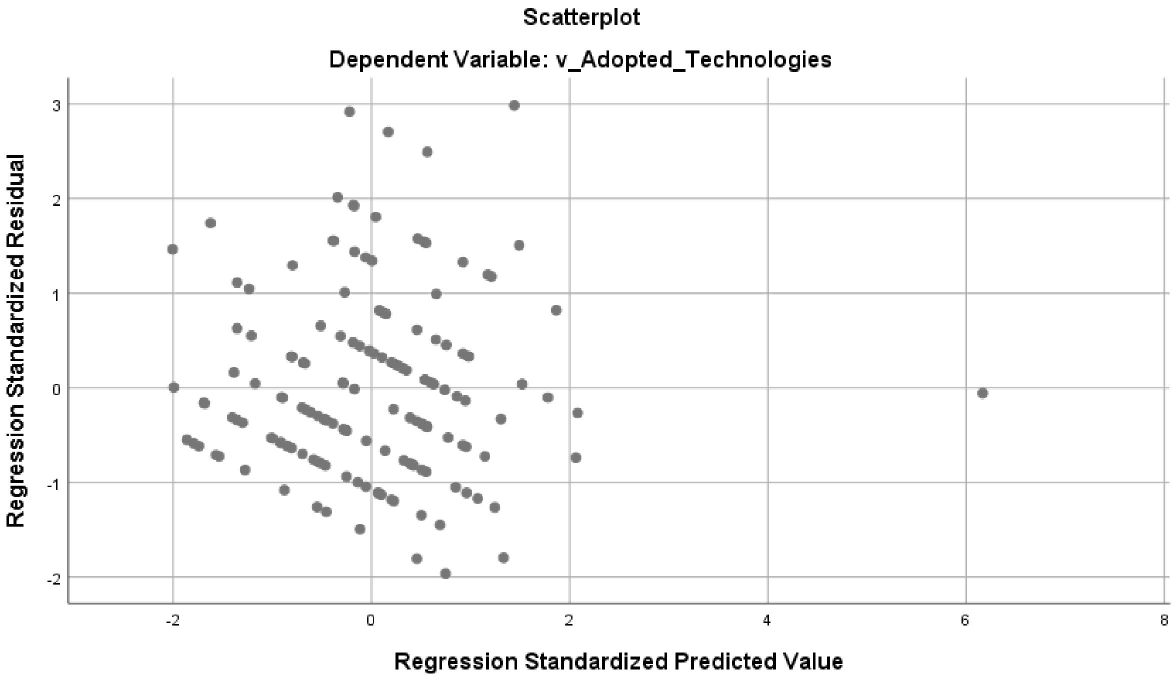
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9745	10.1168	3.2179	1.11917	156
Residual	-4.05652	6.16826	.00000	1.98453	156
Std. Predicted Value	-2.005	6.164	.000	1.000	156
Std. Residual	-1.963	2.985	.000	.961	156

a. Dependent Variable: v_Adopted_Technologies




Normal P-P Plot of Regression Standardized Residual
Dependent Variable: v_Adopted_Technologies
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: v_Adopted_Technologies
Regression Standardized Residual
Regression Standardized Predicted Value
3
2
1
0
-1
-2
4
6
8