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A journey towards Industry 4.0: the supporting role of socio-technical systems

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A JOURNEY TOWARDS INDUSTRY 4.0: THE SUPPORTING ROLE OF SOCIO-TECHNICAL SYSTEMS

Tese de Doutorado submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul como requisito parcial à obtenção do título de Doutor em Engenharia, na área de concentração em Sistemas de Qualidade.

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Esta tese foi julgada adequada para a obtenção do título de Doutor em Engenharia e aprovada em sua forma final pelo Orientador e pela Banca Examinadora designada pelo Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul.

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"There is nothing so practical as a good theory" Kurt Lewin

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RESUMO

Empresas buscam melhorar sua competitividade e produtividade através de inovações em processos, produtos e equipamentos. Tais inovações podem ser feitas através de tecnologias que tragam maior qualidade, flexibilidade, eficiência, controle e monitoramento a sua produção. Nesse sentido, o conceito de uma indústria mais inteligente, automatizada e digital ganhou força e culminou no que se denomina de Indústria 4.0. Muitas empresas visualizam essa evolução da indústria como capaz de entregar melhorias imediatas e diminuir custos de produção. No entanto, creditar somente à tecnologia ganhos de produtividade, qualidade e flexibilidade tem trazido frustrações, diminuição na produção e complexidade aos processos das empresas. Isso se deve, entre outras coisas, à forma como as tecnologias da Indústria 4.0 são entendidas, implementadas, comunicadas e usadas. Estudos empíricos têm demonstrado que as empresas ainda não possuem maturidade tecnológica, cultural e de processos para obter ganhos substanciais com a Indústria 4.0. Com foco nesse processo de implementação de tecnologia, esta tese visa estudar como a abordagem sistêmica e holística proposta pela teoria socio-técnica pode trazer melhorias e ganhos em relação ao ambiente em que as tecnologias como IoT, big data, analytics, robôs colaborativos e impressão 3D são implementadas. Para isso, essa tese tem como objetivo geral identificar como os aspectos socio-técnicos impactam a implementação da Indústria 4.0 e sua contribuição para melhorar os resultados com a sua implementação. Os resultados demonstram que os aspectos socio-técnicos estão associados a níveis mais altos de Indústria 4.0 uma vez que servem de base para que as tecnologias possam operar em um ambiente preparado, com trabalhadores treinados e engajados em seu uso e com uma estratégia clara e delimitada. Os aspectos estratégicos são os que mais impactam no nível de adoção de Indústria 4.0 e são fundamentais para a adoção das tecnologias. Os resultados qualitativos ressaltam tal necessidade e demonstram como as empresas têm feito tal transição tanto através de treinamentos, parcerias com startups e organizações governamentais, assim como buscando capabilidades e conhecimento através de fornecedores, universidades e consultorias. Ainda, os resultados evidenciaram a importância de coletar, armazenaram e possuir capacidade de utilizar dados para melhorias contínuas. Maturidade lean bem estabelecida e a definição de um roadmap estratégico e tecnológico que guie o processo de implementação das tecnologias também foi demonstrado como essencial para que a empresa foque num contexto mais amplo de tecnologias em detrimento de implementações pontuais e usos ad hoc. Finalmente, os resultados também demonstraram que apesar de aspectos de definição estratégica trazerem ganhos importantes para a implementação de Indústria 4.0, melhorias relacionadas a trabalhadores, como engajamento, qualificação e treinamento também são capazes de trazer melhorias na produtividade. Dessa forma, essa tese traz ganhos teóricos para um campo crescente e de interesse da indústria e que demandam investimentos altos, impactando não somente os trabalhadores, mas diversos aspectos organizacionais, sociais e técnicos da empresa. Os resultados discutidos aqui trazem evidências empíricas da importância de uma visão socio-técnica pautada em processos mais organizados, estratégia bem definida e trabalhadores treinados, engajados e participativos na transição para a Indústria 4.0 em contraste a visão tecnocentrista geralmente adotada pelas empresas.

Palavras-chave: Indústria 4.0, Transformação digital, Sistemas-socio-técnicos, Tecnologias na manufatura.

ABSTRACT

Companies seek to improve their competitiveness and productivity through innovation in processes, products, and equipment. This innovation can be achieved via technologies that bring greater quality, flexibility, efficiency, control, and monitoring to their production. In this sense, the concept of a more intelligent, automated, and digital industry gained interest and culminated in Industry 4.0. Many companies view this industry evolution as capable of delivering immediate improvements and lowering production costs. However, only crediting the technology with gains in productivity, quality, and flexibility has brought frustrations, complexity, and reduced production in company processes. This is due to, among other things, the way Industry 4.0 technologies are understood, implemented, communicated, and used. Literature and empirical studies have shown that companies still lack the technological, cultural, and process maturity necessaries to obtain substantial gains with Industry 4.0, especially small and medium-sized companies. Focusing on this technology implementation process, this thesis aims to investigate how the socio-technical theory can bring improvements and gains in relation to the environment in which technologies such as IoT, big data, analytics, collaborative robots, and 3D printing are implemented. For that, this thesis aims to identify how the socio-technical aspects impact the implementation of Industry 4.0 and its contribution to improving the results with its implementation. The results demonstrate that socio-technical aspects are associated with higher levels of Industry 4.0 implementation as they serve as the basis for technologies to operate in a more organized environment, with workers trained and engaged in their use and with a clear and delimited strategy. Strategic aspects are the most impacting aspects of Industry 4.0 implementation and should be considered fundamental for companies adopting its technologies. The qualitative results highlight such importance and demonstrate how companies have made such a transition both through Industry 4.0 ecosystems, as well as seeking capabilities and knowledge through suppliers, consultancies, associations, and startups. Still, the results showed the importance of collecting, storing, and having the ability to use data for continuous improvement. Well-established lean maturity and the definition of a strategic and technological roadmap that guides the technology implementation process were also essential for the company to focus on a broader context of technologies to the detriment of ad-hoc implementations. Finally, the results also showed that although aspects of strategic definition bring important gains for implementing Industry 4.0, improvements related to workers, such as engagement, qualification, and training, can also bring productivity improvements. In this way, this thesis brings theoretical and empirical gains to a field of growing interest for the industry that demands high investments, impacting not only workers but various organizational, social, and technical aspects of the company. The results discussed here provide empirical evidence of the importance of a socio-technical vision based on more organized processes, a well-defined strategy, and trained, engaged, and participative workers in the transition to Industry 4.0, in contrast to the technocentric vision generally adopted by companies.

Keywords: Industry 4.0, Digital transformation, Socio-technical systems, Technologies in manufacturing.

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1. Introduction

Each industrial revolution brought several social, environmental, and technological changes. In this context, the fourth industrial revolution, called Industry 4.0, has also changed companies, bringing innovations in operations, in the implementation of technologies used for manufacturing and expanding the use of data for decision-making, process, and work improvements. Technologies such as the Internet of Things (IoT), cloud computing and data storage (big data), cyber-physical systems (CPS), additive manufacturing, machine learning algorithms, augmented and virtual reality, and vertical and horizontal integration are expected to bring gains in productivity, flexibility and quality (Dalenogare et al., 2018; Enrique et al., 2022). However, Industry 4.0 demands the search for a digital maturity homogeneously by the company instead of specific technology applications. Thus, Industry 4.0 must be supported by organizational aspects that provide the necessary maturity and are guided by clear strategic and operational objectives. Some of these changes are the need for greater availability of data, more constant and technology-focused training, collaboration between worker and machine, decentralization of information, and integration of information within the company's sectors (for example, manufacturing, quality, maintenance, planning, and product engineering and control).

Meindl et al. (2021) analyzed the evolution of Industry 4.0 research after ten years of the theme's proposition at the Hannover Fair. The authors demonstrated that the literature has focused more on aspects related to Smart Manufacturing, while other dimensions have only been explored more recently, as is the case of Smart Working. This cluster of technologies brings a worker-centric view and describes how collaborative robots, virtual reality, and wearable devices can improve work. Some types of uses aim to increase strength using exoskeletons, enhance defect detection using augmented reality, and improve decision-making using artificial intelligence tools (Romero et al., 2020).

The applications of technologies and information systems have been the focus of studies, addressing operational gains in tasks and cost reduction, in addition to the study of adoption and communication standards (Cimini et al., 2020; World Economic Forum, 2016). However, the interaction between workers and technologies in a complex organizational context, such as manufacturing, is not fully addressed (Clegg, 2000; Davis et al., 2014b). These innovations and changes brought by Industry 4.0 are of a socio-technical characteristic (Cagliano et al., 2019) since they are the result of the interrelationship between people (social subsystem) and technologies (technical subsystem) for conducting tasks in an organizational environment. In this sense, the literature emphasizes the need for companies to consider the organizational culture, the level of digitalization of the factory, the types of functions and tasks performed by workers, types of information systems, interactions among technologies, and the impact on human operators for the correct implementation of Industry 4.0 (April, 2013; Cagliano et al., 2019; Kumar & Lee, 2022). However, these concepts tend to be analyzed in isolation. Thus, researchers must consider a socio-technical view of the organizational environment in order to prepare it for the insertion of technologies that can bring complex changes (Sony & Naik, 2020). Otherwise, a boycott of the technologies, lack of preparation of the workers, low adoption and use, and little or no operational and competitive gains could be the results obtained from the investments (Cagliano et al., 2019; Dornelles et al., 2022).

The socio-technical theory has been used to study how technologies change the work environment since its proposal by Trist and Bamforth in 1951 to analyze the implementation of the longwall method, a new equipment in coal mining. Then, the use of the theory and its concepts for the design of work systems grew out of the need to revitalize Europe after World War II in the 1950s with an emphasis on the importance of the organization in an open system

and the need to consider technologies and people together (Kleiner, 2008). The socio-technical systems theory comes from the macroergonomics field and the discipline of Human Factors and Ergonomics (Clegg, 2000; Kleiner, 2008). Macroergonomics arose from the need to expand gains with ergonomic improvements by adopting a broad view of production systems (Kleiner, 2008). Within the socio-technical theory, macroergonomics focuses on the level of work and organization systems, in addition to environmental, personnel, and technological subsystems. As a result, it impacts workers' productivity, health, safety, satisfaction, and organizational culture. Despite the relationship between the theory (socio-technical) and the approach (macroergonomics), this thesis will work with theory and approach within the same umbrella concept of the socio-technical theory that analyzes and proposes a joint consideration of social and technical dimensions in an organization. In this sense, this analysis will be within the scope of the socio-technical system (which is the unit, sector, or group within the organizations), and it recognizes that these systems have limits and actors associated with them and that interactions between these actors occur within these limits, also called subsystems or dimensions (Kleiner, 2008). The higher-order concept of socio-technical subsystems (people/social, technical, work organization, and environmental) comprises socio-technical factors (Kleiner, 2008). The socio-technical factors or aspects are related to the actions, practices, daily activities, and tasks conducted within each subsystem in the organization, which affect Industry 4.0 implementation and are later affected by these technologies as well. Adopting technologies and implementing organizational innovations must consider the needs,

demands, arrangements, and processes of the subsystems that compose the organization (Bednar & Welch, 2020; Soliman & Saurin, 2017). The socio-technical theory analyzes the company from two perspectives, the external environment and the internal environment (Kleiner, 2008). The external environment consists of elements of strategy, interactions with suppliers and customers, business models and market instability, and technological turbulences, for example. The internal environment is divided into three subsystems, social (or personnel), technical, and work organization. Each of them is described below:

- Social (or personnel): consists of the people who work and conduct the organization's tasks. Some examples of components are workers and their demands, insecurities, ergonomics, capabilities, and skills.
- Technical: describes the components used to conduct the activities, such as technologies, tools, systems, procedures, and manuals.
- Work organization comprises descriptions and elements of how the work and workers within an organization are formed, defined, and managed. Procedures, work activities, hierarchies, leadership, and rules are some of the components analyzed.

Since its proposal, the principles of socio-technical systems have undergone several advances and improvements. In this sense, Clegg (2000) describes that the principles of socio-technical theory propose the importance of understanding that the design of productive systems is systemic, guided by the needs of the business, its users, and managers, based on clear values and that these changes are a process shaped by people and are subject to contingencies.

The socio-technical theory's proposed joint vision between people and technologies is even more relevant in Industry 4.0 since its technologies are more flexible, collaborative, and worker-centered (Dornelles et al., 2022; Enrique et al., 2022). Some examples are collaborative robots, wearable devices, virtual reality, and exoskeletons. This level of human-machine interaction and the collaborations between them can bring safety and productivity gains but can also bring problems, difficulties in operation, poorly optimized investments, and insecurities for workers (Dornelles et al., 2022). In addition, the vision of adopting Industry 4.0 through the socio-technical theory and its subsystems is justified given that the vision of the industry and managers

are still very technology-centric (Dalenogare et al., 2018), generating organizational and social gaps that are only identified after implementation (Cagliano et al., 2019). Furthermore, few studies have adopted a holistic view of Industry 4.0 (Meindl et al., 2021), highlighting the need to understand and anticipate how interactions between people and advanced technologies can bring impacts and improvements in companies' production systems.

Based on this context, this thesis addresses the following research questions: (i) what are the socio-technical factors necessary to implementing Industry 4.0? (ii) What is the contribution of different socio-technical factors to the implementation of Industry 4.0 technologies? (iii) What are the socio-technical enabling factors that support the implementation of Industry 4.0? and (iv) what are the socio-technical and Industry 4.0 configurations that allow better digital transformation-driven performance?

1.1 Thesis and thesis objectives

This thesis is part of the Operations Management and Technology themes. The general objective of the thesis is **to identify how socio-technical factors impact the implementation of Industry 4.0 and contribute to operational performance.** In order to achieve the general objective of this work, the following specific objectives are proposed:

- a) To describe how each socio-technical subsystem helps the implementation of Industry 4.0;
- b) To analyze the socio-technical enabling factors for the implementation of Industry 4.0;
- c) To understand the interactions between socio-technical requirements; and
- d) To describe the impact of the socio-technical aspects in performance through the gains provided by Industry 4.0;

Thus, we seek to develop a framework that enables managers and decision-makers to anticipate and evaluate the socio-technical aspects necessary for implementing Industry 4.0 and understand the interactions between these aspects.

1.2 Background to the subject and objectives

This thesis is justified in a theoretical and practical way since there are knowledge gaps about how companies implement and can achieve performance gains through Industry 4.0 technologies considering their internal environment, their social and organizational characteristics, and the barriers and demands of the external environment.

From a theoretical point of view, the literature has shown a growing interest in broader aspects of Industry 4.0 beyond technologies and their functions. For this, studies have sought to analyze the impacts of Industry 4.0 on business models, the number of jobs, ergonomics aspects, and also organizational changes (Frey and Osborne, 2017; Davies et al., 2017; Muller et al., 2018; Weking et al., 2020). However, research still has specific focuses, and a systemic and broad view of the implementation process has been little analyzed, with exceptions such as Cagliano et al. (2019), who addressed a broad view of the impacts of technologies on work design with breadth analysis, autonomy in workers' tasks, cognitive demand and social interactions, in addition to macro impacts such as organizational structure, the centralization of decisions and hierarchical levels in the company. Cimini et al. (2021) analyzed the impact and implications of Industry 4.0 on organizational changes, identifying that more technologies tend to increase the need for nontechnical skills and demand a more autonomous worker profile. Veile et al. (2019) analyzed the lessons learned from implementing technologies and provided necessary aspects such as developing know-how, securing financial resources, integrating workers in the implementation process, and developing an open-minded and flexible culture. Although important and insightful, these studies lack a theoretical lens to their analysis, which is essential for developing a comprehensive understanding of the complex interplay of socio-technical factors that impact the implementation of Industry 4.0. Incorporating a theoretical lens is critical for building a more structured understanding of the socio-technical factors that impact Industry 4.0 implementation and developing theoretical contributions that provide strategies for successful implementation (Kadir and Broberg, 2021; Kleiner, 2008; Sony and Naiki, 2020).

These studies either focus on developed countries with a more suitable scenario for adopting technologies, or they only address specific points of the relationship between people and technologies. Thus, this doctoral thesis is justified since it aims to address both contexts of developed countries (Article 1) and developing countries (Articles 2 and 3). More important than the context justification, this thesis is justified since it addresses the interfaces and interactions between the socio-technical subsystems that make up the organizational environments and their external environment to analyze and discuss the important aspects for the implementation and Industry 4.0 success. To this end, multiple methodological approaches and sources of information were used to expand the generalizability and depth of the results. In addition, this thesis is justified from a practical point of view since the industry has a growing interest in investing in Industry 4.0 technologies to obtain operational, quality, and flexibility gains (Dalenogare et al., 2019; Enrique et al., 2022).

As an empirical analysis has shown, the implementation of these technologies has been done focusing on single technologies (i.e., cobots for quality testing or MES for OEE tracking) and with a focus on solving particular problems, such as quality and process visibility or ergonomics. However, companies lack a broader and contextualized view of this adoption process since they follow generic frameworks or roadmaps for implementing Industry 4.0, leading to a mismatch between the company's context and the Industry 4.0 strategy adopted. This approach leads to failures and investments that are wasted.

A contributing factor is that some technology providers can bias the concept of Industry 4.0 towards a commercial and marketing appeal that leads to expectations of unrealistic gains from technologies that can only come from more complex improvements (such as process and work redesign). Thus, this thesis seeks to provide guidelines for companies and decision-makers to understand and prepare their socio-technical contexts, anticipating demands and foreseeing problems and barriers that may arise from the interactions of new technologies with the organizational environment. In this way, the thesis provides an empirical analysis depicting the technological implementation processes and how social, technical, organizational, and strategic aspects change technology gains when considered in conjunction. Hence, unnecessary expenses can be reduced, and credibility problems linked to technologies and their expected gains can be avoided. The thesis also provides guidelines for adapting the environment and employees to the new context focused on data, intelligence, technology collaboration, and improvements brought by Industry 4.0.

1.3 Study design

This topic details the research and work methods applied for achieving the general and specific objectives within the Implementation of Industry 4.0. Moreover, this thesis is divided into complementing articles that provide results for the relationship between aspects of the sociotechnical environment of companies and their relationship with Industry 4.0 technology implementation and performance, as depicted in **Figure 1**. In this sense, the articles are connected through a theoretical and practical line. Article 1 analyses whether sociotechnical factors are associated with Industry 4.0 implementation. Article 2 expands on the composition of these sociotechnical enabling factors and show how they interact based on cases from companies that have implemented several Industry 4.0 technologies. Finally, article 3 builds on the interactional view of these sociotechnical factors from article 2 to analyze how companies can be classified into sociotechnical configurations. These configurations are emergent from

empirical data and depict a focus on a set of factors that are determinants for performance gains. This concluding article provides a more complex approach to the relationship between socio-technical factors and Industry 4.0 than the linear approach generally used in literature. Therefore, the thesis starts by studying whether socio-technical are important to Industry 4.0 and which are mostly important. Then, Article 2 explores how this relationship happens and what are their interactions. Finally, Article 3 closes the loop by showing the configurations of socio-technical factors that are present in companies, providing a comprehensive and emergent approach to empirically show that only joint improvements among socio-technical factors will lead companies to gains in performance and technology implementation.

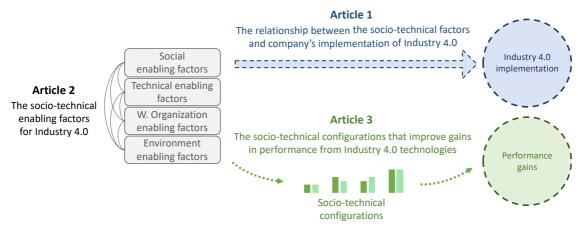


Figure 1 - Connection between the articles

1.3.1 Research Method

This thesis is considered of mixed methods since it applies qualitative and quantitative methods to achieve its objectives. In this sense, for the qualitative study, we used case studies to understand the mechanisms and explore the interactions between the socio-technical subsystems to understand their impact during the implementation process of industry 4.0. The quantitative research encompassed both secondary and primary data in analyzing the impact of socio-technical subsystems on higher Industry 4.0 levels and the use of primary data to understand the impact of Industry 4.0 on performance and how socio-technical subsystems are expected to change such relationships.

The research approach for Article 1 can be classified as deductive and descriptive as it starts from a theoretical proposition of relationships empirically studied to provide insights into how socio-technical aspects contribute to higher levels of Industry 4.0. This article uses secondary quantitative data to address its objective.

Whereas article 2 uses an exploratory design to analyze and deepen the understanding of the relationship between socio-technical enabling factors necessary for adopting and implementing Industry 4.0 for several cases. The exploratory approach allows for analyzing the research problem and describing the mechanisms companies use to develop the necessary enabling factors discussed by the literature on Industry 4.0, as well as their interrelation and contribution to Industry 4.0 implementation. Hence, this article adopts an inductive approach and uses 28 interviews and longitudinal case studies to address its objective.

Finally, article 3 uses a deductive approach to understand how companies develop sociotechnical configurations and test their relationship with the Industry 4.0 impact on performance based on the configurational theory. This article also analyzes which Industry 4.0 technologies are implemented by different socio-technical configurations. It uses a descriptive design to test the proposed relationships. This article uses primary quantitative data to address its objective.

1.3.2 Work Method

This thesis aims at completing a cycle of understanding the problem, analyzing their relationships, and studying their impacts. Therefore, we will develop three articles that start by analyzing the contribution of socio-technical aspects to Industry 4.0. We analyze how this relationship occurs, their mechanisms, and, more importantly, their interactions. Finally, we study how these factors impact performance and lead companies to better Industry 4.0 results. The articles, their research questions, objectives, and methods are described below.

Table 1 - Articles' scope

Article	Research question	Objective	Research method
1	What is the contribution of different socio-technical factors in the implementation of Industry 4.0 technologies?	To analyze the contribution of socio- technical factors in the implementation of Industry 4.0.	Quantitative research 1. Confirmatory factor analysis (CFA) 2. Mean Comparison Tests 3. Logistic regression
2	How do companies develop the socio-technical enabling factors to support the implementation of Industry 4.0? How should these enabling factors support each other to build a socio-technical system for Industry 4.0?	To map how companies developed the socio- technical enabling factors necessary for their Industry 4.0 implementation process.	Qualitative research 1. Semi-structured interviews with companies adopting Industry 4.0 2. Visits to companies 3. Analysis of the interviews grouped by content
3	How are different socio- technical configurations associated with Industry 4.0 technologies and performance outcomes in manufacturing companies?	To analyze the relationship between socio-technical configurations, Industry 4.0, and performance.	Quantitative research 1. Exploratory factor analysis (EFA) 2. Cluster analysis 3. Mean Comparison Tests

Thus, the article titles are as follows:

Article 1: "Socio-technical factors and Industry 4.0: an integrative perspective for the adoption of smart manufacturing technologies"

Article 2: "The socio-technical enabling factors for Industry 4.0 implementation: a holistic approach"

Article 3: "A configurational view of the socio-technical environment of Industry 4.0 adopters"

1.4 Study limitations

This study is limited to understanding the firm-level of socio-technical aspects and the relationships with Industry 4.0 technologies. We do not aspire to analyze sector- or company-level strategic and economic aspects. Even though these contexts would bring important insights, they fall out of our scope and would demand a broader lens, which is not the goal of this thesis. This thesis also attempts to bring a more in-depth analysis of the socio-technical aspects important for Industry 4.0. However, we acknowledge that its findings may differ depending on the companies' context, goals, production system, and leadership style. The findings presented are not an exhaustive list of important socio-technical aspects necessary for Industry 4.0. They are, in fact, a tentative of shedding light on a subject that is still scarce and poorly structured in literature, even though context-specific considerations are always expected to play a major role in the relationship between the organization and the technologies implemented.

Finally, even though we seek to analyze Industry 4.0 according to their different technologies, we assume that companies are following an objective of growing their Industry 4.0 maturity. Thus, we treat Industry 4.0 technologies at a more aggregate level. This approach is due to two main reasons. First, we seek to provide findings and discussions that are generalizable and broad in the sense that several sectors and industries can leverage our results. Secondly, analyzing specific technologies could fall into the trap of even more specificity, leading to less generalizability and discussing technical points instead of the phenomenon itself, which is broader, more complex, and with interactions that arise from the intricated integration of complementary technologies. Thus, a socio-technical system for Industry 4.0 can contain several technologies in integration, increasing its complexity, such as IoT sensors with cloud-operated MES systems connected with a cobot and AGV operating in collaboration with operators using augmented reality or other wearables that provide them more power to make decisions.

1.5 Thesis structure

This thesis proposal is organized into five chapters, including the chapter already presented. The first chapter discussed the research problem, the objectives, and the justifications in addition to the study's method, structure, and limitations. Subsequently, in Chapters 2, 3, and 4, the central articles developed so far that meet each specific objective are presented. The fifth chapter is dedicated to the conclusions, discussing the general objective, theoretical and practical implications, and suggestions for future research.

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2. Article 1 - Socio-technical factors and Industry 4.0: an integrative perspective for the adoption of smart manufacturing technologies

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Abstract:

Purpose: As the level of implementation of Industry 4.0 increases, misalignments between adopted technologies and organizational factors may result in benefits below expected. This paper aims to analyze how organizational factors can contribute to a higher level of adoption of Industry 4.0 technologies. The paper uses a socio-technical perspective lens to achieve this aim. **Methodology**: Using a sample of 231 manufacturing companies in Denmark, a leading country in Industry 4.0 readiness, the paper analyses through cluster analysis and logistic regression whether the development of four socio-technical dimensions – i.e., Social, Technical, Work Organization and Environmental factors – in these companies can benefit the achievement of higher levels of Industry 4.0 technology adoption.

Findings: The results show that companies focused on the development of socio-technical aspects generally present higher Industry 4.0 adoption levels. However, some socio-technical factors are less supportive than others.

Originality: Based on these results, practitioners can plan the adoption of advanced technologies, using a systemic organizational view. This study provides evidence on a growing field with few empirical studies available. The paper contributes by providing an analysis of a leading country in Industry 4.0 implementation, presenting a systemic view on technology adoption in the Industry 4.0 context.

Keywords: Industry 4.0; socio-technical systems; European manufacturing; advanced manufacturing; smart manufacturing; organizational factors.

2.1 Introduction

The concept of Industry 4.0 was conceived by many managers and researchers as a reference to a new industrial paradigm characterized by smart factories operated on cutting-edge base technologies such as the Internet of Things (IoT), cloud computing, big data and artificial intelligence, combined with advanced front-end technologies such as 3D printing, collaborative robots and many more (Frank *et al.*, 2019a; Meindl *et al.*, 2021). Manufacturing companies with higher levels of implementation of Industry 4.0 technologies are expected to achieve better operational performance (Dalenogare *et al.*, 2018). However, such implementation demands substantial investments and changes in the organizational aspects of the company (Büchi *et al.*, 2020).

Prior research on Industry 4.0 has mainly focused on the contributions of technology to manufacturing performance (Dalenogare *et al.*, 2018; Büchi *et al.*, 2020); maturity and adoption levels for the implementation of Industry 4.0 technologies (e.g., Moeuf *et al.*, 2018; Pacchini *et al.*, 2019); and the new manufacturing business models that can be created in such contexts. The new Industry 4.0 production models are characterized by integrating the supply chain with the offering of new products and services (e.g., Benitez *et al.*, 2020; Kahle *et al.*, 2020). However, studies have rarely questioned what is necessary to successfully implement Industry 4.0 technologies in a manufacturing system. Regarding this overall question, it is generally acknowledged that smart factories in the Industry 4.0 context require systemic changes in the way the manufacturing system is currently organized (Horváth and Szabó, 2019). These systemic changes pose challenges of a socio-technical nature, as they encompass a transformation process of social (i.e., individuals and their relationships) and technical aspects and their

interactions in the adoption of new tools, technologies, and management practices (Bednar and Welch, 2019). Amongst many other organizational factors related to the manufacturing system, the implementation of Industry 4.0 technologies may improve workers' capabilities (Fantini *et al.*, 2018; Bednar and Welch, 2019). It may also require changes in operational processes (Cagliano *et al.*, 2019) and manufacturing strategies (Kusiak, 2018; Rosin *et al.*, 2020). Furthermore, these socio-technical aspects may also influence the implementation of Industry 4.0. Therefore, a systemic perspective on the implementation is required to study how different organizational factors could and should support the implementation of Industry 4.0.

The manufacturing management systems literature, e.g., the lean literature, has commonly adopted the socio-technical theory to analyze the success of lean program implementation (Soliman and Saurin, 2017). However, since the Industry 4.0 stream is driven by a technologypush approach (Frank et al., 2019b), it is not a surprise that technology evangelists may sometimes overlook essential social and organizational factors in the manufacturing system (Davies et al., 2017; Horváth and Szabó, 2019). Moreover, it is not yet clear how different sociotechnical dimensions interact with Industry 4.0 technologies, since the interconnectivity of such technologies may result in complex systems that behave differently as compared to the classical mechanics-driven systems (Cagliano et al., 2019; Horváth and Szabó, 2019; Rauch et al., 2020). As argued in prior research, improvements through technology adoption are only achieved when the whole set of organizational aspects are aligned, e.g., workers' activities, motivation, training, the tools necessary, production system, and strategic objectives (Cimini et al., 2021; Veile et al., 2019). Therefore, more research is necessary on the aspects that can support Industry 4.0 and its implementation (Meindl et al., 2021). Thus, a research question emerges for this study: what is the contribution of different socio-technical factors (or subsystems) for the implementation of Industry 4.0 technologies?

To address this research question, this article analyzes specific socio-technical factors that support companies implementing Industry 4.0. The paper hypothesizes that companies concerned with socio-technical aspects are able to implement higher levels of Industry 4.0 technologies, since the success of such an implementation may be based on the support of socio-technical factors of the broader manufacturing system. This hypothesis is tested by analyzing data from the European Manufacturing Survey (EMS) - one of the largest manufacturing surveys in Europe (Dachs et al., 2019). This study used a subset of the EMS data regarding 231 manufacturing companies from Denmark, which is considered one of the leading European countries in terms of digital infrastructure readiness to support the implementation of Industry 4.0 (Castelo-Branco et al., 2019). The results of the study confirm the general hypothesis by showing that companies that are highly focused on socio-technical systems show higher implementation levels of Industry 4.0 technologies. Using logistic regression, the study also demonstrates how much each of the investigated socio-technical subsystems affects the likelihood of a company presenting a high level of Industry 4.0 technologies implementation. The results show differences concerning the level of contribution of each socio-technical dimension involved in the Industry 4.0 technology adoption process. Consequently, this study provides empirical evidence and managerial recommendations to enhance the implementation of Industry 4.0 in manufacturing companies.

2.1.1 Theoretical background and hypotheses development

2.1.1.1 Different approaches to Industry 4.0 implementation

The implementation of Industry 4.0 technologies has been addressed from different perspectives in the literature. One approach considers Industry 4.0 maturity and technology adoption models. It has been widely disseminated in the professional environment through the RAMI 4.0 model (Reference Architecture Model Industrie 4.0) (Hankel and Rexroth, 2015) and through the Acatech Industrie 4.0 Maturity Index from the German National Academy of Science

and Engineering (Schuh *et al.*, 2017). The academic literature has followed this stream with models for assessing Industry 4.0 readiness as well as proposing and designing Industry 4.0 roadmaps (Pacchini *et al.*, 2019; Schumacher *et al.*, 2016). In a nutshell, this stream has been concerned with the correct order of implementation for Industry 4.0 technologies to become more digitized in the production processes (Pacchini *et al.*, 2019).

A second cluster of the literature has investigated the differentiation between the implementation of Industry 4.0 technologies in small, medium-sized and large companies. Such studies have highlighted that the type and intensity of technology implementation may be completely different depending on these different company size profiles and have also been concerned with proposing the most suitable technologies for different company size classes (e.g., Mittal *et al.*, 2018; Moeuf *et al.*, 2018). A third stream of studies on Industry 4.0 implementation has considered the diversity of Industry 4.0-related technologies that a company may implement depending on the strategies it pursues (e.g., Dalenogare *et al.*, 2018; Frank *et al.*, 2019a; Pacchini *et al.*, 2019). This stream of literature has organized technologies can be used, among others, for product development, manufacturing, supply chain management, and product and service offering (Frank *et al.*, 2019a). In each of these applications, companies can implement various technologies with different levels of use intensity (Mittal *et al.*, 2018; Pacchini *et al.*, 2019).

This study uses elements of these three different perspectives to investigate the implementation of Industry 4.0 technologies. Firstly, from the adoption perspective, this study considers that companies will be at different stages in the implementation of Industry 4.0 technologies (Cagliano et al., 2019; Pacchini et al., 2019). However, rather than analyzing the optimized implementation path, this study aims to classify companies according to their levels of technology implementation in order to compare their overall socio-technical aspects. Secondly, regarding the *implementation* of Industry 4.0 according to company size, this paper follows the previous studies that focused on Industry 4.0 in small and medium-sized enterprises (SMEs) (e.g., Mittal et al., 2018; Moeuf et al., 2018). The present study assumes that implementation patterns vary between SMEs and large companies, as demonstrated by Mittal et al. (2018). Therefore, such potential influences are expected to be eliminated by considering only SMEs. Finally, regarding the stream that considers the implementation of different groups of technologies according to their application, this study only focuses on the Smart Manufacturing dimension of Industry 4.0 (Bueno et al., 2020). According to Frank et al. (2019a), Industry 4.0 can be represented by different smart dimensions, such as Smart Manufacturing, Smart Supply Chain, Smart Working, and Smart Products. The current study focuses on the implementation aspects in the Smart Manufacturing dimension because this is where the socio-technical aspects may be more necessary (Koh *et al.*, 2019).

The Smart Manufacturing dimension of Industry 4.0 considers several technologies that help companies to obtain a cyber-physical manufacturing system (Bueno *et al.*, 2020). It is enabled by vertical integration of manufacturing systems by means of real-time data processing for manufacturing planning and control (Schuh *et al.*, 2017). It also comprises automation and management of internal logistics (Kusiak, 2018; Müller *et al.*, 2018; Rosin *et al.*, 2020) and the use of advanced robotics in production processes and logistics (Longo *et al.*, 2017). Furthermore, Smart Manufacturing aims at the use of safe operation systems (human-machine interaction) (Bednar and Welch, 2019; Longo *et al.*, 2017; Segura *et al.*, 2018) and at improving energy aspects (Dalenogare *et al.*, 2018), for instance, by implementing systems for energy recuperation and efficiency (Frank *et al.*, 2019a; Horváth and Szabó, 2019). Finally, additive manufacturing is a growing trend in SMEs with respect to Smart Manufacturing (Frank *et al.*, 2019a). Although the use of 3D printers for additive manufacturing started with prototyping (Pacchini *et al.*, 2019),

the cutting-edge view is to implement this technology in the mass production system to achieve a highly flexible production system (Dalenogare *et al.*, 2018; Moeuf *et al.*, 2018).

Previous literature has reported that many of the mentioned Industry 4.0 technologies are at very different levels of implementation. However, most of the prior studies reviewed only consider the economic factors regarding the different implementation levels (e.g., Dalenogare *et al.*, 2018). In contrast, this study argues that companies with strong socio-technical systems may be better prepared for achieving higher levels of implementation of Industry 4.0 technologies (Meindl *et al.*, 2021).

2.1.1.2 Socio-technical systems theory as a research lens for Industry 4.0 adoption

The socio-technical theory (STS) is grounded on the premise that, for an organization or a work unit to achieve its goals, the social and technical systems of the organization must be jointly optimized, considering its work organization system and environment. The term "socio-technical systems" has been coined in the seminal work by Trist and Bamforth (1951) after studying the work in coal mines in England. Since then, STS theory has been adopted as a lens in the study of several industrial fields, especially manufacturing (Soliman *et al.*, 2018). Building on this stream, this paper analyzes the adoption of Industry 4.0 technologies from the STS perspective, which is increasingly common in recent Industry 4.0 research (Nosalska *et al.*, 2019).

Industry 4.0 benefits from a socio-technical approach that considers both human and technological implications and their interrelationships. For instance, through the involvement of employees in technology implementation, barriers to adoption due to workers' resistance can be reduced, while their contribution to ongoing changes can potentially be increased (Vereycken et al., 2021). Cimini et al. (2021) analyzed the relationship between Industry 4.0, job creation, and organization, showing that companies experienced a considerable change in terms of structural reorganization and hierarchical level reduction during the adoption of Industry 4.0. In addition, more multiskilled and specialized workers are needed due to an increased need for autonomy and a combination of technical and non-technical competencies (Cimini et al., 2021). In relation to workers' relevant future competencies, Veile et al.'s (2019) results highlight the importance of interdisciplinary knowledge, adequate training - especially concerning IT competencies –, and personality traits of willingness to change and communication. In prior studies, manufacturing management systems e.g., lean implementation and its integration with technologies and equipment retrofit were also mentioned as important for Industry 4.0 and organizational aspects related to agile methods such as flat hierarchies, flexible structures, and decentralized settings (Cimini et al., 2021; Veile et al., 2019). These are only some examples from the growing and still scattered literature on specific socio-technical factors mentioned in the Industry 4.0 domain (Meindl *et al.*, 2021).

The socio-technical approach can also help reducing adoption barriers. For example, in the Danish context (aim of our empirical study), some significant barriers to Industry 4.0 are the lack of employee knowledge about technology's use, job uncertainty, managers' failure to perceive the strategic importance of these technologies, and low understanding of the interplay between technology and human beings (Stentoft and Rajkumar, 2019; Stentoft *et al.*, 2020a). Similar barriers are also reported for SMEs, including inadequate process organization, difficulty to find employees with appropriate competencies, and lack of conscious planning and goals (Horváth and Szabó, 2019). These barriers are often the result of managers following a technology-centered perspective, which tends to ignore technology users, the processes where technologies are implemented, and the broader impacts on the company (Davies *et al.*, 2017; Horváth and Szabó, 2019). The socio-technical approach can help overcome these barriers since it provides a holistic, contemporary, and open perspective in the analysis of the requirements and changes that Industry 4.0 tools and technologies will have on the company. Such a

perspective ensures that the implementation process integrates stakeholders, their skills, culture, manufacturing, processes infrastructure and goals (Bednar and Welch, 2019; Davies *et al.*, 2017). It also considers workers' training, their integration in the technology adoption process, the company's definition of clear goals, and the design of a collaborative, open and innovative environment (Bednar and Welch, 2019).

In the Danish manufacturing context, the socio-technical approach in Industry 4.0 adoption is increasingly important since significant concerns about job enrichment, workers' needs, and satisfaction have been historically related to Scandinavian countries (Oudhuis and Tengblad, 2020). Furthermore, the socio-technical principles establish that technological investments and organizational changes must be co-developed and supported by operational actors (Cimini *et al.*, 2021; Vereycken *et al.*, 2021) considering cultural, social, and organizational aspects (Davies *et al.*, 2017). Hence, organizations should leverage technologies to adapt to new processes instead of letting technology guide organizational redesign. Therefore, the rationale for developing the hypotheses in this study was that each subsystem has the potential to affect the adoption and success of implementing new technologies and production processes in companies. For analytical purposes, STS can be divided into four complementary subsystems, i.e.: Social, Technical, Work Organization and Design and External Environment (Hendrick and Kleiner, 2000; Kleiner, 2008; Soliman *et al.*, 2018).

2.1.1.3 Social subsystem

The social subsystem encompasses people involved in the organization (Kleiner, 2008), addressing their development, knowledge, safety, personal interests, skills, experience, engagement, and other human-related elements (Frank *et al.*, 2015; Soliman *et al.*, 2018).

The adoption of Industry 4.0 technologies has many implications in the social dimension. One facet is that the more Industry 4.0 technologies are adopted, the more the production system will demand autonomy and job breadth from its employees (Cagliano *et al.*, 2019). This is the case when employees who previously operated forklifts manually, after the implementation of smart logistics devices were now tasked with solving possible problems with machines that operate autonomously. Such changes give more autonomy to employees, demanding a more proactive profile and less hierarchical control or supervision roles (Cagliano *et al.*, 2019). Another facet is the possibility of encountering social barriers, as employees may feel their jobs are threatened by the implementation of new technology for the automation of manual tasks (Horváth and Szabó, 2019; Szalavetz, 2019).

In mature social systems, however, the implementation of Industry 4.0 technologies may be viewed by employees as a means of human appreciation as it frees employees from simple or repetitive activities and allows them to engage in creative and higher value-added activities (Horváth and Szabó, 2019; Longo *et al.*, 2017). Consequently, the active participation of employees in improvement activities may be an asset in the adoption of Industry 4.0 technologies. The main reason for this positive assessment is that the knowledge of those who are familiar with the (production) process is highly relevant for an appropriate fit between the new technology and the system where it is to be applied (Szalavetz, 2019). Thus, a stronger focus on the social values of employees can be expected to lead to a higher level of adoption of Industry 4.0 technologies, as Industry 4.0 potentially allows for richer and broader jobs, with autonomy. These new, enriched jobs focus on the use of workers' knowledge, value addition, and ergonomics (Cagliano *et al.*, 2019; Szalavetz, 2019). Moreover, they are necessary because the successful implementation of an advanced production planning and control system (as a crucial element of Industry 4.0) requires extensive use of employees' experiences (Szalavetz, 2019).

Following the above argumentation, Industry 4.0 poses disruptive challenges for companies, as the human force is expected to be improved in its technical, social, and psychological aspects.

This shift toward "Human Capital 4.0" (Flores *et al.*, 2020) or Smart Working (Meindl *et al.*, 2021) comprises a holistic change encompassing employees' competencies, education, and well-being, as well as the innovations necessary for the Industry 4.0 workforce. A social system that values such employee qualifications and empowerment reduces the learning curves necessary for the addition of Industry 4.0 technologies and encourages employees to explore and take advantage of the new technology (Bednar and Welch, 2019; Horváth and Szabó, 2019; Müller *et al.*, 2018). To this end, companies can leverage new learning methods (i.e., e-learning, augmented reality, consultancy training, etc.) (Veile *et al.*, 2019). Additionally, future employees will need to become more resilient, interdisciplinary, analytical, digitally literate, communicative, and adaptable to cope with the increased interaction and collaboration that an Industry 4.0 context can pose (Flores *et al.*, 2020; Veile *et al.*, 2019). Based on the aforementioned argumentation, the following Hypothesis H1 is proposed:

H1: Practices for the improvement of social aspects in the manufacturing system are positively related to higher levels of Industry 4.0 adoption.

2.1.1.4 Technical subsystem

The technical subsystem comprises elements of the (production) operation and how it is performed (Kleiner, 2008), encompassing tools, physical spaces and their elements, number of parts such as machinery and inventory, technologies, maintenance, methods, information, etc. (Frank *et al.*, 2015; Soliman *et al.*, 2018). The technical subsystem is usually the most visible subsystem of all STS since its artefacts can be directly observed, in contrast to the subjective characteristics of social, work organization and external subsystems.

In the context of Industry 4.0, prior studies have mainly addressed the technical subsystem through an assessment of the technologies that fit the definitions of Industry 4.0 (Kusiak, 2018). However, from a socio-technical perspective, the technical subsystem is more comprehensive, encompassing process technologies and methods for manufacturing systems in general (Marodin *et al.*, 2016). Therefore, this study is concerned with the investigation of how these general technical aspects may be related to different adoption levels of specific Industry 4.0 technologies. Rosin *et al.* (2020) propose that the relationship between technical aspects of continuous flow, visual management and waste identification are highly associated with IoT technologies and simulation, as they enable monitoring and optimizing of the production system.

Consequently, technical aspects can also serve as a prerequisite for Industry 4.0 because they can help to improve production standardization, eliminate waste and focus on customer value, which are all essential aspects of a successful Industry 4.0 implementation (Cagliano *et al.*, 2019; Rosin *et al.*, 2020). Technical aspects can also co-evolve inside the company and therefore managers should consider the evolution of both areas simultaneously, taking into consideration the synergies that the technology adopted can have with manufacturing management systems (Cimini *et al.*, 2021; Pagliosa *et al.*, 2019).

Based on the above argument, technical aspects are expected to have a positive association with Industry 4.0 adoption. Predefined systematics and policies for inventory management, for example, may facilitate the adoption of e-Kanban, enable electronic production planning and control (Davies *et al.*, 2017), or facilitate the use of waste reduction concepts in simulated processes to plan actions for improved productivity (Dalenogare *et al.*, 2018). Thus, concepts such as process mapping, pull production, task-technology fitness analysis, can lead companies to enhancements in Industry 4.0 adoption and use of automated data, as these tools provide information on the operation, processes, and supply chain of a company (Cagliano *et al.*, 2019; Tortorella *et al.*, 2019). According to this view, one should expect previously improved and stabilized technical aspects to be associated with higher levels of Industry 4.0 adoption. If this is not the case, technology adoption will result in digital complexity without achieving the

expected results (Cagliano *et al.*, 2019; Tortorella *et al.*, 2019). Based on the aforementioned considerations, Hypothesis H2 is proposed:

H2: Practices for the improvement of technical aspects in the manufacturing system are positively related to higher levels of Industry 4.0 adoption.

2.1.1.5 Work Organization subsystem

Work organization considers the way in which work is designed in a firm, comprising aspects such as the rules, operational procedures, work instructions, information flow, team organization, employee shifts, training for the operation, task planning and integration, and other aspects of the work to be conducted (Frank *et al.*, 2015; Kleiner, 2008; Soliman *et al.*, 2018). This subsystem also adds to the idea of joint optimization between the social and technical systems (Hendrick and Kleiner, 2000).

The work organization subsystem can highly determine whether the adoption of new technologies will be successful. Authors such as Frey and Osborne (2017) suggest that the adoption of new technologies implies reallocating low-skilled workers to tasks that require creativity and social intelligence. Consequently, the work organization practices, including procedures and policies for workload distribution and accountability for productivity, may facilitate the transition to the new work context brought on by Industry 4.0. As a further consequence, if technologies advance at a faster pace than the velocity at which the systems adapt their formal structures (e.g., the organizational chart), agreements on work organization become increasingly important to minimize disruptions in work organization and other company systems (Cagliano *et al.*, 2019). According to Davies *et al.* (2017), in the Industry 4.0 context, the executive level will need a more direct relationship with the operational level, as the management system will change from controlling workers at the operational levels will be elevated to the status of "knowledge workers" (Longo *et al.*, 2017), as the decision process becomes more collective, with knowledge shared among hierarchical divisions (Davies *et al.*, 2017).

Consequently, improvements in work organization and design are necessary to help companies achieve good Industry 4.0 results (Fantini *et al.*, 2018). Some of these practices can include, for instance, involving employees in idea generation (Davies *et al.*, 2017), participative management (Davies *et al.*, 2017; Frank *et al.*, 2015; Soliman *et al.*, 2018), training for job-specific functions, integrating tasks (Longo *et al.*, 2017), and improving the work context with instructions and exchange of experiences. Work organization design principles such as goal-driven processes, the interconnection between people and machines, information transparency, decentralized decisions, and incorporating ideas from different hierarchical levels are important because they support and accelerate Industry 4.0 implementation, reducing the necessary financial and organizational efforts (Hermann *et al.*, 2019).

Following the above arguments, work organization is expected to play a key role in Industry 4.0, and a structured and improved work organization and design can be expected to increase Industry 4.0 adoption levels (Longo *et al.*, 2017; Moeuf *et al.*, 2018). Moreover, workers' involvement and work environment improvement enable better results in complex human-technology interactions (Longo *et al.*, 2017). Based on the aforementioned argument, Hypothesis H3 is proposed:

H3: Practices for the improvement of work aspects in the manufacturing system are positively related to higher levels of Industry 4.0 adoption.

2.1.1.6 Environmental subsystem

The environmental subsystem can be seen through two lenses (Frank *et al.*, 2015): (i) external environment factors, which refer to aspects such as market and supply chain, as well as government policies and regional culture that influence Industry 4.0 (Benitez *et al.*, 2020; Frank

et al., 2015); or (ii) internal environment factors on the operational level, which encompass characteristics such as the strategies and policies that may influence the operational activities (Frank *et al.*, 2015). This study addresses the latter, as this is the best unit of analysis for investigating the environmental subsystem (i.e., internal environment factors) due to its direct impact on technology selection and adoption and to its direct connection to the manufacturing system (Mittal *et al.*, 2018).

In the environmental view, companies may adopt Industry 4.0 technologies due to strategic demands, such as market demand, production processes, employee condition improvement, customization, or other strategic choices (Weking *et al.*, 2020). One of these strategic choices is the use of technologies to provide innovative business models, such as servitized solutions (Müller *et al.*, 2018). Manufacturing strategies may also lead companies to adopt specific Industry 4.0 technologies such as sensors, big data, or additive manufacturing, rather than implementing the complete set of solutions proposed by the Industry 4.0 concept (Dalenogare *et al.*, 2018). Thus, technology implementation should be driven by the specific operational target the company is pursuing and requires committed leadership, effective resource allocation, and identifying/managing function needs as well as priorities (Ghobakhloo, 2018; Kagermann, 2015).

The environmental strategy of Industry 4.0 involves defining the functional needs and priorities for the technological transition, conducting a respective cost-benefit analysis, and managing the changes required by Industry 4.0 (Ghobakhloo, 2018). Following these guidelines allows companies to have a clearer view of their operational objectives, leading to sounder investments in Industry 4.0 technologies (Ghobakhloo, 2018; Moeuf *et al.*, 2018; Raj *et al.*, 2020). In this context, companies that are strongly focused on improvements related to manufacturing performance – i.e., productivity, cost reduction, quality, and product customization –, are expected to increasingly adopt Industry 4.0 technologies as a means of improving these metrics (Dalenogare *et al.*, 2018; Moeuf *et al.*, 2018; Raj *et al.*, 2020). Based on the consideration above, hypothesis H4 is proposed:

H4: The definition of clear strategies for the production system is positively related to higher levels of Industry 4.0 adoption.

2.2 Conceptual research model

Figure 2 summarizes the four hypotheses above, which propose a positive relationship between the implementation of the investigated socio-technical systems and higher levels of adoption of Industry 4.0 technologies. This approach assumes that companies can be classified according to different levels of adoption of such technologies (Frank *et al.*, 2019a). Still, it does not define how many adoption levels will depend on the sample characteristics under investigation, as shown in the next section.

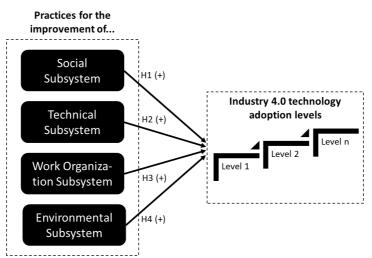


Figure 2 - The studied relationship between the four STS subsystems and the level of Industry 4.0 adoption

2.3 Method

2.3.1 Data collection and sample description

This study used data from the European Manufacturing Survey (EMS). The German Fraunhofer ISI Institute coordinates the EMS survey consortium and organizes it in partnership with 18 European universities and public research institutes (Kirner et al., 2009). The EMS aims to assess the industrial characteristics of manufacturing companies (with at least ten employees) through 24 groups of questions (Dachs et al., 2019). The EMS survey has some core common questions for all countries and allows each partner country to decide a specific block of questions to be added in order to conduct specific research (Kinkel, 2012; Broedner et al., 2009). A subsample of this survey, conducted in Denmark in 2016, was used for this study. Industry 4.0-related technologies were included in this chapter of the EMS because Denmark already presented an outstanding level of Industry 4.0 infrastructure at the time as compared to other European countries, according to the Eurostat database (Castelo-Branco et al., 2019). In this sense, the Danish chapter aimed to assess how engaged companies were in implementing this concept, which had been launched five years before in the German Industry 4.0 initiative. Consequently, the option to study Denmark's manufacturing companies allowed us to consider Industry 4.0 maturity in an advanced technological context (Castelo-Branco et al., 2019). One of the authors of this study participated in the Danish research team that developed the specific EMS questions to be asked to Danish companies in addition to the general questions defined by the international EMS consortium for the master version of the survey. Before collecting the Danish EMS subsample, the English master version of the EMS questionnaire was translated into the Danish language by a native speaker in the national EMS team.

The Danish EMS section selected a total population of approximately 2,800 *production companies* with 10 or more employees from the EXPERIAN Database for Denmark. Given the relatively small number of this full population of Danish production companies from an international perspective, it was not necessary to select a specific sample for the survey. To obtain as many production managers' personal e-mail addresses as possible, a large team of research assistants temporarily joined the Danish EMS team and tried to phone all the 2,800 companies to explain the survey's objective. The original list was thus reduced to a final full population of approximately 2,300 active contacts, excluding companies with outdated contact information or that did not answer the phone after three attempts. If the assistants reached a receptionist or another employee, they introduced the survey and asked for the personal e-mail of the firm's production manager (or someone in a similar role). If the production manager's

personal e-mail could not be provided, the EMS team asked if the survey link could be sent directly to the company's general e-mail address, highlighting that in any case the survey should be answered by production managers or people in similar positions. Overall, a little more than 50% of the successfully contacted companies agreed to providing the personal e-mail address of their production managers.

The Danish EMS team obtained a final sample of 266 responses (11.56% response rate, considering the full population of active contacts). After eliminating incomplete responses and responses from large companies, a final dataset of 231 SMEs was obtained for use in this study (**Table 2**). The study only focused on SMEs and avoided mixing them with large companies because their Industry 4.0 characteristics tend to be quite different from those of large companies, as shown by previous research (Mittal *et al.*, 2018; Müller *et al.*, 2018).

Supply chain position	n	%	Company's size	n	%
B2B	62	26.8%	Small (<50 employees)	124	53.7%
Parts and components	57	24.7%	Medium (50 - 250 employees)	107	46.3%
B2C	49	21.2%			
Systems supplier	35	15.2%			
Contract manufacturer	22	9.5%			
Not defined	6	2.6%			
Total	231	100%		231	100%

Table 2 - Sample composition

2.3.2 Construct definition

The EMS dataset comprises a long list of operations technologies for manufacturing plant management. This study used the group of questions related to smart manufacturing technologies (see **Table 3**), which is the core dimension of the Industry 4.0 concept (Frank et al., 2019a). EMS also comprises other questions related to product design, supply chain management and employment which were not considered in this study. The analysis focuses on the Industry 4.0 front-end technologies, that is, technologies that are used for specific applications (Frank et al., 2019a). Industry 4.0 base technologies, including IoT, Cloud Computing, Big Data, and Artificial Intelligence, on the other hand, are general-purpose technologies that support the front-end technologies considered in Table 3 (Frank et al., 2019a). Given the growing number of technologies associated to the Industry 4.0 concept, the EMS limited the data collection to the cutting-edge technologies that are most likely to be adopted in industrial applications. Moreover, the EMS focused on manufacturing technologies that enable intelligent and autonomous manufacturing systems, which are represented by the highest levels of the Acatech Industrie 4.0 Maturity Index from the German National Academy of Science and Engineering (Schuh et al., 2017). By following the German perspective on advanced levels of Industry 4.0, the list of ten technologies considered in this study does not consider alternatives like smart working-related tools (e.g., augmented and virtual reality), which instead of focusing on highly autonomous systems are geared to enhancing workers' productivity in the system (Meindl et al., 2021).

Regarding the specific technologies considered, the technologies listed in the EMS questionnaire are based on Industry 4.0 initial reports from the German initiative (Kagermann *et al.*, 2013; Kagermann, 2015), which were discussed and adapted by the EMS Danish and international consortium. The study included software and systems technologies, such as systems for automation and management of internal logistics [tech9] (Frank *et al.*, 2019a; Kadir and Broberg, 2021), and near real-time production control systems [tech10] for production monitoring and traceability (Frank *et al.*, 2019a; Moeuf *et al.*, 2018; Segura *et al.*, 2018). Advanced logistics automation [tech4] was also included, which considers technologies such as Automated Guided

Vehicles (AGV) and Autonomous Mobile Robots (AMR) (Frank *et al.*, 2019a; Kadir and Broberg, 2021). Technologies for safe human-machine interaction [tech5] includes technologies with sensors and Artificial Intelligence to interact with workers, such as different types of collaborative robots (Bednar and Welch, 2019; Frank *et al.*, 2019a; Longo *et al.*, 2017). Energy management and optimization were included with three types of technologies [tech6, tech7, and tech8], as this concept is an important driving force for Industry 4.0 adoption (Horváth and Szabó, 2019), especially in European countries where energy resources are a major driving force of the industrial economy (Lerman *et al.*, 2021). These technologies involve different systems that use IoT, cloud, and big data to execute remote monitoring, control, and autonomous energy adaptation (Dalenogare *et al.*, 2018; Frank *et al.*, 2019a). Advanced manufacturing techniques were also considered in the form of emerging technologies like additive manufacturing for product prototyping and manufacturing [tech1 and tech2] (Kadir and Broberg, 2021; Kagermann *et al.*, 2013) and classic industrial robots for manufacturing, both embraced by the Industry 4.0 concept as well (Dalenogare *et al.*, 2018; Frank *et al.*, 2019a; Kadir and Broberg, 2021).

Moreover, a list of variables described in **Table 3** was used to measure the STS dimensions (these variables were already part of previous versions of EMS and were only improved or adapted). The questions used to measure companies' socio-technical aspects are described in Table 3. The variables comprise the main characteristics that compose each subsystem, e.g., the Social dimension [SOCIAL] considers the implementation of activities, tools, and methods oriented toward workers' development. It comprises activities that enhance autonomy, innovation and creativity, as well as motivational aspects such as employee engagement and retention approaches (Tortorella et al., 2018). The Technical dimension [TECHNICAL] comprises methods focused on improving the shop floor processes and manufacturing management systems (Marodin et al., 2016; Marodin et al., 2018). These methods include visual management and workplace organization, which allow for better movement of workers in the factory, a process flow of materials, and products oriented toward rapid changes in the production process – and methods for production process optimization and quality assurance. The third dimension, Work Organization [ORGANIZATION], considers the work procedures aimed at obtaining benefits from practices to help workers focus on their tasks and on the production process flow. This dimension includes standardized routines, on- and off-the-job training to improve technical skills, using job rotation and task integration (i.e., machine operators participate in the planning and control of the processes in which they are involved) (Cagliano et al., 2019; Longo et al., 2017). Lastly, the Environmental dimension [ENVIRONMENT] considers operational strategies that define targets for the production system (Dalenogare et al., 2018; Weking et al., 2020). The set of questions asked regarding the socio-technical dimensions of Danish companies with the detailed items and scales used to assess the concepts are presented in Table 3.

Table 3 - Construct defini	ion from the EMS dataset
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Technology assesse	ed in t	he EMS questionnaire
Which of the follow	ing te	chnologies are currently used in your factory?
Likert scale: "1 – no	t ado	pted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to
a medium extent, 5	– ado	opted to a high extent.
Industry	4.0	[tech1] Additive manufacturing technologies for prototyping
technologies		[tech2] Additive manufacturing technologies for mass production
[TECHNOLOGIES]		[tech3] Industrial robots in the production process
-		

HNOLOGIES][tech3] Industrial robots in the production process
[tech4] Industrial robots in the handling process
[tech5] Technologies for safe human-machine interaction

[tech6] Control-automation systems for an energy-efficient process

[tech7] Control system for shut down of machines in off-peak periods

[tech8] Technologies for recuperation of kinetic and process energy

[tech9] Systems for automation and management of internal logistics

[tech10] Near real-time production control system	
Socio-technical Questions assessed in the EMS questionnaire	
Social subsystem (SOCIAL): Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent.	Factor Loading
IT-based self-learning programs (e-learning) Standardized methods of job design to improve health or safety (e.g.: TMT measurements) Tools to promote employee engagement (e.g.: free canteen, childcare) Tools for retaining older employees or their knowledge in the company (e.g.: composition of teams with a focus on age diversity)	0.60 0.53 0.66 0.45
Training opportunities with an interdisciplinary focus	0.42
Training and development of employees' skills geared towards creativity and innovation	0.43
Technical subsystem (TECHNICAL) Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent.	Factor Loading
Panels in production processes and displays for work activities (e.g.: visual management) Detailed descriptions of workplace accommodation and adjustment of equipment and storage of semi-finished products	0.65 0.67
Binding process flow to optimize the changeover (e.g.: SMED, qCO) Methods for ensuring the quality of production (e.g.: preventive maintenance, TQM, TPM) Methods of operations management using mathematical analysis of production (e.g.: 6 Sigma) Methods for continuous improvement of production processes (e.g.: CIP, kaizen, quality circles)	0.61 0.58 0.60 0.73
Methods for improving internal logistics (e.g.: VSM)	0.66
Mark Organization and Design subsystem (ODCANIZATION)	
Work Organization and Design subsystem (ORGANIZATION) Which of the following concepts are currently used in your factory?	Factor Loading
Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 –	
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments 	
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) 	Loading 0.59 0.53 0.66 0.45 0.42
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 	Loading 0.59 0.53 0.66 0.45 0.42 0.42 0.43 Factor
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 – important to a medium extent, 5 – important to a high extent. Level importance of shorter lead times when investing in and implementing technologies Level importance of higher precision and uniformity when investing in and implementing technologies	Loading 0.59 0.53 0.66 0.45 0.42 0.43 Factor Loading
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 – important to a medium extent, 5 – important to a high extent. Level importance of shorter lead times when investing in and implementing technologies Level importance of lower labor costs when investing in and implementing technologies Level importance of lower labor costs when investing in and implementing technologies 	Loading 0.59 0.53 0.66 0.45 0.42 0.43 Factor Loading 0.67 0.69 0.53
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 – important to a medium extent, 5 – important to a high extent. Level importance of shorter lead times when investing in and implementing technologies Level importance of lower labor costs when investing in and implementing technologies Level importance of higher capacity when investing in and implementing technologies 	Loading 0.59 0.53 0.66 0.45 0.42 0.43 Factor Loading 0.67 0.69 0.53 0.79
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 – important to a medium extent, 5 – important to a high extent. Level importance of higher precision and uniformity when investing in and implementing technologies Level importance of higher capacity when investing in and implementing technologies Level importance of higher capacity when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies 	Loading 0.59 0.53 0.66 0.45 0.42 0.43 Factor Loading 0.67 0.69 0.53 0.79 0.49
 Which of the following concepts are currently used in your factory? Likert scale: "1 – not adopted, 2- plan to adopt within 2 years, 3 – adopted to a low extent, 4 – adopted to a medium extent, 5 – adopted to a high extent. Involving employees in idea generation (e.g.: feedback to management) Standardized detailed work instructions (e.g.: labor standards) Training opportunities with a job-specific focus Training on the job (e.g.: work instructions, exchange of experiences with colleagues) Formalized periods of job rotation between functions and possibly departments Task integration (e.g.: planning, drive or control functions placed with machine operator) Environment subsystem (ENVIRONMENT) Mark the level of importance for the following parameters when adopting technologies. Likert scale: "1 – not important, 2- important to a low extent, 3 – important to some extent, 4 – important to a medium extent, 5 – important to a high extent. Level importance of shorter lead times when investing in and implementing technologies Level importance of lower labor costs when investing in and implementing technologies Level importance of higher capacity when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies Level importance of improving energy efficiency when investing in and implementing technologies	Loading 0.59 0.53 0.66 0.45 0.42 0.43 Factor Loading 0.67 0.69 0.53 0.79

2.3.3 Construct validity and reliability

The Industry 4.0 technologies (**Table 3**) were used as single variables to define the technology adoption groups using cluster analysis (Section 3.4.1). Moreover, the STS dimensions were applied as reflective constructs represented by the concepts considered in **Table 3**. To consolidate the STS constructs as variables for the analysis, a set of validity and reliability tests were conducted, using Confirmatory Factor Analysis (CFA) (Hair *et al.*, 1998; Shah and Ward, 2007). Convergent validity was tested by initially testing each socio-technical construct with its corresponding variables based on the value for Cronbach's alpha (should be >0.7) and composite reliability (>0.7). As measures of goodness of fit, the Comparative Fit Index (CFI) was used (>0.9), as well as the root mean square error of approximation (RMSEA) (<0.08), as parameters to check the adequacy of the variables analyzed (Hair *et al.*, 1998). The results obtained a good fit for all constructs, as shown in **Table 5**. Subsequently, the overall model fit was evaluated by testing a complete model with all constructs and their respective variables in a single CFA model. The model also presented satisfactory fit indices (χ^2 (293) = 464.10, RMSEA = 0.050; CFI = 0.90). Additionally, all construct factor loadings were significant, demonstrating an adequate model fit (Hair *et al.*, 1998).

Discriminant validity was assessed by a two-factor model estimation (Bagozzi *et al.*, 1991). In this model, two CFA models were initially applied for each pair of constructs for comparison of their goodness of fit (six comparisons). In the first model, the correlation between the two constructs was restricted to unity. Thus, all items of both constructs were supposed to load on one single construct. In the second model, the goodness of fit of the original constructs was calculated. The chi-square changes of the first and second model were compared and evaluated according to threshold values ($\Delta\chi 2 > 3.84$ and p-value <0.05) (Bagozzi *et al.*, 1991). All of the constructs presented discriminant validity ($\Delta\chi 2$ for the comparisons were all significant at the p <0.001 level).

2.3.4 Common method bias

Two approaches were used to check for potential bias of our statistical analysis, one procedural and the other statistical (Podsakoff *et al.*, 2003). Firstly, procedural aspects that could indicate a low risk of common method bias were checked. The survey was pretested with scholars and professionals to better ensure the quality of the answers. The items used to build the STS constructs are distributed in different parts of the questionnaire, which provides more reliability as respondents will not associate them *a priori* to build a concept unity. Moreover, measures used in this study for the dependent and independent variables were placed far from each other in the questionnaire layout to prevent respondents from predefining causality while assessing them. In terms of respondent reliability, the EMS addresses production plant managers who are expected to have a clear view on the variables used in the questionnaire.

Secondly, statistical approaches were used to check for potential method bias. Harman's singlefactor test was conducted by using an exploratory factor analysis and no single factor accounted for the majority of variance in the model (25.7%). Finally, four constructs with the corresponding variables' mean for each observation were created (Marodin *et al.*, 2018). **Table 4** presents the correlation matrix and the descriptive statistics of the variables used in the study, as well as composite reliability.

2.3.5 Data analysis

2.3.5.1 Cluster analysis

Companies were clustered according to their similarities in terms of implementation of Industry 4.0 technologies (see technologies in **Table 5**). To achieve this aim, a two-step cluster analysis was conducted (Hair *et al.*, 1998). First, a hierarchical clustering analysis was performed to identify the adequate range of clusters to be tested for the dataset. The hierarchical clustering

was conducted using Ward's method in the clustering process and the Euclidian distance as a measure of similarity among respondents. A dendrogram was obtained representing the similarities between companies based on their patterns of Industry 4.0 adoption, which resulted in clustering solutions ranging from two to five clusters. To determine the number of clusters to be formed in the K-means step and the quality of the clustering procedure, the Silhouette Index (SI) was used. The SI indicates how well each Industry 4.0 adopter fits into the destination cluster: the closer to 1, the better the clustering procedure. Afterwards, cluster membership was refined using the K-means technique, which also determines the variables that effectively discriminate the clusters obtained (Hair *et al.*, 1998). This technique allowed us to visualize those technologies that help clustering companies into different Industry 4.0 adoption groups.

2.3.5.2 Multivariate Analysis of Variance (MANOVA)

A MANOVA was conducted to verify whether there are significant differences in the four sociotechnical aspects for companies when considering their level of Industry 4.0 adoption (lower or higher), as proposed in the tested hypotheses (H1, H2, H3, and H4). MANOVA uses the covariance between dependent variables to test the statistical significance of means' difference (Hair *et al.*, 1998). Finally, each dependent variable was analyzed separately using individual ANOVAs (as shown on the bottom of **Table 5**).

By conducting this analysis, the MANOVA statistical assumptions of linearity were also tested by examining scatterplots of the variables. Independence was assured as much as possible in the survey research by randomly selecting respondents. Another critical assumption, that of homoscedasticity, was tested through the equality of covariance matrices for the dependent variables with Box's M test (which was not significant at p<0.01), as proposed by Hair *et al.* (1998). Afterwards, the residuals were examined to confirm the normality of error term distribution through graphical analysis and through descriptive analysis of Skewness and Kurtosis (values ranged from -0.608 to 0.879 for Skewness and from -0.265 to 1.134 for Kurtosis). Variables can be assumed to be normally distributed if Skewness and Kurtosis are between -2.58 and 2.58 (Hair *et al.*, 1998).

Variables	Mean	S.D.	tech1	tech2	tech3	tech4	tech5	tech6	tech7	tech8	tech9	tech10	SIZE	SOCIAL	TECH	ORG	ENV
tech1	1.32	0.91	1														
tech2	1.10	0.53	.497**	1													
tech3	2.02	1.55	.166*	0.124	1												
tech4	1.84	1.47	0.064	0.104	.221**	1											
tech5	1.40	1.06	0.037	0.042	.286**	.199**	1										
tech6	1.99	1.47	0.005	0.04	0.106	.277**	0.127	1									
tech7	1.42	1.05	0.042	.131*	0.092	.179**	0.062	.472**	1								
tech8	2.11	1.54	0.093	0.092	.159*	.227**	0.123	.436**	.311**	1							
tech9	1.46	1.02	-0.04	0.056	0.014	.153*	0.116	0.098	.281**	.276**	1						
tech10	2.25	1.53	-0.03	-0.031	0.046	.158*	.150*	.341**	.248**	.197**	.311**	1					
SIZE	-	-	.012	.014	005	.140*	005	.088	.005	.070	.042	.128	1				
SOCIAL	1.99	0.90	0.09	0.063	.135*	.239**	0.103	.282**	.271**	.271**	.327**	.211**	.147*	1			
TECHNICAL (TECH)	2.55	1.04	0.04	0.081	0.09	.374**	0.095	.294**	.229**	.244**	.241**	.376**	.300**	.535**	1		
ORGANIZATION (ORG)	3.08	0.90	0.11	.137*	0.035	.184**	0.115	.330**	.243**	.307**	.281**	.340**	.150*	.612**	.662**	1	
ENVIRONMENT (ENV)	3.70	0.73	0.065	0.049	.154*	.209**	0.089	.295**	.225**	.230**	.137*	.196**	.079	.139*	.229**	.208**	1
Cronbach's alpha														0.73	0.83	0.70	0.78
CFI														0.95	0.98	0.96	0.93
RMSEA														0.08	0.05	0.06	0.09
Composite Reliability														0.93	0.98	0.96	0.98

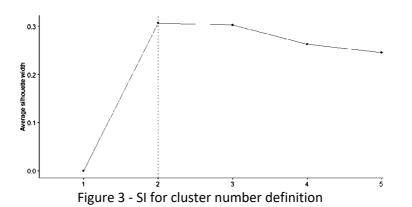
Table 4 - Descriptive statistics, correlations and construct validity **p< 0.01; * p<0.05

2.3.5.3 Logistic regression

Finally, a logistic regression was conducted aiming to understand which socio-technical aspects are determinants of achieving higher Industry 4.0 adoption patterns. The dependent variable, Industry 4.0 adoption level, was defined by the cluster analysis (Section 3.4.1.) as dummy variable (0 = lower Industry 4.0 adoption and 1 = higher Industry 4.0 adoption). Such a characteristic favors a logistic regression statistical procedure rather than a multiple regression analysis (Hair *et al.*, 1998). Additionally, logistic regressions require fewer assumptions than multiple regression analyses, such as a normal distribution of independent variables or equal within-group variances (Hair *et al.*, 1998). Logistic regression uses the logistic curve to represent the relationship between the independent variables (here represented by the socio-technical constructs) and the dependent variable (Industry 4.0 adoption level).

2.4 Results

The hierarchical cluster analysis was conducted based on a graphical analysis of the dendrogram¹. Then, based on the range of cluster solutions presented by the dendrogram (see the results for the SI test, depicted in **Figure 3**), the configuration with k=2 clusters was used, as it presented the highest average silhouette and allowed for a clear interpretation of the results.



As shown in **Table 5**, the first cluster is characterized by lower levels of technology adoption, while the second cluster has higher levels of Industry 4.0 adoption. It is worth noting that – as this study is analyzing SME manufacturers – it is not surprising that even the high adopters do not present means near the highest level of adoption. The results in **Table 5** also show that additive manufacturing technologies (tech1 and tech2) do not distinguish between the two clusters and are adopted to a low extent in the sample.

Table 5 - Results for the K-means cluster a	analysis and MANOVA test
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Industry 4.0 technologies from EMS	Clusters		
industry 4.0 technologies from Ewis	Lower	Higher	F-values
[tech1] Additive manufacturing for prototyping	1.28	1.42	1.20
[tech2] Additive manufacturing for mass production	1.08	1.17	1.53
[tech3] Industrial robots in the production process	1.83	2.45	8.25**
[tech4] Industrial robots in the handling process	1.43	2.79	51.98**

¹ The dendrogram plot was omitted due to its large size caused by the large sample.

[tech5] Technologies for safe human-machine interaction		1.23		1.79	14.68**
[tech6] Control-automation systems for an energy-efficient p	rocess	1.26	3.65		294.55**
[tech7] Control system for shut down of machines in off-peal	k periods	1.04		2.30	102.14**
[tech8] Technologies for recuperation of kinetic and process	energy	1.48		3.52	137.96**
[tech9] Systems for automation and management of internal	logistics	1.26		1.90	20.96**
[tech10] Near real-time production control system		1.81		3.24	52.58**
MANOVA – Wilk's lambda test		Df1	Df2	Value	F-value
Model (Social, Technical, Organization, Environment)		4	229	0.776	16.34**
Socio-technical dimensions (ANOVA tests)	Lower		Highe	er	
	1	C D \	1		
	(mean ± :	S.D.)	(mea	n ± S.D.)	F-values
SOCIAL	1.78 (±0.7			n ± S.D.) (±0.98)	F-values 31.98**
SOCIAL TECHNICAL	•	78)	2.46 (/	
	1.78 (±0.1	78) 97)	2.46 (3.09 ((±0.98)	31.98**
TECHNICAL	1.78 (±0.) 2.31 (±0.)	78) 97) 88)	2.46 (3.09 (3.58 ((±0.98) (±0.98)	31.98** 32.09**
TECHNICAL ORGANIZATION	1.78 (±0. 2.31 (±0. 2.86 (±0.	78) 97) 88)	2.46 (3.09 (3.58 ((±0.98) (±0.98) (±0.75)	31.98** 32.09** 36.30**
TECHNICAL ORGANIZATION ENVIRONMENT	1.78 (±0. 2.31 (±0. 2.86 (±0. 3.55 (±0.	78) 97) 88)	2.46 (3.09 (3.58 (4.04 ((±0.98) (±0.98) (±0.75)	31.98** 32.09** 36.30**

Table 5 shows that Wilk's lambda is significant at p<0.001 for the MANOVA test. **Table 5** also shows significant differences between averages for the STS constructs with regard to Industry 4.0 level, thus confirming hypotheses H1, H2, H3, and H4. Consequently, companies with a higher Industry 4.0 adoption level are also more mature in the socio-technical subsystem than companies at a lower Industry 4.0 level with a high confidence level (p<0.01), as the STS average for the higher Industry level is greater than for the lower level of adoption.

Table 6 shows the results for the logistical regression. The model was significant at p<0.01 with a classification accuracy of over 75%. Because the sample is composed of 160 companies of low Industry 4.0 adoption level and 71 companies with high levels of Industry 4.0 adoption, the classification accuracy in connection with random choice would result in $(71/231)^2 + (160/231)^2 = 57.42\%$. Thus, the logistic regression model has higher discriminating power than the random choice model. Hair *et al.* (1998) suggest that a classification accuracy is acceptable if it is 25% more accurate than the random choice model (i.e., 1.25*57.42 = 71.77%). Therefore, the model exceeds this threshold, as it presents an accuracy of 76.62%.

Findings also show that the Social (p = 0.06), Work Organization (p = 0.08) and Environment aspects (p < 0.01) are significant predictors of a higher Industry 4.0 adoption level. The final model also indicates a pseudo-R² (Nagelkerke) of 0.31 (Hair *et al.*, 1998), demonstrating the percentage of variance of the dependent variable explained by the independent variables in the model. Furthermore, the model's goodness-of-fit was tested using the Hosmer-Lemeshow test, which splits data into deciles of predicted probabilities and computes a chi-square from observed and expected frequencies. The result of this test indicates that the model analyzed is not significantly different (p= 0.84) from a perfect model that can correctly classify companies into their respective groups: lower and higher Industry 4.0 adoption (Chau & Tam, 1997; Ilin et al., 2017).

Multicollinearity was also tested based on the variance inflation factor (VIF), which measures the collinearity among the predictors through multiple linear regressions. The tests found no signal of multicollinearity, with the mean VIF being 1.545 and therefore below the threshold of 10, indicating no problem of multicollinearity (Hair *et al.*, 1998). Finally, the significance of the regression coefficients was examined to test and support the formulated hypotheses rather than their coefficients. The results obtained support H1 [SOCIAL], H3 [ORGANIZATION] and H4 [ENVIRONMENT]. However, the findings could not support H2 [TECHNICAL]. In addition, the control variable for small and medium sizes was not significant in the model tested, demonstrating that size does not significantly influence the level of Industry 4.0 adoption.

Independent variables	β	S.E.	Wald	DF	Exp(B)	Sig.
SOCIAL	.425	.228	3.482	1	1.530	.062
TECHNICAL	.219	.214	1.047	1	1.245	.306
ORGANIZATION	.481	.278	3.005	1	1.618	.083
ENVIRONMENT	.944	.264	12.821	1	2.570	.000
SIZE (control)	.349	.338	1.063	1	1.417	.303
Model significance	χ2(5)= 57.8					0.00
Cox & Snell R ²	0.22					
Nagelkerke R ²	0.31					
Hosmer-Lemeshow test	χ2(8)= 4.23					0.84
-2 Log likelihood	227.24					
Overall classification accuracy	76.62%					

Table 6 - Logistic regression results for Industry 4.0 implementation

2.5 Discussion

The results of this study show the importance of developing different socio-technical subsystems to create an appropriate framework for technology adoption. Companies that pursue Industry 4.0 technologies without focusing on the complementary socio-technical aspects may risk failing in their path to Industry 4.0 implementation (Cagliano *et al.*, 2019). This result helps to expand the understanding of Industry 4.0, since most studies have focused on the technological contribution of this concept (Dalenogare *et al.*, 2018; Xu *et al.*, 2018). Only recent studies have begun addressing further managerial aspects, including technical aspects such as the contribution of manufacturing management systems (e.g., Rosin *et al.*, 2020; Tortorella *et al.*, 2019), workers' management (e.g., Cagliano *et al.*, 2019; Longo *et al.*, 2017), and operational strategy (e.g., Horváth and Szabó, 2019).

Such results complement prior works conducted in the Danish SMEs context. The studies by Stentoft and colleagues considered different aspects of Danish SMEs and Industry 4.0, including the impact of Industry 4.0 on reshoring decisions of these companies (Stentoft and Rajkumar, 2019), the motivation of these companies to adopt additive manufacturing specifically (Stentoft et al., 2021), the influence of Industry 4.0 on cost-driven motives to reallocate manufacturing (Stentoft et al., 2020b) and the drivers and barriers to Industry 4.0 readiness (Stentoft et al., 2020a). The present study adds to such findings by highlighting the organizational perspective of the manufacturing activity, which has been proven necessary to support Industry 4.0 adoption in SMEs. Stentoft et al. (2020a) showed that SMEs in Denmark did not have very high Industry 4.0 maturity levels as compared to large firms. The fact that Industry 4.0 is more difficultly adopted by SMEs was also observed by Frank et al. (2019a) and is substantiated by the results of this paper, since few of the technologies analyzed showed an average level of adoption above the middle point of the scale used (Table 5). Only technologies for energy efficiency [tech6 and tech8] and real-time production control [tech10] presented an average value above this middle point. However, as Stentoft et al. (2020a) argued in their study about Danish SMEs and as Castelo-Branco et al. (2019) showed for companies of different sizes, Denmark SMEs have a better level of Industry 4.0 technology readiness than SMEs in other European and OECD countries. That is what makes this such an important context for analysis. These findings suggest that the main reason why Danish SMEs have relatively better Industry 4.0 implementation levels is their emphasis on developing the STS dimensions. As shown in Castelo-Branco et al. (2019), Finland and Sweden are countries besides Denmark with high levels of Industry 4.0 readiness. These three countries have been historically related to the socio-technical perspective on manufacturing, with strong concerns regarding workers' rights and needs (Oudhuis and Tengblad, 2020; Thomassen et al. 2017). In this sense, the findings help to enlighten the connection between these two aspects: STS and the level of Industry 4.0 adoption in SMEs.

The findings of this paper corroborate prior studies that propose a broad view on Industry 4.0 implementation (Cagliano *et al.*, 2019; Cimini *et al.*, 2021; Flores *et al.*, 2020; Veile *et al.*, 2019; Vereycken *et al.*, 2021) by quantitatively analyzing the importance of the socio-technical context to Industry 4.0 in a holistic way. The results corroborate the increasingly important role of workers in Industry 4.0, both in assisting technology implementation and in leveraging these technologies in production activities (Cagliano *et al.*, 2019; Meindl *et al.*, 2021; Veile *et al.*, 2019). Prior studies have suggested that investing in developing employees' skills and encouraging them to find solutions to problems may help companies to become leaders in Industry 4.0 adoption (Vereycken *et al.*, 2021). The literature has also suggested that flattening hierarchical levels and decentralizing decision-making are necessary measures for Industry 4.0 (Cimini *et al.*, 2021), which will also be favored by an environment with more openness to collaboration, learning, and creativity as means to develop an entrepreneurial mindset (Veile *et al.*, 2019). The findings of this study corroborate these points, confirming the importance of a socio-technical preparation for Industry 4.0 implementation.

Based on these general findings, a key aspect of this study refers to the social and work organizational dimensions. Both dimensions are connected to the workers. The former focuses on workers' development, while the latter seeks workers' efficiency through the establishment of operational routines. As shown in the findings, both dimensions make a strong contribution to higher levels of Industry 4.0 implementation. Although theory has so far considered Industry 4.0 as a way to improve workers' capabilities (Cagliano *et al.*, 2019; Longo *et al.*, 2017; Schuh *et al.*, 2017), empirical results from prior research have shown that companies are more concerned with rising productivity and reducing labor costs, overlooking the contributions of Industry 4.0 to the quality of work (Büchi *et al.*, 2020; Dalenogare *et al.*, 2018). The results of this study demonstrate that such a view, although commonly followed by practitioners, is incorrect because Industry 4.0 technologies are implemented to a higher degree when work-related aspects are integrated.

Furthermore, a recent stream of studies has called attention to the important role of the Operator 4.0 (Fantini *et al.*, 2018; Rauch *et al.*, 2020; Romero *et al.*, 2020) and to the future digital skills of workers (Autor *et al.*, 2020). Such future skills are as important for the achievement of a smart factory as technological and technical factors (Bednar and Welch, 2019; Cagliano *et al.*, 2019; Fantini *et al.*, 2018). The results of the present study show that, if manufacturers wish to achieve higher levels of Industry 4.0 implementation, they should also consider social aspects. In this sense, our results help bridge the research gap on the role of workers and social systems in Industry 4.0, highlighted by Meindl *et al.* (2021). These authors conducted an extensive literature review considering ten years of research on Industry 4.0. They concluded that one of the main gaps in the literature is regarding the role of workers and social aspects. The present findings thus add to the literature by providing further evidence on the positive association between this STS dimension and Industry 4.0 adoption levels.

Following the above argumentation, managers should strive to provide better conditions for workers to grow in this new context. This requirement is part of the managers' role in digital leadership. They should also support initiatives aimed at making operators more accepting and motivated to use the new, Industry 4.0 technologies (Cagliano *et al.*, 2019; Müller *et al.*, 2018). This is important because employee involvement is highly associated with Industry 4.0 adoption (Vereycken *et al.*, 2021), as it surely helps to overcome barriers to adoption (Horváth and Szabó, 2019). Workers' involvement can be obtained by simply disseminating information in meetings or by an increased openness to proactive participation, for instance, employing employees' knowledge of daily work practices in the implementation process (Vereycken et al., 2021). Furthermore, such involvement strategies can also support workers' adaptation to the increased

job complexity and skills required by Industry 4.0 technologies (Veile *et al.*, 2019; Vereycken *et al.*, 2021).

Besides, manufacturers should qualify workers and better organize their routines (work organization dimension), allowing them to make better use of their expertise and skills in relation to Industry 4.0 technologies. In other words, nothing will be worse for the implementation of Industry 4.0 than discouraged and untrained workers, as suggested in the findings. In this regard, companies must focus on developing the necessary technical competencies and train their employees to develop new job profiles (Cimini et al., 2021). This is particularly true for SMEs, where the job profiles must include tasks that demand continuous learning throughout the adoption of Industry 4.0 (Vereycken et al., 2021). Both internal and external training can help to provide these competencies. Regarding the latter, vocational education institutions act as important promoters of such training in European manufacturing companies (Lund and Karlsen, 2020). Moreover, Bosman et al. (2019) studied companies in the United States and concluded that training and governmental agencies should assist in this demand by providing professional education in several technology areas. The results of the present study concur with prior research findings in showing that internal training can be provided with workshops, scenario-based learning, e-learning approaches, or even based on employee performance and specific tasks through data analytics (Veile et al., 2019; Vereycken et al., 2021)

Another contribution of the findings of this paper refers to the environment dimension. These results call attention to the importance of an alignment between strategy and Industry 4.0 adoption (Moeuf *et al.*, 2018; Weking *et al.*, 2020) by showing that this is indeed the strongest dimension of the socio-technical view in terms of differentiation between the lower and the higher adopters. The current literature affirms that companies should adopt the types of Industry 4.0 technologies that meet each organization's demands (Bosman *et al.*, 2019). Otherwise, there is a risk that manufacturers might follow Industry 4.0 trends without understanding what they are pursuing (Mittal *et al.*, 2018; Müller *et al.*, 2018; Raj *et al.*, 2020). Although this is well-known, SMEs may have no clear focus on their maturity needs (Mittal *et al.*, 2018) or may be extensively focusing on investment costs (Moeuf *et al.*, 2018). Thus, to avoid underinvestment or misalignments, the results of this study go along with the literature suggesting that companies must conduct strategic analyses, starting from the problem to be addressed using Industry 4.0 technologies, and reckoning Industry 4.0 as a philosophy of continuous improvement of the manufacturing needs (Bosman *et al.*, 2019).

Consequently, this study demonstrates that a good understanding of the companies' targets is important for the successful implementation of these technologies. Industry 4.0 should therefore be leveraged at the strategic level, moving beyond the advanced automation of the established manufacturing system (Dalenogare *et al.*, 2018; Moeuf *et al.*, 2018; Weking *et al.*, 2020). As an example, Frank *et al.* (2019a) showed how difficult it is for companies to achieve operational flexibility in the Industry 4.0 context even though this should be one of the main achievements of this concept. Similar results were shown by Dalenogare *et al.* (2018) at the industry level. Consequently, a clear definition of the operations strategies (environment dimension) will be useful to enhance the implementation of Industry 4.0 technologies in the manufacturing system.

Finally, the results of the present study demonstrate that the technical dimension – which is related to manufacturing management systems, such as lean manufacturing practices and tools – is strongly associated with higher levels of Industry 4.0 implementation (**Table 5**). However, this dimension does not explain the likelihood of a company to be a higher adopter of Industry 4.0 (**Table 5**). This insight can represent the "chicken or the egg" dilemma in the following question: "what supports what – do manufacturing management systems support Industry 4.0 or is it the other way around?". Although both are related, companies may have a high level of

adoption of technical factors related to, e.g., lean, without this development resulting in more intense adoption of Industry 4.0. Such an argument would be aligned with a classical perspective on manufacturing, in which technology investment should not be made without prior and thorough investigation of the root causes of problems. Moreover, technology should serve the purpose of the manufacturing management systems, not the opposite (Tortorella *et al.*, 2019). Finally, a more intense adoption of Industry 4.0 may also focus on enhancing manufacturing management systems like lean, as well as performance, as suggested by Tortorella *et al.* (2019).

2.6 Conclusion

This paper investigated the contribution of socio-technical aspects to higher levels of Industry 4.0 technologies adoption. As the findings suggest, there is a significant difference between low and high Industry 4.0 adopters regarding the development of the social, technical, organization, and environment dimensions. These findings open new avenues for theory as they help to explain why different manufacturing companies within the same context (in this case, Denmark) can achieve lower or higher levels of Industry 4.0 adoption. These research findings have implications for the body of knowledge in Industry 4.0. The results provide new insights that challenge preconceived maturity models or roadmaps designed to guide Industry 4.0 implementation. They suggest that, in this context, frameworks for Industry 4.0 implementation should also consider non-technological steps, including actions focused on developing sociotechnical aspects, departing from an approach based on technology escalation towards another one, built upon solid socio-technical foundations. This aspect can enable the manufacturing system to keep pace with the technological improvements demanded by Industry 4.0.

Another relevant theoretical implication of this article is shown in the results regarding the business environment (i.e., companies' strategies and policies). The results showed that this is the most significant predictor of higher levels of Industry 4.0. Two messages can be drawn from this finding: first, and most obvious, companies need to commit to clear operational targets (e.g., shorter lead times, increased productivity, quality, flexibility, amongst others) to implement Industry 4.0 technologies. Industry 4.0 is usually associated with productivity gains; however, it is necessary to define specific strategies for productivity gains. Some companies may emphasize more automation to reduce labor costs, while others may emphasize increased capacity utilization through a higher mix of products manufactured in the plant or a technology-intensive worker enhancement. These are different goals that will serve as input for Industry 4.0 implementation. Moreover, other competitive strategies, like gaining flexibility, will demand different Industry 4.0 paths to achieve higher maturity levels.

The second message regards the relevance of the environmental aspect and its alignment with the holistic view of the socio-technical theory. In this sense, higher adoption of Industry 4.0 technologies can be found in companies actively concerned with understanding and developing manufacturing through a systemic approach, where the environment dimension attracts a larger portion of managerial attention. Furthermore, this study showed that manufacturing companies that focus on workers' operational processes and social needs (i.e., organizational and social subsystems) as preconditions for Industry 4.0 implementation are more prone to achieve higher levels of maturity in technology implementation. Rather than having a competition between technology and workers, the latter should support the former for an adequate implementation of Industry 4.0.

2.7 Managerial implications

Some managerial implications arise from this study. Firstly, managers should give much more attention to socio-technical aspects to begin their Industry 4.0 journey. Technology should be pulled and not pushed by the manufacturing system. Thus, the organizational conditions should be prepared for the new technologies before their adoption, rather than taking the common

reactive approach of adapting the companies' processes, workers, and production processes after the technology arrives. To operate this concept, managers should deploy metrics specifically developed to assess the performance of socio-technical dimensions, in addition to traditional performance metrics. This will facilitate an assessment of the gap between the current and future state of the socio-technical dimensions. Additionally, this aspect could help clarify causal relations between managerial interventions and outcomes since many operational benefits achieved during the Industry 4.0 journey may come from the socio-technical improvements that companies are compelled to make to adopt new technologies.

As a second practical implication, managers should be concerned with workers' development programs to ensure that they will be engaged in the digital transformation process rather than resisting it. This is a condition for them to achieve higher levels of Industry 4.0 implementation. For instance, the results presented showed that work organization aspects, such as involving employees in idea generation, training employees on the job, developing creativity, and promoting the exchange of experience between employees, are important tools for technology adoption. These practices can help to reduce workers' resistance to technology, creating an open and collaborative technology environment.

Based on existing literature, this study also showed and confirmed that technical factors are associated with Industry 4.0. Therefore, this paper recommends that Industry 4.0 adopters should be aligned with the technical system (e.g., manufacturing management systems) rather than the opposite. Consequently, SMEs should follow a method-driven rather than a technology-driven manufacturing approach in which the company first establishes how the manufacturing process will be executed and then assess which technologies can serve the purposes of the manufacturing activities.

Finally, as the results in this paper show, managers should be aware that some socio-technical factors are less supportive than others in predicting the level of Industry 4.0 technologies adoption. Therefore, managerial attention should firstly be focused on the business environment aspects of the socio-technical dimensions to leverage the adoption of Industry 4.0 technologies. This was the dimension that presented the highest differentiation between lower-and higher-level Industry 4.0 technologies adopters in the current study.

2.8 Research limitations and future research

Among the limitations of this study, it should first be noted that the research sample only considered SME manufacturers from Denmark. This is not necessarily a weakness, since size and regional delimitations offer the relevant conditions for further comparative studies inasmuch as they allow researchers to assume a homogeneous context between the firms investigated. This, however, is a limitation in that it reduces the generalization of the findings. In this sense, future studies should be conducted in national (and international) contexts where social aspects are not as stressed as in Northern countries. The emphasis given to socio-technical factors in Northern manufacturing companies could result in a different scenario as compared to other countries.

As a second limitation, the statistical tests were conducted using data from the European Manufacturing Survey (EMS), which was restricted to the factory domain. Thus, the choice of variables to represent the tested constructs was limited to the smart manufacturing dimension of Industry 4.0. Other Industry 4.0 dimensions such as smart supply chain or smart product-service systems can also be supported by further development of socio-technical dimensions (Meindl *et al.*, 2021). Therefore, future studies should investigate the relationship between STS and the other 'smarts' of Industry 4.0. Furthermore, another limitation of using the EMS data is that the current study was able to consider only cross-sectional data, while a longitudinal quantitative study could shed more light on causality and evolutionary effects of Industry 4.0 implementation and the development of socio-technical subsystems. Additionally, including

large company samples and comparing profiles between SMEs and large-sized enterprises would also be useful to understand the extent to which conclusions on STS and Industry 4.0 can be taken.

A third potential limitation is that the data was collected in 2016. More recent data could provide useful insights on new advances in the Industry 4.0 domain. However, this should not be a major limitation since more recent surveys have shown similar patterns of Industry 4.0 adoption in different countries (e.g., Frank et al., 2019; Tortorella et al., 2019). Furthermore, a very recent systematic review of more than 5,000 studies in the Industry 4.0 field has shown that sociotechnical factors have been under investigated in this field over the last ten years, even when considered more recent data (Meindl et al., 2021). Therefore, future studies could collect complementary data to the present findings, especially regarding adopting AI and new IoT-based applications for Industry 4.0 solutions. In such a case, they should use the findings of this present study as evidence of the strong correlation between socio-technical factors and the adoption of advanced technologies.

Finally, qualitative approaches such as case studies would be most useful to uncover the mechanisms that explain how socio-technical dimensions support higher levels of Industry 4.0 adoption. In future investigations, researchers should also study the reverse path, that is, the impacts of Industry 4.0 technologies on the socio-technical system of a company after its implementation. The reason for this suggestion is that unexpected changes to the whole system may occur, such as fear of layoffs among workers and technology integration issues, or, on the other hand, positive changes such as a decrease in work injuries and accidents and the rise of new leadership roles in the digital transformation domain.

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3. Article 2 - The socio-technical enabling factors for Industry 4.0 implementation: a holistic approach

This paper was awarded the Nada Sanders Emerging Economies Doctoral Dissertation Award for Latin America and the Caribbean region at the 33rd Annual Production and Operations Management Conference in Orlando.

Abstract:

Introduction: Industry 4.0 refers to the integration of advanced technologies such as artificial intelligence, the Internet of Things, and big data into manufacturing. Its implementation significantly changes the company's social, technical, organizational, and environmental aspects. **Objectives:** This study aims to discuss how companies develop the enabling factors necessary for successfully implementing Industry 4.0 and the mechanisms driving these changes.

Methods: A qualitative approach was employed to analyze the different socio-technical enabling factors with 28 companies implementing Industry 4.0 technologies.

Results: The results show how the companies develop strategic guidelines, such as top management support and open innovation with partners and startups. Companies should start by defining an implementation roadmap, training leaders in technical concepts with technology providers and technical schools, and providing management support with company-wide programs for Industry 4.0. Also, we describe how hierarchical flexibility with increased autonomy for workers via their participation in the decision process, data training, and open communication means are developed. Interactions between dimensions include upskilling workers with technology providers, aligning technologies with worker profiles and tasks, and incorporating data collection and use into processes.

Conclusion: Previous research has mainly addressed the enabling factors for Industry 4.0 through an individualized view. We analyze their interactions and discuss how companies developed these enabling factors. We highlight the complexity and the need for a joint analysis of these enabling factors, which can help companies navigate the challenges of this complex process.

Keywords: socio-technical theory; operations management; technologies in manufacturing.

3.1 Introduction

Conceived in 2011 in Germany, the Industry 4.0 concept marked ten years in 2021 as an industrial policy platform to increase manufacturing competitiveness through digital transformation (Meindl et al., 2021). The first decade of Industry 4.0 focused on defining the best technologies that represent its concept and structuring the framework of definitions in a digital economy (Sturgeon, 2021; Frank et al., 2019). In this decade, research was also concerned with assessing the effectiveness of digital technologies in increasing operational performance and justifying the high investments necessary (Dalenogare et al., 2018). Hence, reference models were proposed, such as the one disseminated by the German Academy of Science and Technology (ACATECH) that comprises maturity steps to implement advanced automation and digital technologies to bring digital capabilities to factories (Schuh et al., 2017). During this time, the literature on Industry 4.0 technology implementation grew exponentially (Meindl et al., 2021).

This first decade consolidated a view of advanced automation through digital technology that was not necessarily at the core of the initial conception of Industry 4.0 (Dornelles et al., 2021). Rather than focusing on substituting workers, the Industry 4.0 concept was coined as a sociotechnical system (Sony and Naik, 2020). However, the last decade predominantly discussed how to achieve an autonomous and flexible production system through such technologies.

Therefore, several studies called for more research using a worker perspective to offset the technological-centered approach that dominated the discussion around Industry 4.0. For instance, in their systematic review of the first decade of Industry 4.0, Meindl et al. (2021) investigated more than 5,000 studies and showed that the "smart working" dimension of Industry 4.0 is still an under-investigated topic, although it started to grow recently. The narrow stream using this perspective have considered the role of the Operator 4.0 (Romero et al. 2020), the interactions and interfaces between humans and machine (Kumar and Lee, 2022), and the use of digital technologies to create a smart working 4.0 environment (Dornelles et al., 2021). This counterbalance of the human role inside the advanced digitalized system proposed by Industry 4.0 has also been addressed by the European Union. They labeled this perspective "Industry 5.0", which comprises a better integration between workers and technologies for a sustainable industrial system (Maddikunta et al., 2022). In this vein, recent studies focused on such a balance by including organizational and work environment factors combined with social and technological challenges in implementing Industry 4.0 technologies. Marcon et al. (2022) investigated this socio-technical balance and demonstrated its effectiveness in achieving higher Industry 4.0 technology implementation levels. Such results are also in line with the findings that showed the necessary balance of worker skills, the manufacturing system, and technology implementation to create a better and more productive factory (Autor et al., 2020).

Since this is still an emerging topic, more recent studies highlight the opportunities for integrating workers and technologies in an Industry 4.0 manufacturing system (Cagliano et al., 2019; Dornelles et al., 2022). Further, studies that considered socio-technical factors involved in implementing digital technologies do not bring a systems perspective on how these factors support each other. Rather, the elements are analyzed linearly, focusing on how each socio-technical dimension (such as people, organization, environment, and infrastructure) independently supports Industry 4.0 (Cagliano et al., 2019; Marcon et al., 2022). However, as noted in a recent study by Prim et al. (2022), organizational aspects for Industry 4.0 are systemic and demand a leadership view that integrates all elements in a balanced and interrelated socio-technical system view. Organizational models that define the production flow, such as lean production, are interrelated with the role of workers and the leadership, which will also shape the way the company embraces advanced technologies in the factory (Mittal et al., 2018). Thus, a complex system of interrelated socio-technical factors must be considered in implementing complex technological solutions as proposed by Industry 4.0 models.

Studies have shown that when only a technical approach is used, Industry 4.0 encounters challenges related to use, integration, and support from the actors involved in the process. This approach usually fails and wastes resources and digital endeavors within the company. Without a more holistic approach, companies risk not adapting the technologies to their situation or objectives or excessively focusing on their financial needs (Moeuf et al., 2018). Also, companies tend to implement technologies that are solely focused on meeting technical requirements and enhancing productivity while neglecting process adaptation, work organization changes, and a long strategy, leading to a problematic implementation of Industry 4.0 technologies (Cimini et al., 2020; Stentoft et al., 2020; Veile et al., 2019).

Since such socio-technical elements are still new to the Industry 4.0 context, how companies achieve them and their inter-relationships must be investigated to provide managers with guidelines for their Industry 4.0 journeys and also to create a clear framework for researchers that sheds light on the organizational aspects that support the digital transformation of manufacturing systems. Therefore, we propose the following two research questions: *(i) How do companies develop the socio-technical enabling factors to support the implementation of Industry 4.0? (ii) How should these enabling factors support each other to build a socio-technical system for Industry 4.0?*

To address these two research questions, we adopt a qualitative research approach based on the analysis of multiple case studies (Eisenhardt & Graebner, 2007; Voss et al., 2002). We investigate 23 manufacturers that lead in Industry 4.0 implementation, using interviews, plant visits, and longitudinal follow-up case studies. Following the socio-technical theory, we use data from the qualitative investigation to describe how companies achieved important enabling factors and interrelationships between the different socio-technical elements investigated. We also offer practical insights for manufacturing managers regarding the decisions to prepare factories to embrace digital technologies.

3.2 Theoretical background

3.2.1 The socio-technical perspective of technology implementation

The socio-technical theory originates in the seminal work of Trist & Bamforth (1951). It recognizes the inseparability of the social and the technical dimensions of work, which interact and compose a socio-technical system. Manufacturing environments are prominent illustrations of socio-technical systems (Davis et al., 2014). A cornerstone of socio-technical systems theory is joint optimization, which proposes that improvements in one dimension cannot produce optimal results unless the other dimension is also considered (Clegg, 2000; Soliman & Saurin, 2017). This theoretical background helps understand and address broad company changes, such as technological innovations, new manufacturing paradigms, and new work relationships.

The socio-technical theory is grounded in complexity science (Hettinger et al., 2012) that poses that the observable features of a system are an emergent property that may not be contained in its constituents (Nair & Reed-Tsochas, 2019; Ponte et al., 2016). Thus, the theory focuses on the elements' interactions rather than the elements' specificities (Heylighen et al., 2007). This is relevant to the investigation of technology adoption since practitioners and researchers may illegitimately credit the technologies alone as the source of many operational benefits of process innovations. The socio-technical theory proposes that "design is systemic" so, changing one part of the system, such as implementing Industry 4.0 technologies, can promote changes to other parts (Reiman et al., 2021).

Two approaches can be employed when considering organizational changes through the sociotechnical view, the reactive and proactive. The first considers the impacts generated by a technological change in the system after the change was conducted and results are seen. The other perspective understands, anticipates, and, more importantly, prepares the system's maturity for the change to increase the chances of success (Cherns, 1976; Clegg, 2000). The former perspective is built into Chern's (1976) design principles and states that key choices for success of socio-technical systems include designing the system's overall operation, its management, organization, the technologies required to support work, and the necessary organizational systems (Clegg, 2000). While the first approach usually reflects a socio-technical perspective used as an afterthought, the second approach allows anticipating such results and preparing the system to avoid problems. Our study seeks to provide how companies developed the necessary enabling factors by employing the second approach based on the results and impacts discovered by the first approach. This is important to increase the chances of success and prevent technological innovations from losing credibility due to an unfortunate start. Hence, the socio-technical enabling factors can guide companies in their Industry 4.0 implementation process and assist their technical and personnel preparation.

3.3 Socio-technical systems research in Industry 4.0

The Industry 4.0 concept emerged from the technological improvements that aim to connect equipment and the entire production system, enabling better control and adapting operations in real-time (Meindl et al., 2021; Moeuf et al., 2018). Industry 4.0 is a socio-technical

environment that brings new opportunities to integrate machines and people in the workplace through the creation of cyber-physical systems operated by digital technologies like the Internet-of-Things (IoT) and Artificial Intelligence (AI) (Frank et al., 2019; Sony & Naik, 2020). In the implementation of Industry 4.0 technologies, some socio-technical enabling factors are important to prepare the environment and the organizational maturity for the innovations and changes posed by more data, complex activities, increased worker participation, and decisionmaking decentralization (Cagliano et al., 2019; Cimini et al., 2020; Laubengaier et al., 2022). The study developed by Marcon et al. (2022) was one of the first to consider a socio-technical perspective of Industry 4.0 implementation. The authors analyzed the difference in Industry 4.0 adoption between companies with more advanced socio-technical dimensions and others with lower levels. This study demonstrated that higher levels of socio-technical practices are necessary for achieving more mature Industry 4.0 levels. However, the study only considered a limited and predefined list of socio-technical elements related linearly to implementing Industry 4.0 technologies but not to each other. This approach brought initial insights for Industry 4.0 implementation; however, it is still a first step since it does not provide the rich diversity or the means companies employ to develop the necessary enabling factors for their digital transformation journey. Also, the interrelated nature of the socio-technical dimensions is a fundamental point of socio-technical systems yet to be studied, as these interrelations provide a managerial structure necessary for technology implementation (Clegg, 2000).

3.4 Socio-technical systems research in Industry 4.0

Marcon et al. (2022) showed that the social subsystem comprehends the enabling factors related to the personnel/people. This dimension analyzes how workers are affected by changes in processes and technologies and consider aspects of workers' skills, age, autonomy, job security, technology acceptance, and training for technologies that will be implemented. In the Industry 4.0 implementation context, the enabling factors that companies should prepare for are treated by literature mainly describing the need for workforce training, involving workers in the implementation process, and providing support to workers and job security (Horváth & Szabó, 2019; Neumann et al., 2021). These factors allow for a smoother transition to a more digital environment considering a central piece of the Industry 4.0 implementation process, the workers. When they are not developed, Industry 4.0 implementation can significantly alter social dynamics and lead to a failed journey due to social problems, such as untrained and unmotivated workers, elevated stress and cognitive loads, and reduced autonomy (Kadir & Broberg, 2021; Reiman et al., 2021).

Several studies mention training as an essential enabling factor related to people (Marcon et al., 2022; Laubengaier et al., 2022; Caliş Duman et al., 2021; Leyer et al., 2019). These articles highlight the need to train workers in the workplace or through professional development programs to improve their capabilities of dealing with data, automation, computers, and devices (Caliş Duman et al., 2021). Research discusses that training programs can use scenario-based settings or e-learning to increase skills and competences required by the new job profiles from Industry 4.0 (Kamble et al., 2018; Kiel et al., 2017; Viele et al., 2019). Workshops, learning by doing, and individual lessons are important training means that help workers get relevant knowledge from various disciplines such as data and graph analysis, programming, agile management, and lean production (Flores et al., 2020; Viele et al., 2019). However, few empirical papers discuss how companies provide training, the providers used and the challenges overcame.

The second factor refers to worker involvement, which for Industry 4.0 is relevant since integrating people in technology selection, implementation, and validation helps overcome resistance and increase use (Caliş Duman et al., 2021; Veile et al., 2019). Studies showed that workers can be involved in several moments, such as the problem/technology definition,

process adaptation, and idea generation and inclusion programs (Kadir and Broberg, 2021; Marcon et al., 2022; Tabim et al., 2021). When involved, workers help customize the process according to their needs, anticipate future problems, and reduce redundant work, if provided with access to information, resources, and support (Calis Duman et al., 2021; Leyer et al., 2019). These concepts also align with the enabling factor of the need to support workers and job security. Supporting workers ensures that the efforts related to them and technologies are balanced and that the company is making the necessary efforts to ensure their safety and wellbeing (Laubengaier et al., 2022), due to the disruptive challenges posed by Industry 4.0. Thus, they must be supported and assisted to be resourceful, adaptable, and resilient enough to meet these changes (Flores et al., 2020). Therefore, production systems should be designed to support ergonomic physical work and aid operators in complex tasks such as coordination, supervision, and decision-making (Rauch et al., 2020). To this end, workers must have access to support either for technical issues or for emotional and cognitive challenges (Cagliano et al., 2019; Leyer et al., 2019). The support can come from developing company-wide programs to assist less technology-acquainted workers and developing a help-chain environment that supports the exchange of knowledge and skills among employees, for example (Leyer et al., 2019; Veile et al., 2019). According to Stentoft et al. (2020), this is still a major problem that managers should address, as lack of employee knowledge and preparation for Industry 4.0 were the most acknowledged barrier to Industry 4.0 implementation.

Second, the technical dimension includes the enabling factors related to the tools, technologies, machinery, software, hardware, data used, and infrastructure associated with production systems necessary to perform work activities (Reiman et al., 2021; Soliman et al., 2018). This is the most visible facet of manufacturing systems (Behdani, 2012) as it analyzes how hardware and software are implemented and integrated to aid work activities. It also focuses on the technology's integration and adaptation to the production processes. Literature on the technical enabling factors for Industry 4.0 mostly discusses technology maturity, data integration and use, and the internal infrastructure necessary (Cagliano et al., 2019; Nosalska et al., 2019; Tabim et al., 2021).

Big data, analytics, IoT, and artificial intelligence are the base enabling factors for Industry 4.0 technological maturity (Frank et al., 2019). Technologies for production monitoring are also important enablers, such as panels in production processes for visual management, software for production analysis, and shop floor technologies with improved usability (Marcon et al., 2022; Reiman et al., 2021). Technology maturity is important since it makes workers and managers more familiar with an environment that relies on data, technologies, and computerized equipment to operate and maintain. Moreover, increasing the number of technologies enables companies to experiment with them and grow toward a smart factory level (Cagliano et al., 2019).

Studies found that the enabling factors related to data, its use, and integration are another essential to Industry 4.0. These studies address data integration along the processes and with the supply chain, big data storage and analytics to predict and monitor production aspects, and cybersecurity actions to avoid breaches (Tabim et al., 2021; Frank et al., 2019; Kaggermann et al., 2014). To integrate databases, sources, and communication, companies start by integrating mainly data from the production phases level before growing to integrate other departments and the full operations processes (Cagliano et al., 2019). Principles of technical enabling factors related to data integration were reported by Tabim et al. (2021) in the process of vertical integration of MES, ERP, PLM, and SCADA systems that allow communication to flow between production processes and decision-making (Kaggerman et al., 2013). The authors show that manufacturers should customize the solutions to the systems they own beforehand, plan for future expansion, test the solution, and make improvements on a trial basis before the effective adoption of the system. Finally, cybersecurity measures were shown to be important enabling

factors, which are achieved via controlled access and training on cyberattack prevention to avoid data breaches (Castelo-Branco et al., 2022).

The internal infrastructure is another enabling factor companies must prepare to implement Industry 4.0. To this end, internet connection, process digitalization, IT infrastructure, IoT sensors, data collection, big data storage, and information systems are essential requirements to develop the technical environment for Industry 4.0 (Schuh et al., 2017; Tabim et al., 2021; Machado et al., 2021). To analyze infrastructure readiness, research proposes models to assess if the IT's portfolio, support, and infrastructure are in line with the organizational readiness to implement technologies (Machado et al., 2021). In this sense, companies evaluate if they own the technical resources of IT, connectivity, storage, and maintenance that are necessary, as well as the innovation valence, cognitive readiness, and the providers necessary to develop the infrastructure for Industry 4.0 (Machado et al., 2021; Benitez et al., 2020; Lokuge et al., 2019). When these factors are not observed, the company risks owning only isolated technologies, developing information islands, having data breaches, or simply not realizing the expected gains (Dornelles et al., 2022; Schuh et al., 2017; Veile et al., 2019). These challenges should be analyzed and anticipated; otherwise, they might discourage new digital technologies efforts. The organizational dimension refers to the interplay between people and technologies and how they interact and conduct activities in manufacturing (Hendrick & Kleiner, 2000; Reiman et al., 2021). It encompasses aspects related to tasks and processes, rules, production methods, routines, and other attributes of the internal environment (Marcon et al., 2022; Marodin & Saurin, 2015). This dimension provides enabling factors on the changes in work tasks resulting from people and technology interactions, discussing the impacts on processes, complexity, variability, and ergonomics. Building on the findings of previous studies, Industry 4.0 implementation demands enabling factors related to process improvement, decision-making decentralization, and hierarchical changes to deliver gains and improved productivity (Cagliano et al., 2019; Horváth & Szabó, 2019; Marcon et al., 202). These factors are necessary due to the technologies impacting not only worker's tasks but the whole decision-making process due to data collection and analysis and the flexibility and autonomy that technologies such as AI, wearables, IoT, and big data allow (Dornelles et al., 2022; Marcon et al., 2022; Laubengaier et al., 2022).

The enabling factor of process improvement has been discussed in studies that described the drivers for Industry 4.0 and those that analyze lean production's role. Studies discussed that lean production tools, such as Kanbans, kaizen meetings, poka-yoke, and concepts of pulled production and value stream mapping help the implementation of Industry 4.0 (Tortorella et al., 2019; Yilmaz et al., 2022). Thus, processes with reduced variability, standardized practices, and lower inventory provide the basis for properly implementing cobots, IoT and big data solutions (Cimini et al., 2020; Rosin et al., 2019). In this sense, lean programs, training, visual management, and value stream mapping have been depicted as important tools to integrate both concepts (Rosin et al., 2020; Tortorella and Fettermann, 2018).

As for the decision-making and hierarchical changes, literature describes that Industry 4.0 demands changes toward an organic organizational design that allows more collaboration (Leyer et al., 2019). Hierarchical changes towards decentralization, worker empowerment, and lower formalization are important enabling factors to make the company more suitable for an innovative and changing environment (Cimini et al., 2020). Moreover, an environment with workers with autonomy in work procedures and problem-solving and fewer hierarchical levels allows for more agile decisions and promotes an entrepreneurial spirit (Cagliano et al., 2019; Veile et al., 2019). Hence, some companies developed independent and specialized business units that allow employees to have simplified decision-making and communication to transfer the knowledge generated to other contexts of the company and promoted access to data

analytics and communication with experts, to increase their problem-solving capabilities and motivate them (Laubengaier et al., 2022; Leyer et al., 2019; Veile et al., 2019).

When there is no process improvement, decentralization, and hierarchical changes, literature shows there are higher chances of employee resistance, decreased workers' well-being, organizational friction, and inadequate adoption practices since the technologies bring changes to both operational and middle management and change the number of tasks performed by operators, their complexity, and variation (Kadir and Broberg, 2021; Stentoft et al., 2020)

Finally, the environmental dimension refers to how the company approaches the external aspects that impact it. They are strategic enabling factors external to the manufacturing system, such as strategic decisions, investment approval, market changes, etc.) (Marcon et al., 2022). This dimension proposes that technology implementation decisions must consider complex factors instead of only local operational gains, such as partnerships, investment capacity, and production targets. For the Industry 4.0 journey, the environmental enabling factors are related to the definition of the Industry 4.0 strategy, top management support, and external partnerships (Benitez et al., 2020; Kahle et al., 2020; Machado et al., 2021). These factors prepare the company to define the technologies to be adopted in a structured way, along with assuring the necessary stakeholders are involved and interested and that the company has access to a network of partners to overcome barriers and uncertainties that may arise (Ghobakhloo, 2018; Marcon et al., 2022; Stentoft et al., 2020).

The strategic definitions help guide companies in the technologies that are important in the short and long term and in structuring how they build on each other (Marcon et al., 2022; Schuh et al., 2017). Literature reports that companies use roadmaps and maturity models to help them share with stakeholders their technology journey and structure the changes necessary for people and processes (Ghobakhloo, 2018; Mittal et al., 2018). Maturity models comprise strategy, leadership, customers, products, operations, culture, people, governance, and technology. They are important for defining the Industry 4.0 strategy as they help companies reach organizational improvements following a step-by-step process (Mittal et al., 2018). This enabling factor is important to align the technologies with the company's operational goals and mission, assuring that technologies serve a broader purpose, not only local gains.

The enabling factor of defining an Industry 4.0 strategy also aligns with the need for top management support. Top management support is essential to provide a consolidated message within the company and ensure the necessary funding and long-term previsibility of projects (Srivastava et al., 2022). Stentoft et al. (2020) and Horváth and Szabó (2019) showed the importance of top management's understanding of the opportunities brought by Industry 4.0 to provide the financial resources necessary, develop the competencies, face the risks, and motivate the other stakeholders to embrace the technologies. To this end, companies must have a clear view of the Industry 4.0 benefits expected and share the support from top management with workers and leaders through a dedicated team to improve Industry 4.0 knowledge or promote better communication internally to disclose the strategy and expectations and reduce resistance by employees and middle management (Horváth and Szabó, 2019; Machado et al., 2021; Marcon et al., 2022)

Finally, external partnerships and an ecosystems approach have been increasingly highlighted as important enabling factors for Industry 4.0 in the environmental dimension (Benitez et al., 2020; Kahle et al., 2020). Since Industry 4.0 is a complex system with interrelated technologies connected and integrated, it is hard for companies to keep track of them. Thus, developing a network with technology providers, startups, and partners is important to share knowledge and business cases toward more technical maturity. Thus, business cases, workshops, benchmarking, and meetings help companies benefit from these partnerships by exchanging information, identifying trustful providers, and anticipating challenges, which improves

technology selection and implementation (Benitez et al., 2020; Machado et al., 2021; Shet & Pereira, 2021)

Without considering these environmental enabling factors, companies risk following generic models of technology adoption that do not fit their objectives or find an environment that lacks commitment and investments from top management, who do not understand the strategic importance of Industry 4.0, and also lose important knowledge exchange opportunities that decrease complexity and risks in Industry 4.0 implementation as demonstrated by several studies (Marcon et al., 2022; Mittal et al., 2018; Shet & Pereira, 2021; Srivastava et al., 2022; Stentoft et al., 2020).

Although the literature on the socio-technical enabling factors for Industry 4.0 implementation discusses these factors, the mechanisms of how these factors are managed and changed to provide a better environment for Industry 4.0 technologies are still limited. The literature on these fields lacks more studies that analyze how companies developed and managed these enabling factors holistically as proposed by the socio-technical principles (Clegg, 2000; Cagliano et al., 2019). Thus, we explore the socio-technical enabling factors and their complexity instead of isolated actions or benchmarking cases, which are not representative of the companies environment (Cimini et al., 2020; Marcon et al., 2022; Sony and Naik, 2020).

The enabling factors that characterize each socio-technical dimension provide directions for exploring and identifying how companies developed these factors within the Brazilian context by managing their resources, people, organizational, and strategy in a holistic way. However, the enabling factors from literature presented above are not a rigid or exhaustive review, as different socio-technical systems will present particularities, and other contexts might find different factors. Figure 3 represents the conceptual research framework of our study, depicting the four socio-technical dimensions that support Industry 4.0 implementation (Marcon et al., 2022). Our empirical investigation aims to respond to the interrogations represented in **Figure 4** by analyzing the main enabling factors discussed by literature. We describe how companies developed the enabling factors of the subsystems and the enabling factors at the interaction between subsystems. To our knowledge, no other study has employed an approach with such an extensive data set.

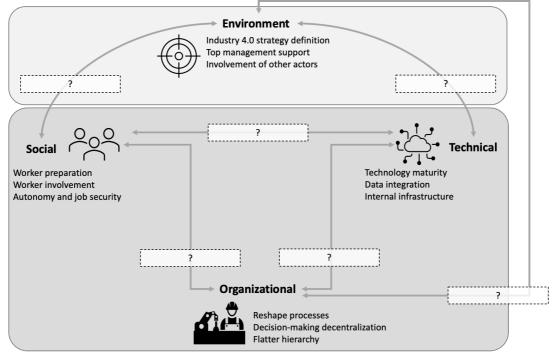


Figure 4 – Conceptual research framework

3.5 Research Method

We adopted a qualitative approach with mixed methods. First, interviews were conducted and complemented with the longitudinal analysis of 4 cases of companies implementing Industry 4.0. This complementary approach provides methodological depth and triangulation of data. Longitudinal case studies are important means to complement the data gathered from the interviews and amplify the level of detail and capacity for analyzing the enabling factors and changes developed during the Industry 4.0 context (Benitez et al., 2020). To this end, we followed adopters' actions, insights, and challenges related to their Industry 4.0 journey. This mixed approach is important and suitable for collecting information, building theory, and understanding complex organizational behavior (Eisenhardt & Graebner, 2007; Voss et al., 2002). Regarding the methodological procedures, our research followed Voss et al.'s (2002) recommendations for qualitative studies in operations management for theory building. These steps are explored in the next sections.

3.5.1 Sampling

The cases were collected in the Brazilian industry. Although Brazil is an emerging economy, the country has strong manufacturing capabilities and advanced implementation of digital technologies (Dalenogare et al., 2018). Also, the country has an Industry 4.0 program disseminated by governmental agencies that aim to accelerate digital transformation in companies (Benitez et al., 2020; 2021). For decades, the country has focused on technology acquisition and R&D/product-launch activities as drivers for industry innovation (Frank et al., 2016). However, companies that used the technology-acquisition strategy for industry innovation, based on machinery and equipment acquisition, found a negative impact on innovation output. Understanding how to improve the technology adoption process in such a context can shift such negative results in innovation and bring important productivity gains and advantages for the Brazilian industry.

We selected companies using a maximum variation approach (Voss et al., 2002). We predefined the companies based on the technology intensity classification list provided by the Brazilian National Confederation of Industries (CNI, 2016), which is based on the classification of the Organization for Economic Cooperation and Development (OECD, 2011). CNI (2016) has studied Industry 4.0 in Brazil and classified the investigated industry sectors into four technology intensity levels. We defined seven as the target number of companies for each technology-intensity level, i.e., 28 companies interviewed. We aimed to select leading technology adopters in these four categories to understand how they best use the technologies available and how they organize their systems. We used a snowball procedure by asking industry associations (e.g., Association of Equipment Manufacturers and Association of Electric and Electronics Manufacturers) and the Brazilian Industry 4.0 Chamber for suggestions for Industry 4.0 lighthouses in Brazil. After analyzing the reference list provided by these associations, we aimed to obtain a balanced sampling between national and multinational companies. We first contacted the companies to find the most representative companies for each category and assess their engagement in Industry 4.0.

After this preselection, we interviewed operations managers or any equivalent position with direct contact with workers and dealt with technology usage in the factories. Besides the interviews, we selected four cases to follow longitudinally during their Industry 4.0 implementation, one each technology-intensity level. The criteria of the longitudinal cases sample were: large companies with manufacturing activities and that had ongoing Industry 4.0 projects (more than two technologies). The companies also had to accept providing access and data over six months to allow a deeper view of the technology implementation. **Table 4** provides

the sampling characteristics of the technology adopters and the interviewees. Such a large sample also allowed for augmenting external validity and avoiding observer bias (Voss et al., 2002).

The main technologies implemented were: cobots, AI for quality and maintenance prediction, IoT and RFID for data collection, cloud storage, 3D printing, AGVs, and MES for vertical integration. Companies also mentioned 3D printing, AR, and VR applications.

3.5.2 Data collection procedures

Data was collected from April 2019 to July 2021. Data collection procedures were based on data triangulation, using interviews, participant observation, and documental analysis (Yin, 2003). For the interviews, we developed a protocol summarized in Appendix 1. These interview guidelines were structured as follows. First, we considered a general overview of the company, the interviewee, and the company's view on the Industry 4.0 concept. Then, we considered characteristics of the technologies provided or used in the Industry 4.0 context, including types, purposes, and strategies of implementation or provision. This part evaluated the characteristics of the technological and organizational subsystem (Figure 4). After, we asked questions regarding the specific relations of these technologies and organizations with work, such as the required skills, the workers' profile, new demands, and job opportunities or automation. We also considered social aspects such as cultural characteristics, workers' readiness for technology adoption, technology engagement, leadership, the company's priorities on job protection, or any related social issue. The final part of the protocol considered external factors of the sociotechnical subsystems, including education and skilled workers availability, job opportunities, technology market, and external factor related to technology and work. The questions were developed based on the socio-technical systems and Industry 4.0 literature, as shown in the framework proposed in the theoretical background section.

Technology intensity level	Companies	Industry sectors	Interviewee	Plant visit	Codename	Size/Scope	Technologies Implemented
High	Adopter 1	Computers and electronics	Engineering manager		ComputerCo1	Large, Multinational	Product traceability, exoskeletons, and AI for maintenance prediction
	Adopter 2	Computers and electronics	Plant manager		ComputerCo2	Large, Multinational	Real-time big data, machine vision system, AI decision system, dashboard, and integration with cyber- physical systems.
	Adopter 3	Computers and electronics	Industrial manager	Yes	ComputerCo3	Large, National	Real-time operations monitoring and quality parameters via SCADA/MES
	Adopter 4	Air industry	Industrial manager	Yes	AirplaneCo	Large, Multinational	AI, check more techs
	Adopter 5	Computers and electronics	Industrial manager		HomeApplianc esCo	Large, Multinational	Simulation, predictive maintenance, cobots
	Adopter 6	Computers and electronics	Industrial manager		ElectronicsCo1	Large, Multinational	MES, RFID, performance monitoring, remote maintenance through IoT sensors
	Adopter 7	Computers and electronics	Plant manager,	Yes	ElectronicsCo2	Large, Multinational	AI
	Longitudinal Case Study 1	Computers and electronics	Director, Industrial director	Yes	ElectronicsCo3	Large, Multinational	MES, cobot, and IoT
Medium- High	Adopter 8	Chemicals	Production engineer	Yes	ChemicalCo	Large, Multinational	IoT and AI for predictive maintenance solutions
	Adopter 9	Machinery and equipment	Program manager		ElevatorCo	Large, Multinational	AR, IoT, and preventive maintenance solutions with cloud connection
	Adopter 10	Machinery and equipment	Head of R&D, Automation engineer	Yes	MachineryCo1	Large, Multinational	Vertical integration, APS, MES

Table 7 - List of technology adopters of the multiple-case study approach

	Adopter 11	Automotive components	Executive manager		TruckCo1	Large, Multinational	Simulation for preventive maintenance, real-time KPIs, AGV, MES, IoT, AI demand prediction, vertical integration, and cobots.
	Adopter 12	Automotive components	Manufacturi ng manager		TruckCo2	Large, Multinational	AGVs, simulation, 3D printing, IoT, cloud computing, vertical integration, AR, big data and analytics, cybersecurity, and cobots
	Adopter 13	Other transport equipment	Industrial director	Yes	MachineryCo2	Large, Multinational	Simulation, cloud computing/storage, and analytics, exoskeleton, AR, AGV
	Adopter 14	Vehicles Manufacturer	Plant supervisor		CarCo	Large, Multinational	AI for failure prediction, exoskeletons, cobots, simulation, AGV, analytics, and machine monitoring
	Longitudinal Case Study 2	Chemical	Industrial leader and director	Yes	BeautyCo	Large, Multinational	AGV, IoT, machine vision
Medium- low	Adopter 15 (2 interviewees)	Basic metals	Plant and Industry 4.0 Manager		ForgingCo	Large, Multinational	Platform integration, 3D printing, AI, AR, automated sensing, computer vision, drones, VR for training, and RFID.
	Adopter 16	Metal products	Industrial director	Yes	CutleryCo	Large, National	MES integrated with cloud computing, cobots for quality tests, and AGVs
	Adopter 17	Metal products	Project engineer		CarpartsCo1	Large, Multinational	Al and cobots
	Adopter 18	Metal products	Production manager		CarpartsCo2	Large/National	Simulation and RFID
	Adopter 19	Metal products	Product Manager		CarpartsCo3	Large, Multinational	MES, RFID, and Cobots
	Adopter 20	Metal products	Industrial Engineer		CarpartsCo4	Large, Multinational	RFID, Simulation, M2M communication for traceability
	Adopter 21	Plastic products	Plant supervisor, Director	Yes	PlasticCo	Large, National	Real-time operations monitoring and quality parameters via SCADA/MES
	Longitudinal Case Study 3	Metal Products	Plant manager	Yes	ChassisCo1	Large, Multinational	Simulation, IoT-based production monitoring, AI solutions
Low	Adopter 22	Food	Industrial Director		BakeryCo	Large, Multinational	Robots with remote maintenance based on data analytics

Adopter 23	Furniture	Operations director	Yes	FurnitureCo1	Large, National	Data analysis, cloud computing, and 3D printers to build prototypes.
Adopter 24 (2 interviewees)	Beverages	Plant supervisor, Director		BeverageCo1	Large, Multinational	Cobots, 3D printers, IoT for online parameter measurement, APS
Adopter 25	Beverages	Engineering manager		BeverageCo2	Large, Multinational	LGVs, MES, IoT data collection, and vertical integration
Adopter 26	Textiles	Operations manager		TextileCo	Large/National	Machine monitoring, IoT, MES, big data for demand prediction, AR, AGV
Adopter 27	Footwear and parts	Operations manager		FootwearCo1	Large, Multinational	3D printing, remote machine operation, and monitoring, MES
Adopter 28	Footwear and parts	Manufacturi ng Director and Manager	Yes	FootwearCo2	Large, National	Tablets
Longitudinal Case Study 4	Furniture	Manufacturi ng Director	Yes	FurnitureCo2	Large, National	Cobots, MES, RFID, and AI for predictive maintenance

Interviews lasted an average of 75 minutes. Two researchers conducted the interviews; another helped with notes and complementary questions. The final transcripts contained 377,328 words representing approximately 60 hours of records. Transcripts were complemented by the additional notes taken during the interviews and field visits. We also randomly selected two companies in each technology intensity level for further plant visits, i.e., 14 plant visits. Such visits allowed us to compare field data with data collected during the interviews. Visits were also useful in further understanding the socio-technical subsystems and work. For the plant visits, we followed a protocol similar to the interview questions. Three to four researchers participated in all visits.

The documental review was also used as a data source for the triangulation process. Business news on these companies' manufacturing activities, industrial reports from consulting companies, and websites were reviewed to understand the companies' context better. We also used social media to map the interviewees' backgrounds and experiences in the topic discussed in the interviews. Finally, the data from longitudinal cases were collected for at least six months (for BeautyCo) to up to 12 months (in the cases of FurnitureCo2, ElectronicsCo1, and ChassisCo1). On average, these companies were visited once a month, where we asked follow-up questions on the technologies implemented with managers and workers and visited the shop floor to observe technology changes. Data collection was divided into:

- a) Interviews with managers, leaders, and workers to understand the organizational culture, management support, operational objectives, and overall technology acceptance.
- b) Process, technology, and information system mapping to understand the company's structure, complexity, and technology interactions.
- c) Interview and document analysis from technology providers and prospect providers.
- d) Visits, monitoring of work change, and worker acceptance during and after technology implementation.

3.5.3 Data analysis - validity, reliability, and interpretation

The interviews' transcripts were analyzed and codified by three researchers. Two separate researchers analyzed each interview transcript, and a review from a third researcher settled inconsistencies. Researchers could assign a given code, aggregating them into categories that were classified into one (or more) of the socio-technical subsystems according to the enabling factors mapped in literature (e.g., Cagliano et al., 2019; Marcon et al., 2022; Romero et al., 2020; Sony & Naik, 2020) that helped us to define whether different characteristics should be considered in a specific socio-technical subsystem (see Figure 4 – research framework). For example, codes related to social demands (such as retaining older employees and providing leadership support) reported by companies were grouped into subcategories of social programs, and top management support, respectively, were placed inside the social and environment subsystem set of codes. The notes, documents, interviews, and any material collected during the longitudinal case studies were also coded and linked to one of the socio-technical subsystems. For example, we recorded videos of FurnitureCo2 employees working with cobots and testing their applicability. The videos' notes and content were coded and attached to the technical subsystem describing the cobot's technical integration challenges and the organizational subsystem describing the processes and operational changes necessary to use the technology.

This step was supported by *Taguette*, a software to classify qualitative data into labels and categories (Rampin & Rampin, 2021). The support of an analytical software was important to operationalize the data interpretation after this initial analysis since many quotations present interrelated categories that allow placing the quote in multiple socio-technical subsystems.

Using this approach, we could easily identify redundancies and interrelations between different subsystems. Triangulation of data with notes from the field visits, videos, data from providers of technologies for these companies, and the document analysis allowed us to review and check the construct validity of the categories created (Voss et al., 2002). Inter-coding agreements between the researchers conducting independent analysis allowed us to check the reliability of the analytical procedures (Goffin et al., 2019). We also conducted an external validity process in our analysis by presenting our preliminary results to representatives of a technical school in Brazil, which oversaw the main professional education system for the manufacturing industry of this country, in November 2019 and collected feedback for further improvement of our data analysis (Voss et al., 2002). A similar approach was used by discussing parts of the findings with other scholars and representatives engaged in the MIT Global Research Network, a network focused on integrating research on Industry 4.0 and work worldwide. Finally, after reading and interpreting the labels and categories from the interview excerpts, we analyze and discuss the means companies used to develop the socio-technical enabling factors necessary for Industry 4.0.

3.6 Results

The results are described based on the socio-technical subsystems. We initially describe the social, technical, work organizational, and environmental enabling factors and their interactions with the other subsystems.

3.6.1 Social enabling factors

The social enabling factors of Industry 4.0 were related to the necessary new set of analytical skills, workers involvement in the process, and the autonomy and job security for the transition process. Implementing Industry 4.0 demands providing knowledge and training for workers on the technologies implemented. Companies mentioned that concepts of programming, basic statistics interpretation, and technologies such as IoT, machine vision, cobot augmented reality increase the insecurities of operators because they fear missing their jobs, not being able to work with them, or getting injured. Industry 4.0 technologies are often more complex, require more skills and knowledge, and overall digital maturity. For example, cobots, augmented reality, and wearables are often more integrated and interconnected through information systems, involve collaboration and interaction between humans and machines, and increase work complexity. Thus, companies have resorted to online courses through platforms, *in-loco* training from providers, and technical institutions for training. For example, TruckCo1 provided their workers with more than 15 thousand hours of training for their new and most digitally advanced truck assembly factory, teaching robotics basics, safety procedures, simulation concepts, equipment programming, and lean principles.

Hiring external companies or technical institutions to provide training and knowledge was also mentioned by interviewees. Machine vision, wearables, and AI applications often require specialized skills and knowledge to operate, maintain, and customize. As a result, companies rely on technology providers and technical schools to acquire these skills and ensure that their employees can effectively use and manage the technologies since Industry 4.0 technologies are more integrated, with information exchange and data collection and analysis, demanding more analytical skills. In this sense, professional education institutions in Brazil were used to promote technical courses focused on applications of the technologies, such as cobot configuration and maintenance, and electronics and mechanical technical skills. Partners and equipment providers also provide training, usually via contractual clauses of knowledge transference attached to the equipment purchasing.

In higher hierarchical levels, such as administrative, engineering, and management, there is a movement toward self-learning or using internet-based platforms, such as YouTube, Coursera,

EdX, and other tools that allow faster and frequently free content. Internet forums, discussion groups, webinars from university and consulting firms, and network meetings were also reported as important means for information exchange. Also, several companies are training and upskilling these workers through their own Industry 4.0 programs, such as ForgingCo's Digital program, CarCo's Industry 4.0 project, and MachineryCo2's Smart Manufacturing program. Moreover, some managers were enrolled in an MBA in Industry 4.0 to prepare for the upcoming managerial changes.

Companies also reported the importance of worker involvement to ensure the technologies are accepted and used. One approach reported is to provide employees with opportunities to experience the technology. In this case, Industry 4.0 showcases, seminars, and demonstrations with suppliers allowed workers to see how cobots, AI, wearables, and AGVs can support their work and provide ideas on their uses. Two cases reported sharing the company's Industry 4.0 projects and strategy constantly through a communication channel showing the implemented changes. The companies also defined a team that guides employees during this change process, discussing with them and helping in local implementations to involve workers in the process. Programs also included collecting their ideas and feedback via open channels to select and prioritize technologies. Companies reported that this approach makes workers own the project. This approach was used to develop AI algorithms for shop floor problems by structuring a team with a worker involved with the changed process, making it easier to convince other workers to adopt new solutions.

Finally, leadership change was also mentioned as impacting technology implementation. Industry 4.0 impacts digitalization, data transparency, and employee empowerment due to the implications of analytics, IoT data, smart devices, cobots, etc. So, companies reported that leaders became even more important in the technology implementation process since they increase worker buy-in and safety and can provide inputs on how the technologies can be improved. Additionally, leaders must be more autonomous since the technologies give them more information to make more important decisions on the spot. To this end, the cases reported that leaders were trained and received incentives to increase the use of the technologies, data, analyzing graphs, codeveloping technological solutions, adjusting the processes, and assisting workers. As demonstrated by the BeverageCo1 interviewee:

"We have a leadership development plan, and the team leader shares knowledge with operators to empower them to solve small daily problems."

In this sense, companies reported that a multidisciplinary, open, and innovative leadership profile is an important social enabling factor due to their role in assisting in the transition process through technical knowledge and social influence that can lead other users to be more open to the technologies.

3.6.2 Technical enabling factors

Industry 4.0 presents challenges and technical changes for companies looking to implement these technologies. Data collection and monitoring using IoT sensors, retrofitting and upgrading older equipment, data privacy, and cybersecurity concerns have become more prominent enabling factors in the Industry 4.0 context due to how valuable data has become and the interconnectivity of systems.

The first technical enabling factor for Industry 4.0 implementation is related to technology maturity, which refers to the familiarity and openness to work with technologies. Several companies achieved this by hiring more IT workers to do the integrations and processes necessary, such as retrofitting equipment. Also, more people to organize and analyze data were hired. However, companies reported problems finding people capable of working with more advanced technologies, i.e., 3D printing, cloud storage, and machine learning applications. This

shows that high skills are necessary for data analysis and technical maturity for technology maintenance, especially for medium-sized companies with lower Industry 4.0 maturity.

Moreover, problems with suppliers meeting the defined standards or providing operational data and resistance from IT staff to work with new technologies made companies resort to external suppliers that are experts in data analytics, cloud providers, and implementing more advanced technologies. Some reported relying on startups and small suppliers to codevelop these solutions and internalize technical knowledge, whereas others sought large suppliers to ensure reliable deliveries. Some companies prefer a hybrid approach balancing global and local suppliers' flexibility and security tradeoffs, such as TruckCo2.

Another enabling factor is the data collection, integration, and analysis demanded by big data, cloud computing, analytics, and artificial intelligence. The integration and interoperability of the new technologies and systems and the compatibility with existing systems and processes were highlighted. Also, moving from standard solutions, such as regular spreadsheets, to databases and from *ad hoc* data analytics to consolidated frameworks that streamline the analysis with good coding practices, data rules, and registered procedures helped companies grow their data integration. Moreover, interviewees highlighted the need to use common data models and communication protocols, such as OPC-UA and IO-Link, to ensure technology integration and data exchange for effective data management. This enabling factor also involves retrofitting and upgrading older equipment to collect their data, which is especially important for Industry 4.0 to improve decision-making. Even though some companies have had better results in their retrofitting efforts, such as CarCo (retrofitted a 35-year-old machine with a startup solution) and MachineryCo1 (connecting PLCs to their MES for advanced scheduling and data collection), this is still a challenge due to the costs involved. Several companies reported overcoming problems with data integration with consulting projects with data startups or hiring more data analysts.

These technologies are complemented by technical enabling factors related to the internal infrastructure necessary for Industry 4.0. Since the seamless exchange of data and information among systems and devices is necessary due to real-time data generation and analysis, Industry 4.0 requires stable and reliable cabled and wireless networks, such as Ethernet, Wi-Fi, and, more recently, 5G, to connect machines, sensors, and systems within the factory or across locations. Some companies reported struggling in this aspect because areas of the shop floor still lack connectivity due to infrastructure difficulties, making cloud-based solutions even more challenging. In this sense, startups and integrators were the solutions found by companies that did not have a strong internal infrastructure for connectivity and data collection. Thus, adopters built partnerships and made contracts for technical infrastructure development, shop floor cabled internet connection, IT consulting to modernize processes, and data collection and dashboards to develop the base enablers of technologies that rely on data, such as predictive maintenance and cloud computing.

Finally, the most important enabling factor related to the internal infrastructure was cybersecurity due to the impacts of cloud storage and analytics in operations and decisionmaking and the problems resulting from data breaches in these systems. They can have severe consequences, such as the loss of sensitive data, disruption of operations, and damage to reputation. Therefore, companies reported implementing robust cybersecurity measures to protect themselves and their customers from these threats. This includes local data storage, encryption, authentication, access control, network monitoring, and incident response to ensure their data and systems' confidentiality, integrity, and availability. For example, TruckCo2 generates more than 150 GB of monthly sensitive manufacturing data, which requires developing a large infrastructure to handle this data. Some companies reported more radical approaches, such as local storage in servers due to unreliable internet providers and problems with cloud providers' choices for server location.

3.6.3 Organizational enabling factors

The enabling factors related to the organizational aspects encompass process redesign, decision-making decentralization, and the need for a flatter hierarchy. The enabling factor of reshaping and structuring processes for the new technologies was mentioned by companies highlighting that lean manufacturing has been the main way to streamline processes, optimize movements, and standardize tasks. Kaizen projects, value stream mapping, production leveling, total production maintenance, and training to develop lean facilitators were used by companies that implemented technologies such as cobots, AGV transportation, big data analytics, AI predictions, and augmented reality, for example. Lean is important to identify waste and increase worker participation. In this view, lean programs were implemented to prepare the system before investing in technology. This enabling factor is even more important considering that technologies such as cobots, 3D printers, AGVs, and AI allow flexibility and adaptation to processes which can result in the automation of inefficiencies. Thus, companies reported training employees in lean concepts, promoting kaizen events and using several tools to streamline processes. Moreover, Industry 4.0 technologies were used as a means to achieve lean principles and help workers, such as diminishing lot sizes using IoT sensors with information systems, AI for guality assurance, and 3D printers to develop poka-yoke devices for shop floor applications, such as conveyor belt modifications. In this sense, Industry 4.0 serves a two-folded approach; the technologies serve lean purposes and are improved by lean principles since the processes are more controlled and streamlined.

Complementarily, decision-making decentralization was described by companies as a relevant enabling factor since technologies related to data analytics (quality monitoring, maintenance prediction, process transparency) and wearables provide information for decision-making, making the process more transparent and enriched with data. Workers receive information on the process based on sensors, IoT, and automated algorithms that recognize advanced patterns, such as monitoring engine overheat, quality, and process conformity. Interviewees highlight that worker responsibilities and tasks changed allowing them to make more decisions through displaying the information and data analyzed on computers and tablets on the shop floor. When these decisions become recurrent, they are integrated into the process. An example is tracking production batches and analyzing causes of quality failure with machine vision and IoT solutions that allow workers to make changes directly on the shop floor. Thus, IoT, smartwatches, and cobots collect data that can assist workers in maintenance activities, for example, with historical IoT data and remote assistance from experts with AR, as reported by ElevatorCo.

Another enabling factor is a hierarchy with lower levels, which is a requirement for agile management, trial-and-error approaches, and constant insights from a broader range of actors within the manufacturing process. Thus, more data-enriched and paperless tasks give workers insights into the necessary processes and changes. In this sense, companies highlight that a hierarchy with lower levels incentivizes innovation and shared responsibilities, but more importantly, it makes problems more visible and open for solutions related to quality, maintenance, and product movement. As reported in several cases, companies made KPIs visible and productivity and quality data available on the shop floor with TVs, *andon*, and wearables to empower workers to improve the process constantly, conduct more complex tasks, and make decisions reducing the need for so many hierarchical levels to oversee their operations. Workers identify changes in process parameters and use the information for adaptations of operations.

3.6.4 Environment enabling factors

The environment is an essential and strategic point to the success of Industry 4.0 implementation. Interviewees highlighted that the strategic definition and clear business and industrial alignment are essential to a successful journey. To define the Industry 4.0 strategy, most companies developed an Industry 4.0 roadmap to ensure that technology adoption is

grounded on a long-term strategy. The roadmap defines the guidelines for the technology implementation, considering their enabling factors, costs, and priority. More importantly, the roadmap allows the translation of the industrial and business strategy into different levels of technology implementation. This allows for a coordinated approach to Industry 4.0, as mentioned by BeverageCo1's interviewee:

"We have a global structure responsible for this digital roadmap supporting the modernization process. Our 3D printer is a global initiative, but we have the autonomy to develop local projects, for example, cobots."

As companies described, since the technologies build on each other's data, processes, and skills necessary, companies had to define and follow implementation phases. For example, FurnitureCo2 defined a roadmap to achieve production visibility which will demand several steps and technologies, such as a digital twin and wearables. Before the roadmap, the company implemented a cobot to discover it was too advanced since it still lacked an MES system, product traceability, and digitized operational standards. Unlike other automation technologies, Industry 4.0 technologies are networked and demand data integration internally and externally. These technologies, their communication patterns, information flow, process integration, and touchpoints must be clearly defined at a technical level, especially in the Industry 4.0 context. To this end, companies resorted to consulting firms, internal dedicated projects, or a committee with periodical meetings to discuss technological projects and define the goals for each technology, their precedence, organizational changes, and expected challenges. This is a shift of perception, according to FurnitureCo1, as in early Industry 4.0 implementation phases, they reported adopting an experimentation approach, implementing technologies *ad hoc*, and in isolated spots.

Given these strategic enabling factors, companies stressed the importance of top management support as an enabling factor. The cases reported that such support could come from internal projects, investments, communication, and company-wide funding. Some companies interviewed assigned an Industry 4.0 leader that coordinated a committee to continuously manage the digital transformation and manage the implementation chronogram, advances, and integration. Alternatively, MachineryCo2 annually shares its Industry 4.0 efforts and results for workers and stakeholders, describing experiences with AI applications for quality improvements with computer vision, cloud computing, and even complaints. Managers also reported working with key stakeholders and users during the implementation to incentivize use as a form of bottom-up motivation, such as in the case of AR used to check product quality.

The implementation also demands more partnerships and interactions with other companies, such as technology and software suppliers, but also other users, integrators, and industrial players. Companies integrated external actors involving providers, especially startups, to technology testing, piloting, and customization. This was done through a network of companies interested in Industry 4.0, round tables, and viability studies with experts and technology providers. These actors transfer knowledge, adapt the process to the technology, and allow closer contact with the problems and changes required. Universities and technology centers are also important knowledge sources in developing the company's technological proofs-of-concept and roadmaps of competences and skills. Thus, companies developed formal partnerships, consulting projects, workshops, and joint activities with universities to gather expertise on the challenges related to the technology implementation. The big data and AI projects for shop floor improvements created by ForgingCo and FurnitureCo2's Industry 4.0 roadmap codeveloped with a large university are examples of this enabling factor.

Industry 4.0 suppliers and other partners were also necessary to be closer to the company to build and adapt the solutions according to its reality and needs. In implementing predictive maintenance with augmented reality glasses ElevatorCo had to develop a close partnership to develop a maintenance solution with cloud computing and augmented reality glasses with a

large cloud hardware provider. Another example is TruckCo2, which partnered with an AGV supplier to automate their main assembly line based on the provider's know-how of process and product flow instead of only purchasing the equipment. This opposes the more traditional, closed innovation approach used for automation projects. Thus, companies hired providers to enter the factory to help optimize the processes around the technologies, as providers own the skills and know-how to implement and integrate them with their systems.

Finally, other enabling factors from external actors highlighted by the cases studied are the support and funding from public policies through credit lines and supporting agencies (industrial associations, universities, and RTO projects) since they allow the company to take larger steps into technologies with the necessary investment and expertise. These credit lines from government sources usually focus on bringing long-term competitiveness to the industry and supporting technological innovations, especially for small and medium companies, which makes them less costly and usually are integrated with university projects that allow knowledge exchange and diminished risks. The financial support usually comes from public calls and processes that evaluate the company's capability of implementing, using, and gaining productivity improvement with the technology.

3.6.5 Shared enabling factors

Industry 4.0 enabling factors were also reported on the intersection between different subsystems of the socio-technical theory. We address these shared enabling factors below. The shared enabling factors between the environment and other subsystems are present first, given their role of providing the guidelines to the other subsystems and strategic directions for Industry 4.0 implementation.

3.6.5.1 Environment-shared enabling factors

The environment and social shared enabling factors concern the company's need to analyze and address the social gaps encountered in Industry 4.0 implementation to assure technology acceptance and that the organizational culture fits the technologies. To this end, several companies mentioned developing a "digital movement/program" that seeks new technologies and solutions and structures actions to address the social needs of Industry 4.0. They also reported developing a framework that maps and improves people's skills and motivates them to use technologies. This type of action is important to anticipate skill and profile changes necessary to this new context, as described by ForgingCo's interviewee.

Cultural enabling factors also represent an important aspect that must follow the environmental guidelines for the company's Industry 4.0 journey. Thus, companies stressed that when cultural aspects, such as age, skills, experience with digital technologies, and union compliance, were not considered, employees usually boycott the technologies implemented. Industry 4.0 demanded that companies engage older workers with a closer approach, with individual training and upskilling. This was done with projects for engaging employees with technical difficulties using digital leaders and allocating individualized training for these employees.

Another enabling factor reported refers to the increasing need to develop a digital culture inside the company to incentivize working with more modern technologies. To do this, companies created incentives for employees that suggested technology solutions such as apps, equipment, algorithms, and wearables for daily problems. For example, understanding the basic concepts of lean and RFID, machine vision, and analytics allowed workers to propose improvements in nonergonomic activities at MachineryCo2's case.

The environment and technical enabling factors reported mainly refer to aspects of technology standards and technology definitions. In this sense, Interviewees highlighted that they had to identify flexible Industry 4.0 providers that could co-develop solutions adapted to their needs. Thus, they searched for startups that could develop, improve, and customize Industry 4.0

solutions. These companies have a flexible workflow, more accessible investments, and engaged professionals in the technology implementation process. Startups also share technical knowledge and skills, which are especially important in applications of machine learning, 3D printing, machine vision, system integration, and advanced planning and scheduling due to the lack of maturity on the technologies from adopters. For example, ChassisCo1 relied on a 3D printer provider to use new 3D printing techniques since they did not know how to use specific materials.

Environment and organizational enabling factors are associated with strategic alignment and support for technologies and the changes toward Industry 4.0-ready tasks. Technology funding and legal aspects of the worker-technology interactions were the most mentioned factors brought by Industry 4.0. Hence, interviewees reported their companies developed long-term investment policies long for Industry 4.0 technologies, since they involve base infrastructure with cloud, connectivity, systems investments, worker training for soft skills, and leadership changes. These investments demand a longer payback and ongoing updates, which differ from more immediate solutions such as wearables, exoskeletons, or 3D printers that operate locally. To this end, interviewees mentioned seeking governmental support and funding to assure predictability, support, and credit at lower interest rates. To this end, universities, industry associations, and companies with high Industry 4.0 maturity have become key partners in these projects due to contract demands from funding providers.

3.6.5.2 Social, technical, and organizational shared enabling factors

The shared enabling factors between social and technical subsystems reported in the cases refer to employees and the technical concerns for Industry 4.0 implementation. Consequently, companies reported increased efforts in upskilling workers in technical knowledge. To this end, they map the workers' skillset and action plans according to their Industry 4.0 roadmap. This is the case of some operational work activities that had analytical tasks added to them. To map the development and improvement of skills and capabilities, a skill radar was developed with a general view of the necessary skills necessary to support workers, track the capabilities of the workforce to work with basic digitalization (spreadsheets, simulated environments, equipment programming, and ML algorithms for quality inspection), data-based decisions, MES usability, and augmented reality.

This context of agile, self-paced learning posed by Industry 4.0 technologies demands managing knowledge, practices, and skills and retaining them in the company. Thus, the companies had to develop solutions to consolidate and systematize technical knowledge since isolated projects that were not formalized or shared among other stakeholders (such as IT, engineering, and managers) were mostly abandoned when the workers left the company. Thus, companies started developing processes for technical standards, data frameworks, common programming languages, and record-keeping to manage solutions developed internally.

In the shared enabling factors among social and organizational subsystems, interviewees reported task automation as a challenge to workers since AI and cobots in operational activities and drones for inventory management require higher technical expertise. In these cases, companies started communication activities to be more transparent with their actions related to Industry 4.0 and had some workers be part of the implementation teams helping with the process and with suggestions to improve technology's use. Otherwise, companies faced diminished usage due to boycotts and dismissal fears, as reported by an interviewee that said workers only utilized 20% of the potential of a cobot and machine vision systems solution.

This context also made workers worry about job losses. In this context, companies highlighted that corporate communication and leadership transparency were important to reduce noise in the implementation process. Several companies highlighted to workers that their focus on the technologies had ergonomic, productivity, or data purposes and not dismissal. Also, workers

were included in brainstorming sessions, kaizen events, and technical training and received institutional communication pieces to provide them with the assistance and information necessary during technology implementation. Also, to increase use and reduce fear, companies started developing some solutions internally to engage users and customize solutions to fit the organizational culture, as reported in an AI application for furnace problems and an MES implementation with IoT data.

Finally, the shared enabling factors between the technical and organizational subsystems revolved around how operational and managerial activities had to be prepared to receive and use information collected via RFID and IoT sensors for decision-making. This adaptation demands incorporating data use and collection in the processes. In this sense, AirplaneCo redesigned its operational processes to automate aircraft engine repair with AI algorithms in machining equipment. Other cases highlighted the need to incorporate the data collected and analyzed in the operations, such as depicting real-time productivity metrics, quality deviations, and accessing standard operating procedures instantly. FurnitureCo2 shifted data collection from manual processes to an RFID system that was faster and more reliable, but that changed the layout of the internal logistics. Thus, if data collection and use are inserted without considering value-adding purposes or work balancing, they can even diminish productivity, as in the case of a cobot implementation in ElectronicsCo3's manufacturing line that decreased production throughput.

In this context, it is crucial to improve and prepare IT and maintenance supporting activities to effectively work with AGVs, cobots, IoT for traceability, 3D printers, and AI, as these technologies are interconnected. Maintenance teams must be equipped to handle complex solutions such as vibration/temperature IoT sensors or machine vision systems, which serve as central sources of quality and safety data. Some companies outsourced maintenance services by remotely connecting cobots and robots' data to suppliers. Conversely, less mature companies have kept all maintenance processes and information in-house to avoid dependence on external providers. In such cases, technical schools and technology providers have become valuable technical knowledge and training sources.

Additionally, IT plays a crucial role in orchestrating and coordinating the operations of these technologies on the shop floor. They can effectively integrate different technologies, optimize data management, and leverage cloud-based solutions to enhance operational efficiency. However, some companies reported IT's acceptance of technologies as a barrier to implementing Industry 4.0. Thus, companies have developed top-down projects, such as appointing Digital Leaders who actively drive innovation and technological changes in IT, maintenance, and operations, promoting an Industry 4.0 mindset. These Digital Leaders are part of an Industry 4.0 committee, a cross-sectional department, or the IT and automation sectors, and are responsible for identifying problems that require digital solutions, with top-management support, visiting branches, and managing Industry 4.0 projects with autonomous funding to assure implementation success and use.

3.6.6 Resulting Framework

We identified how companies developed important socio-technical enabling factors for an Industry 4.0 journey and how these enabling factors interact in different socio-technical subsystems. Based on this analysis, **Table 8** presents the research framework that summarizes the enabling factors for each socio-technical subsystem and the shared enabling factors.

Socio-technical enabling factors	How companies developed the socio-technical enabling factors
	Social

Table 8 - Summary of the results

Worker	Provide online courses through platforms, in-loco training from providers, and
preparation	technical institutions. Incentivize self-learning (internet platforms, forums, discussion groups, webinars,
	and network meetings).
Worker involvement	Promote Industry 4.0 showcases, seminars, and demonstrations with suppliers. Develop formal communication channels.
	Develop programs to include ideas and feedback and open communication. Build Industry 4.0 teams with workers from the process of interest.
Autonomy and	Train and incentivize leaders to help increase the use of technologies, and assist
job security	workers.
Job Security	Technical
Technology	Involve external suppliers of data analytics, cloud, and advanced technologies.
maturity	Codevelop solutions with startups and small suppliers and internalize technical knowledge.
Data integration	Use consolidated frameworks that streamline the analysis.
Data integration	Employ good coding practices, data rules, and common communication protocols.
	Retrofit equipment with startups and integrators.
Internal	Connect machines, sensors, and systems on the shop floor with ethernet, Wi-Fi,
infrastructure	or 5G.
	Build partnerships, and contracts for technical infrastructure development, with
	IT consulting firms for more modern processes and data collection.
	Develop cybersecurity infrastructure actions (local data storage, encryption,
	access control, network monitoring, and incident response).
	Organizational
Reshape	Use lean tools to optimize movements and standardize tasks (kaizen projects,
processes	value stream mapping, production leveling, total production maintenance, and training).
Decision-making	Change worker responsibilities and tasks to allow them to make decisions by
decentralization	displaying the information and analyzing data.
Flatter hierarchy	Make KPIs and productivity data visible on the shop floor with IoT, AI, andon, and wearables to empower workers to improve the process constantly, conduct more
	complex tasks, and make decisions.
	Environment
Strategy	Develop an Industry 4.0 roadmap.
definition	Hire partners and develop a committee to discuss technological projects and
	define goals, organizational changes necessary, and challenges.
Top management	Develop company-wide projects, investments, and communication channels.
support	Assign an Industry 4.0 leader to coordinate and manage the digital transformation
	project.
	Work with key stakeholders to increase acceptance.
Involvement of	Involve providers and startups in round tables, hackathons, and viability studies
other actors	for technology testing, piloting, and customization.
	Optimize processes around the technologies with technology providers.
	Access public policies and credit lines from supporting agencies with technical
	institutions.
Shared enabling fac	
	Environment-shared enabling factors
Diminish social	Develop a digital movement/program to address the social needs and gaps for
gaps	Industry 4.0.
Cultural	Engage older workers with a closer approach, incentivizing their integration with
alignment	individual training and upskilling.
Subunction	Develop solutions internally.
Digital culture	Create incentives for employees that suggest solutions such as apps, equipment,
	and wearables for daily problems.

Technology	Involve startups to develop, improve, and customize Industry 4.0 solutions.								
standards and									
definitions									
Long-term	Seek for governmental funding to assure predictability and credit at lower rates.								
funding									
	Social, technical, and organizational shared enabling factors								
Technical skills	Develop a skill radar with a general view of the necessary skills to support workers.								
Manage	Systematize technical knowledge around technical standards, data frameworks,								
knowledge	and information related to solutions developed internally.								
Task automation	Integrate users in technology rollout, brainstorming sessions, kaizen events, and								
	technical training.								
	Provide corporate communication and leadership transparency.								
	Develop solutions internally to engage users and customize solutions.								
Task redesign for	Collect data automatically and display information for task optimization.								
data use									
IT and	Outsource complex maintenance services and its data analysis.								
maintenance	Train on complex maintenance and IT concepts.								
preparation	Structure a digital leader role and committees to drive implementations.								

3.7 Discussions and conclusions

The enabling factors mapped are the means for the preparation for the technology implementation (Sony and Naik, 2019). Our results show that Industry 4.0 implementation demands several enabling factors that are new and more complex than the third industrial revolution or technological implementations based on single technologies, such as the case of robotization or computerization. We show the complexity of developing these enabling factors through several companies' experiences. Due to its composition of complex technologies, the increasing social concerns (aging workforce and worker inclusion), and tasks that are more powered with data, the enabling factors from Industry 4.0 become inevitably more entangled and interdependent (Benitez et al., 2020; Laubengaier et al., 2022). Skill development for the workforce, leaders training for technological and organizational changes, and developing a concrete roadmap are some examples of enabling factors (Laubengaier et al., 2022). Given these changes, technology triggers organizational changes such as information systems providing access to relevant data on the shop floor, leading to information democratization and a flatter hierarchy, or lean production principles being enabled by the implementation of Bluetooth beans or RFID devices that bring more transparency to operations (Laubengaier et al., 2022; Rosin et al., 2020). We describe several means to cope with these changes and show how organizational and technological aspects can be improved in conjunction, which is essential to ensure technology's valuable use (Laubengaier et al., 2022).

Previous literature discussed and brought important views on how Industry 4.0 changes social aspects within the company, as well as organizational and environmental subsystems (Cagliano et al., 2019; Marcon et al., 2022; Sony & Naik, 2020). For example, Weking et al. (2019) showed the changes brought by technologies into companies' business models, leading to smarter offers centered around data that provide predictive maintenance, supply chain integration, and servitized offers. On the social subsystem, Industry 4.0 impacts workers' sense of safety and job value, potentially causing work impoverishment and increased pressure/stress. We show that organizational and work tasks were changed by Industry 4.0 by automating repetitive tasks, allowing standardization of processes through algorithms and wearables, and replacing operators in less ergonomic tasks. This is in line with the findings related to smart working from Dornelles et al. (2022).

Literature provides *a posteriori* analysis that brings an important view of how companies and workers perceive the impact of cobots, AR, AI, digital twins, IoT, and other important

technologies. We build on these results and bring a complementary perception of how to achieve these improvements and prepare the system to avoid barriers in Industry 4.0 implementation in anticipation. Our findings shed light on an important discussion regarding how Industry 4.0 increasingly considers people, their capabilities, and the changes in the worker profile instead of solely discussing technical or worker-substituting technologies (Bednar & Welch, 2020; Pinzone et al., 2020). We provide the mechanisms for these changes, showing that the social subsystem is important to ensure worker's development and preparation for technology, the organizational subsystem establishes operational standards, prepares tasks for data use, and needs to provide a flatter hierarchical setting for technologies and the operation of IoT, guality and maintenance prediction using AI. Finally, we show that the environmental subsystem is the most important predictor and contributor to higher levels of Industry 4.0 since it defines the implementation strategy and the maturity steps, encompassing long-term decisions, structuring the necessary support from top management, and defining partnerships and open innovation approach and subordinating technologies to operational objectives before thriving their digital journey. Financial sources, business model changes, and work improvements are essential aspects of the implementation process (Dalenogare et al., 2018; Mittal et al., 2018). Otherwise, adopters risk simply following generic maturity models, not adapting to their situation or objectives, or excessively focusing on their financial investment needs (Moeuf et al., 2018).

This shift of focus from technical competences towards organizational and human aspects is an evolution of the Industry 4.0 concept. The most recent European literature has named such evolution Industry 5.0. Industry 5.0 stress the need to empower workers, provide evolved training, and improve safety, diversity, and well-being (Breque et al., n.d.; Commission et al., 2021). Technologies such as smart additive manufacturing, predictive maintenance, cobots, cyber-physical cognitive systems, edge computing, digital twins, blockchain, and future 6G systems compose this revolution (Maddikunta et al., 2022). Our results show that social aspects related to improving operators' skills, addressing social gaps (age and digital literacy), and involving operators in technology implementation are already recognized by managers as important enabling factors in their Industry 4.0 efforts.

The Industry 4.0 concept was reported by several advanced implementors as demanding a human-centric approach where operators use technologies to increase their importance in decision-making activities (Pinzone et al., 2020) by allowing physical and cognitive support to humans, linking together machines and data in high-performing systems (Romero et al., 2020). Our analysis reinforces this view as the interviewees mentioned changes towards operator empowerment, participation in the implementation process, and the development of digital culture as some of the most important conditions discussed. Thus, through sensors, cobots, adaptative manufacturing equipment, AR, exoskeletons, and wearable devices, possible negative impacts of tasks on the operator's physical and mental health can be minimized. Our results also show that AR, VR, AGVS, and cobots allowed making tasks less cognitively demanding, more balanced, and data-enriched, which leads to decreased stress.

Finally, it is important to highlight the need for developing a data-driven culture inside the company, as our results demonstrated that it increases technology acceptance. Digital culture can increase workers' confidence in AI, cobots, VR, and exoskeletons (Dornelles et al., 2022). Thus, training, soft skills, promoting kaizen events, and allowing employees to be part of the development team are important means to disseminate digital concepts, especially in small and medium enterprises organizational, where organizational changes usually occur after the technological introduction (i.e., Industry 4.0) (Cimini et al., 2020). Per our findings, the literature highlights that a new job profile with more training and autonomy is necessary, combining technical and non-technical skills (such as the Industry 4.0 enabling factors of developing employees with problem-solving skills and self-learning capabilities reported by companies).

These enabling factors can be achieved by hiring new employees or developing their skills inside the company with training and partnerships with educational institutions and online platforms. Thus, we show that not only a technical or an upskilling strategy must be conducted when implementing Industry 4.0, but an intertwined approach guided by a strategic roadmap that plans changes to tasks, processes, technologies, and people based on long-term operational goals and technical standards and patterns that allow information exchange between equipment. Moreover, we show how complex and intense in partnerships the implementation process is, which demands companies to be open to collaborate and take risks in their Industry 4.0 journey (Benitez et al., 2020).

3.8 Managerial Implications

The findings from this study also bring implications for decision-makers. They can use the framework proposed in **Table 8** to implement the main enabling factors and elements to help increase the socio-technical maturity and acceptance of the technologies. Based on the framework, companies can translate the enabling factors for their context and structure joint efforts with their technological roadmap. Thus, Industry 4.0 adoption can be planned based on long-term operational goals and social demands.

Managers should also consider important enabling factors of top management support and the necessary development of partnerships with external actors. This will ensure that Industry 4.0 technologies align with the company's overall strategic goals and objectives and that complex solutions become more feasible as knowledge is transferred between parts. Another key enabling factor is providing leadership and support to employees, including technology sponsoring, communication, worker engagement, and training. This will ensure they use the technologies and can contribute to the company's Industry 4.0 efforts.

Also, the enabling factors studied can demand external efforts to complement internal actions. We show what managers should consider before and during their Industry 4.0 implementation process, such as the need for technical training, the necessary inclusion of workers in the technology definition/implementation/operation, the growing concern of data collection and use, and its security for long-term sustainability.

3.8.1 Limitations and guidelines for future research

However, we highlight some limitations of the study. First, since we analyze qualitative data from cases, the results might represent a more stratified sample of companies (i.e., lower technology maturity companies, consistent with developing countries). To help overcome such limitations, we sought to analyze multiple cases and multinational companies that replicate their business processes and technologies in Brazil.

Finally, we did not consider the motivational aspects of leadership necessary to drive digital transformation. For example, leadership "charisma", authority, and personal aspects might be important indicators of organizational readiness (Tortorella et al., 2018) and should be addressed in future work. We also suggest future studies to analyze the socio-technical configurations and their association with Industry 4.0 technologies, as some companies may present an adoption pattern related to their focus on one or another socio-technical subsystem. Understanding this association can provide a glimpse into their next steps.

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Appendix 1 – Interview guideline

General description of the company and products offered

a) Could you briefly overview the company's history, products, and markets?

Technical impacts

- a) What technologies has your company adopted that are relevant to Industry 4.0?
- b) What are these technologies and services used for? In which business functions are they used (e.g., design, production, service, and distribution)?
- c) How is the company engaging with the vendors that provide Industry 4.0 technologies? Are solutions customized?
- d) Are specific or special preconditions or requirements needed before your company can implement Industry 4.0 products or services?

Technology and work impacts

- a) What are engineers, managers, or workers able to do with Industry 4.0 technologies? How are jobs changed as a result?
- b) Are jobs being created, displaced, or substituted due to adopting Industry 4.0 technologies? Please describe.
- c) Are jobs becoming simpler or more complex as a result?
- d) Do workers seem reluctant to adopt these technologies?
- e) What new skills and training are needed for workers, engineers, or managers?
- f) Do your workers need new skills and training to use Industry 4.0 technologies?

Technology impacts

- a) Can you describe the impacts of Industry 4.0 technologies on your operations?
- b) How is the adoption of Industry 4.0 technologies enabling the adoption of new business models and business functions at your company?
- c) Are the products or services created with Industry 4.0 technologies opening markets for your company or your customers? Please describe or provide examples.

Environment impacts

- a) Do you pay import or other taxes on Industry 4.0 equipment, software, or services?
- b) Are there other regulatory barriers to using international technology resources, such as cloud storage or technology imports, or the use of foreign technology workers or technicians?
- c) Are there government-funded technology development or training programs for Industry 4.0 that are useful? If not, what would be helpful?

4. Article 3 - A configurational view of the socio-technical environment of Industry 4.0 adopters

Target Journals: International Journal of Production Economics, Technological Forecasting and Social Change, Industrial Marketing Management

Abstract:

Industry 4.0 implementation requires processes, people, work, organizational culture, and strategy changes. While some companies are better prepared and leverage technologies to achieve greater operational performance, others struggle to benefit from the data integration, automation, and information sharing. Our study analyzes how different configurations of sociotechnical (ST) systems are associated with Industry 4.0 technologies adoption and operational performance. To this end, we analyzed 132 companies, their socio-technical configurations, Industry 4.0 technologies, and their performance improvements in productivity, quality, flexibility, and worker safety. Our results show that companies can belong to one of four different configurations and that socio-technical masters are associated with better overall performance than companies that focus only on people, organizational improvements in isolation. Low and socio-technical masters configurations differ in Industry 4.0 implementation for technologies analyzed. We propose theoretical and practical discussions and develop a House of Industry 4.0 framework that can guide companies in leveraging their ST configuration to improve performance through Industry 4.0. We also propose alternative pathways to companies that cannot reach the Socio-technical mastery level.

4.1 Introduction

Industry 4.0 has broad social impacts on companies, including effects on hierarchical structure, workers' skills, cognitive workload, task complexity, and routines (Cagliano et al., 2019). Thus, Industry 4.0 technologies, such as IoT, artificial intelligence, vertical integration, cobots, and wearables, require a human-centered view to improve work, worker capabilities, production processes, and data availability for decision-making (Dornelles et al., 2021). In this sense, Industry 4.0 implementation requires social improvements to provide the expected performance, ergonomics, and safety gains (Cagliano et al., 2019; Marcon et al., 2022), in addition to the technical concerns such as system integration, data patterns, and technology compatibility (Akter et al., 2016; Schuh et al., 2017; Tabim et al., 2021).

Companies implementing these technologies tend to focus heavily on the technical aspects of Industry 4.0 without considering the environment where the technologies will be implemented (Marcon et al., 2022). However, approaching them through such a reductionist perspective, i.e., addressing isolated socio-technical (ST) subsystems, does not capture the interrelated and interactive relationships between these subsystems and the Industry 4.0 technologies. The ST configurations varies from company to company as they may focus more on practices that align with their culture, production processes, or operational objective. These resources, personnel efforts, practices, strategy, and operational activities make distinct organizational configurations. The configuration approach allows considering these complex ST patterns from a holistic perspective instead of the reductionism of analyzing isolated efforts to manage workers, processes, technologies, and strategic decisions in the Industry 4.0 implementation process (Flynn et al., 2010).

According to Flynn et al. (2010), the configurational approach focuses on establishing emerging patterns or profiles from the organization that reflects the company's strategy, systems, or practices. Analyzing these configurations allows the development of an empirically based taxonomy by discussing the underlying competition structures from the operations' perspective

analytically (Miller & Roth, 1994). For example, a company may focus on process improvement and adaptation to the technology, eventually neglecting worker training and engagement; or technology-related efforts without a deeper analysis of the impacts on production flexibility or business models (Enrique et al., 2022; Marcon et al., 2022).

Previous studies have proposed preliminary ST (socio-technical) configurations for an improved Industry 4.0 environment (Dalenogare et al., 2018; Marcon et al., 2022). Some configurations, such as high operator autonomy, multi-tasking teams, cognitive-demanding tasks, and flatter hierarchies, can host a more welcoming environment for Industry 4.0 than others (Cagliano et al., 2019; Kleiner, 2008). However, these studies do not consider all ST dimensions, focusing on one or two dimensions such as workers and their activities or processes and technologies (Dorneles et al., 2021; Cagliano et al., 2020), or they provide a generic analysis of how the ST dimensions interact and compose configurations (Mittal et al., 2018). We propose that Industry 4.0 implementation and its outcomes will differ based on the type of configuration the company pursues. Therefore, identifying the configurations that bring the best results is key to adapting ST systems to Industry 4.0.

The analysis of the configurations is consistent with the tenets of the ST theory, which proposes that companies must jointly optimize their organizational elements - including social, technical, work, and strategic aspects - with the technologies implemented rather than attributing the benefits of innovations solely to IoT, AI, cobots, or other technologies (Marcon, Soliman, et al., 2022). However, the literature has yet to discuss how these ST aspects interrelate into configurations and their association with Industry 4.0 dimensions (Flynn et al., 2010; Marcon, Soliman, Gerstlberger et al., 2023; Soliman & Saurin, 2017). Empirical studies tend to analyze a limited number of cases, focusing on a narrow scope, or analyzing individual ST aspects and their relationship to Industry 4.0. Our analysis is important in the practical sense since Industry 4.0 technologies require large investments, process changes, and data infrastructure. However, companies struggle to define and optimize their ST configurations with Industry 4.0 technologies that match their operational objectives and organizational and process changes (Kamble et al., 2018; Stentoft et al., 2020). By understanding how ST, Industry 4.0 technologies, and technology-driven performance are connected, companies can better design their organizational environment and the roadmap of technologies that align with their objectives. Therefore, to clarify such a problem, we propose the following research question: "How are different socio-technical configurations associated with Industry 4.0 technologies and performance outcomes in manufacturing companies?"

We address this question by analyzing 132 companies and their configurations, investigating their technology patterns, contextual and demographic aspects, and gains in performance with technologies. To this end, we employ a quantitative method that allows analyzing configurations that emerge from companies' practices, generating typologies, and associating them to Industry 4.0 technologies and gains in performance. Our study provides specificity by analyzing the configurations available for the companies in the context of a developing country, but also generalizability by describing how these ST configurations are composed and how companies can leverage the practices from different configurations to achieve different performance objectives.

The results show that companies can present four different configurations: low ST configuration, focus on people, focus on organizational aspects, and those that improve both to achieve the ST Masters level. ST Masters show increased productivity, quality, flexibility, and work safety. Moreover, the companies that focus on organizational aspects better organize their processes, strategy, and leadership model and are associated with higher gains in quality and work safety when compared to Low ST configurations or that focus on people. Finally, we provide the theoretical and practical contributions of the study.

4.2 Theoretical Background

4.2.1 The ST systems and Industry 4.0

The ST theory is grounded on the assumption that systems must be designed and improved not only considering the technical/technological aspects but through the joint optimization of the internal environment (people, technical, and work organization) and external aspects (strategy, market, and changes) to avoid technology frustration and poor use (Davis et al., 2014; Kleiner, 2008). At its core, ST theory posits that the design and performance of new systems can be optimized only when the elements are treated as interdependent aspects of a work system rather than as separate components (Clegg, 2010). As described in the principles proposed by Cherns (1976), designing and implementing innovations in production systems involve making several choices that are social at its core, such as how the system will operate, how the work will be organized, the technologies required, and what other organizational aspects are necessary. These decisions are neither independent nor deterministic in the sense that a focus on one aspect of manufacturing does not fully determine a choice in another due to complexity and process needs (Clegg, 2010). Such principles describe how ST system design allows concurrent investments, actions, and activities within the company. We focus on analyzing how these investments, actions, and activities compose ST configurations by analyzing similarities of ST patterns between the companies.

The ST theory focuses on the design of ST systems, and it was proposed by Trist and Bamforth in 1951, emphasizing the role of the environment in an open system and the need to involve and consider both technology and people in changes to manufacturing systems (Bednar & Welch, 2020). These principles grew in importance in the 1950s, during Europe's revitalization after World War II, and became increasingly relevant as technologies played a more central role in performance improvements. Especially as Industry 4.0 becomes more widespread and its potential benefits become apparent, some managers may excessively prioritize gains solely through technical enhancements, resulting in poor outcomes and posing challenges, stress, and frustration for workers (Kadir & Broberg, 2020; Sony & Naik, 2020).

Studies found several gains in using the joint optimization approach in system design and changes, such as increasing motivation, productivity, and well-being when companies have flexible decision-making processes and empowering workers to solve problems at their sources (Davis et al., 2014; Kadir & Broberg, 2020). The ST theory has been used to analyze innovations in organizations such as new information systems, work relations, and frequently, the impact of a technology or a set of technologies on a work system (Marcon, Soliman, et al., 2022; Sony & Naik, 2020). While the technologies are expected to improve the work environment, critics state that managers must avoid using the ST principles to mitigate the impact of IT on work the organization by gaining user support and allowing users to influence the design itself (Davis et al., 2014).

In the case of technology implementation, the ST theory proposes that focusing on individual aspects is important but does not consider the complexity of the system, such as articles analyzing how processes should be redesigned for lean production, strategic changes for Industry 4.0, and the capabilities necessary for workers and business models (Longo et al., 2017; Marcon, Soliman, et al., 2022; Tortorella et al., 2019). Studies also show that companies concentrate more efforts on technical challenges and strategic aspects than on engaging and training workers, integrating them into the technology rollout process, empowering their decision-making, and adapting processes (Enrique, et al., 2022; Marcon et al., 2023).

According to the ST theory, companies implementing new technologies should provide top management support, workload balance, standardized processes, and assure technology fit (Kadir & Broberg, 2020), which is especially true for Industry 4.0, given that the technologies allow flexibility and data analysis for process transparency. Moreover, training workers on the use of the technology, involving them in decision-making and technology implementation, and

making information more transparent are important to increase technology acceptance and use (Kadir & Broberg, 2020; Marcon et al., 2022). However, companies tend to employ more efforts in some areas, which results in ST configurations with a specific focus that reflects how the company deals with its Industry 4.0 journey and its general strategy.

4.2.2 ST configurations and Industry 4.0

The configurational theory proposes that configurations are a group of multiple explanatory factors that allow examining the factor's interdependencies and impact on an outcome of interest, which in this article, are composed of ST factors related to activities and efforts toward workers, processes, and strategy (Heredia et al., 2023; Ragin, 2009). The configurations emerge from a company's strategy, processes, and practices, allowing for defining and developing taxonomies based on these patterns. As a result, ST configurations will emerge due to companies' emphasis on different ST elements due to their operational objectives, access to resources, or strategy, making them more contextually accurate than predefined taxonomies (Flynn et al., 2010). For example, a company seeking more flexibility may focus on worker training and adaptation, layout changes, and implementing technologies such as cobots, pick-by-light, tablets, and traceability; meanwhile, a company seeking productivity may invest in a configuration with constant process improvement, lean tools (single-minute exchange of die, Kanban, and modular workstations), and technologies of big data, Al for production and maintenance, and IoT (Buer et al., 2018; Dalenogare et al., 2018; Enrique et al., 2022; Frank et al., 2019).

We analyze the ST configurations that can better host and leverage Industry 4.0 technologies and increase technology impact on performance. Literature has shown that companies focusing on developing workers, streamlining operational routines, and defining a clear strategy have higher levels of Industry 4.0 adoption (Marcon et al., 2022). However, when ST configurations and Industry 4.0 technologies are not integrated, technology acceptance and adoption are hindered, resulting in poor training programs and support, inadequate communication and collaboration, and low business goal alignment (Calış Duman & Akdemir, 2021; Kamble et al., 2018; Stentoft et al., 2020). Additionally, unexpected consequences can arise in both physical and cognitive ways, such as experiencing pain when using AR glasses and increased stress and mental workload from receiving information through HMIs and screens while performing tasks (Kumar & Lee, 2022). Hence, companies are expected to host or adapt their ST configurations to leverage Industry 4.0 technologies or focus on the technologies that fit their ST configurations with lower friction.

Such as the analysis that found that companies in the early stages of supply chain integration should configure their environment with a foundation of internal integration and progress toward customer integration for performance. (Flynn et al., 2010), we expect that ST configuration with higher levels of practices will provide a better configuration for Industry 4.0, leading to better performance.

4.2.3 Industry 4.0 implementation

Industry 4.0 implementation and technology concepts have been widely researched. Several authors focused on understanding how Industry 4.0 technologies are implemented, what are the necessary steps to prepare the organization for its Industry 4.0 journey, and how technology implementation varies among different companies. Among these studies, in their seminal work, Kaggerman et al. (2013) proposed the Industry 4.0 concept and the integration of information systems through technologies for vertical integration, horizontal integration, and end-to-end engineering. In addition, Frank et al. (2019) analyzed from the application perspective and grouped the technologies into five dimensions based on the area the technologies are implemented, namely smart manufacturing (AI for planning and maintenance, robots, 3D

printing, and vertical integration systems), smart working (AR and VR for maintenance and training, and cobots), smart supply-chain (digital platforms with suppliers, customers, and other units), and smart products and services (product connectivity, monitoring, and autonomy). These analyses describe technology structures and how the technologies can work in complementary ways to provide gains in operators' skills, production processes with more data, connected supply chains, and products and services that allow connection for manufacturing and innovative business models (Dornelles et al., 2022; Marcon, Le Dain, et al., 2022).

Later, as the concepts evolved, studies proposed the technologies that should also be implemented considering the digitalization maturity, operational objectives, organizational environment, and worker preparation (Cagliano et al., 2019; Dalenogare et al., 2018; Marcon et al., 2022). Frank et al. (2018) found that companies start with technologies for vertical integration, traceability, and cloud, then move to automation and virtualization with IoT. Finally, they implement line flexibility technologies such as additive manufacturing, big data, and analytics. Looking at the ST environment, studies found that to implement and integrate a higher number of technologies into manufacturing (i.e., additive manufacturing, traceability, automation, advanced machines, and digitalization of processes), companies must have an environment with operator autonomy, cognitive tasks, hierarchical interactions, and decisionmaking decentralization (Cagliano et al., 2019). Moreover, companies that prepare their social, technical, work organization, and strategic aspects showed greater technology implementation in small and medium companies in general (Marcon et al., 2022). In this regard, the most important factors for higher levels of Industry 4.0 are a clear strategy towards people, technologies, and production, an environment that incentivizes self-learning, and employee engagement, retains knowledge, rotates jobs, and has standardized work procedures (Marcon et al., 2022).

4.2.4 Hypotheses

These studies provide a glimpse at Industry 4.0 technologies and their relationship with the organizational environment but only consider individual ST aspects or without considering the company's environment and configurations, which leads to generic implications (e.g., Cagliano et al., 2019; Marcon et al., 2022; Sony & Naik, 2020). We propose a complementary approach to these studies by jointly analyzing the internal structure, processes, and people and their relationship to the type of Industry 4.0 technologies implemented instead of studying them individually. We expect that as manufacturing companies improve their internal environment, organizational structure, and people, they move from less mature (and consequently) less supportive ST configurations to more structured configurations. Thus, companies with unstandardized processes, poor worker engagement and training, and unclear production and leadership strategies will not be able to implement a high number of technologies. This limitation occurs because skilled and motivated workers, lean processes, and a clear digital strategy provide a better infrastructure for the use, integration, and success of technologies such as AR, AI, cobots, and vertical integration (Dornelles et al., 2022; Sony & Naik, 2020; Tortorella et al., 2019) allowing their expansion.

In this sense, organizations that jointly develop their ST structure will have more advanced ST configurations than those that fixate on one aspect. They will also present higher Industry 4.0 maturity since the company can implement and connect the technologies. Thus, we propose the following hypothesis:

H1: Companies with complementary ST configuration are associated with higher levels of Industry 4.0 technology adoption.

Alongside this logic, research has also addressed the impact of Industry 4.0 on performance metrics to show whether technologies such as AR, IoT, automated-guided vehicles, cobots, and

Al increase productivity, flexibility, quality, and innovation of companies (Calış et al., 2021; Enrique et al., 2022; Sarbu, 2021). Industry 4.0 technologies and big data analytics positively impact innovation and the intensity of product innovation for service companies (Sarbu, 2021). Also, studies showed that complementing technologies allow more systemic gains, such as frontend solutions (i.e., augmented reality, cobots, simulation, and 3D printing), improving supply chain adaptability to changing markets, as they boost sourcing and delivery (Enrique, Lerman, et al., 2022). Also, Industry 4.0 technologies drive gains in quality, customer feedback, energy efficiency, and production processes (Calış Duman & Akdemir, 2021). Studies also showed that Industry 4.0 reduces lead times and quality problems when integrated with lean practices to reduce human errors with e-Kanban systems to automatically regulate process flow or increase productivity with process optimization through value stream maps created with simulation tools (Yilmaz et al., 2022).

The improvements brought by Industry 4.0 are not new (Dalenogare et al., 2018). However, literature shows that technologies alone cannot bring improvements since organizational aspects are essential levers for the performance impacts of Industry 4.0 (Cagliano et al., 2019; Tortorella et al., 2019). In this regard, research has analyzed how some ST aspects deliver increased performance when integrated with Industry 4.0. For example, lean-related practices for product flow (i.e., designing factory layout based on the family of products and assuring a continuous flow by grouping products based on their processes) with cloud services, IoT, or big data analysis generate high operational performance (Tortorella et al., 2019). Moreover, organizational aspects such as openness to new technologies and the capacity to implement Industry 4.0 technologies (such as cobots, IoT, additive manufacturing, simulation, and vertical integration) in several value chain stages can result in greater flexibility, quality, and increased production capacity opportunities (Büchi et al., 2020).

These results provide a glimpse of how organizational factors allow improved performance with Industry 4.0 by involving employees in the change, optimizing value streams, training, and motivating workers, and defining clear long-term strategies for manufacturing, technology, and personnel (Büchi et al., 2020; Kadir & Broberg, 2020; Marcon et al., 2022).

Although these aspects are important to Industry 4.0 implementation, their impact is analyzed in isolation. Hence, a gap in the literature remains regarding which aspects related to ST configurations increase the performance achieved with Industry 4.0 technologies, and a more systemic view of this relationship needs to be provided. Thus, alongside hypothesis 1, we propose that as companies progress from less mature ST configurations to more structured ST configurations, they will have a better organizational structure, streamlined processes, and a workforce that enables using these technologies with more effectiveness and reach performance gains in productivity, quality, flexibility, or work safety. Whereas less mature configurations are less prepared to use and leverage Industry 4.0 technologies since they host an unbalanced ST configuration. This is summarized in our following hypothesis:

H2: Companies with complementary ST configuration are associated with higher gains in operational performance from Industry 4.0.

4.3 Methodological procedures

4.3.1 Sample

We conducted a cross-sectional survey with Brazilian manufacturing companies in the southern region of Brazil. We focused our data collection on the Machinery and Equipment Association, which allowed us to obtain a sample of companies with different maturity levels on Industry 4.0. We directed the survey to Chief Executive Officers and Operational Directors and assured their participation by enquiring about the respondent's positions. We addressed Brazilian companies since it is a market that has been interested in Industry 4.0 and innovates through technological improvement on the shop floor (Frank et al., 2016). The questionnaire was sent to 240

companies registered in the association that partnered in this research, with a total of 132 responses (response rate of 55%). **Table 9** presents the composition of the sample. The questionnaire was collected online in 2021. As depicted in **Table 9**, small, medium, and large companies are balanced in the sample. Most of the companies' country of origin is Brazil, which is also the main market for more than 75% of our sampled companies. To increase response and precision, we offered respondents a personalized report on their industrial sector, which would only be possible if they accurately assessed their technological maturity in the survey. **Table 9** provides the sample's characteristics.

Company's sector	%	Nationality	%
Manufacture of machinery	23.85%	Brazilian	70.45%
Manufacture of industrial machines	13.08%	International	29.55%
Manufacture of automation machines	9.23%	Main market	
Manufacture of machinery, equipment, and		Regional	5.30%
accessories for agriculture	9.24%		
Manufacture of vehicles	2.31%	National	76.52%
Manufacture of electrical and electronic		International	18.18%
devices	2.31%		
Others	40.00%	Source of financial resources	
Size		Bank	12.12%
Micro (<10 employees)	6.06%	Own resources	69.70%
Small (<100 employees)	34.85%	Subsidies	3.79%
Medium (<500 employees)	31.06%		
Large (>500 employees)	28.03%		

Table 9 - Sample characteristics

4.3.2 Variable definition, operationalization, reliability, and validity of measures

Following the conceptual framework proposed, we developed four blocks of questions regarding the Industry 4.0 technologies adopted, the level of ST dimensions, the company's gains in performance with digital transformation, and sample characteristics/demographics.

The ST aspects implemented were assessed with statements that ranged from 1 to 5, with completely disagree being 1 and totally agree to the affirmative being 5. The third block of questions was about the gains in performance due to digital transformation (namely productivity, quality, flexibility, and work safety gains). To measure Industry 4.0 variables, we used a Likert scale with 5 points, ranging from 1- we do not own this technology, 2 – we are interested in implementing, 3- we have a project to implement, 4 – we have it implemented for specific uses, and 5 – we have an advanced implementation. The technologies surveyed were based on previous studies (Dalenogare et al., 2018; Frank et al., 2019; Kagermann et al., 2013). Before the survey application, we refined the questions, technologies, and other variables by discussing the survey with 3 Industry 4.0 specialists, showcasing them at an Industry 4.0 seminar, and pretesting the questionary with ten respondents. We made small changes in wording,

scales, and sample characteristics. We used Exploratory Factor Analysis to identify latent constructs of Industry 4.0 technologies. We used the varimax rotation to extract orthogonal components from the broad range of technologies survey to examine unidimensionality, such as in other studies identifying latent digitalization metrics and groupings (Dalenogare et al., 2022). This procedure is in line with the approach of evaluating the features of interrelated technologies rather than examining their

individual associations with ST clusters. Thus, we ran the analysis with 30 technologies and used three criteria to assess the adequacy of our data to the technique: the Kaiser–Meyer–Olkin (KMO) test, Bartlett's sphericity test, and the anti-image matrix for Measures of Sampling Adequacy (MSA) (Hair, 2018). The results showed a good explanation capacity for the constructs

(communalities > 0.463, mean of 0.702). The KMO test also showed a good sample adequacy of 0.858 (the recommended threshold is 0.5), Bartlett's Test of Sphericity showed significance lower than 1% (p-value <0.001), and Cronbach's alpha for the variables was 0.930. The antiimage matrix showed a good fitting, with correlations above 0.5. We tested the normality of the data by examining skewness and kurtosis values. Overall, the data are normally distributed since the values for skewness and kurtosis were between +- 2.58 (α = 0.01) (Hair, 2018).

Besides Crohnbach's Alpha, we evaluated CR values for the main constructs for convergent validity. For all constructs, there is the goodness of fit since the values were above the suggested (i.e., > 0.6) (Hair et al., 2018). These tests show a good fit of the variables to the test (Hair, 2018). Our results generated six factors (i.e., groups of Industry 4.0 technologies) that explain 68,73% of the variance, as shown in **Appendix 2**.

4.3.3 Response bias, common method variance, and robustness check

We employed procedural and statistical remedies for potential response bias (Podsakoff et al., 2003). Firstly, procedural aspects were checked by pretesting the survey with scholars and Key respondents (CEOs, Directors, and Managers) to ensure the quality of the answers. The items used to build the STS clusters and Industry 4.0 factors were distributed in different parts of the questionnaire, which provides more reliability and diminishes possible associations between groups of variables, or with outcome variables to prevent respondents from predefining causality while assessing them (Hair et al., 2009). Regarding respondent reliability, the questionnaire addressed plant managers and directors expected to have contact with and be responsible for the technologies and practices addressed in the questionnaire.

Secondly, we used a statistical approach to check for potential common method bias through Harman's single-factor test using exploratory factor analysis. No single factor accounted for the majority of variance in the model since the first factor only explains 30.3% of the variance observed (Podsakoff et al., 2003). Thus, no major factor accounts for most of the covariance among measures, and any level of common method bias that may exist should not be of significant concern.

4.3.4 Data analysis

The analysis consisted of 5 steps, depicted in **Figure 5**. In Step 1,we analyzed how the Industry 4.0 variables could be grouped according to their meaning and behavior similarity. To this end, we performed an Exploratory Factor Analysis (EFA) that allows summarizing the information of several variables in a smaller set of dimensions (factors) that are orthogonally distributed and represent a bigger concept instead of individual variables (Hair et al., 2009). As mentioned, this resulted in six factors representing the level of implementation of Industry 4.0 concepts composed of 4 to 8 technologies, such as the Vertical Integration concept comprising ERP, MES, and SCADA systems.

The final factors are Traceability, Smart Products, Virtualization, Supply Chain Integration, Vertical Integration, and Advanced Manufacturing. Traceability included variables related to the use of technologies to trace defects, materials, and components, supplies within the production line and the plant, and traceability of supplies and finished products. Smart Products and Services refer to product connectivity that provides failure detection, maintenance, operation monitoring, product autonomy, AI-based, and remote maintenance services. Virtualization comprises simulation variables at the equipment, process, and plant levels and digital twin and augmented and virtual reality for activity checklists and operational procedures. Supply Chain Integration comprises technologies related to data integration to connect and integrate data from offline sources in real-time to check the availability of products from suppliers and distributors and synchronize activities with these actors. Vertical Integration represents the integration of manufacturing data across different levels of the organization. These systems are

used to register, organize, and control production processes and include computerized local equipment operations, supervisory data capture (such as through SCADA), and connected equipment for data integration (such as through a Manufacturing Execution System) to enable the seamless flow of data across different levels of the organization. Finally, the Advanced Manufacturing factor is composed of variables of technologies of 3D printing and collaborative robots that allow for the automation of activities and improved customization.

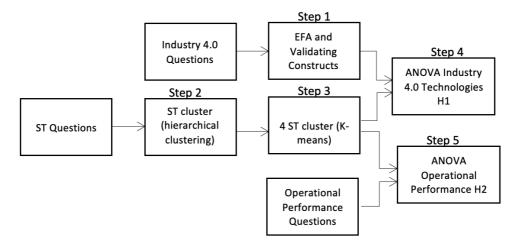


Figure 5- Data analysis steps

In steps 2 and 3, we analyzed the ST configurations through clustering analyses. This 2-step analyses comprised the hierarchical clustering technique, which indicates a range of clusters to be defined through a dendrogram. Then, we proceeded with the k-means technique, where *k* was the number of ST clusters indicated by the dendrogram (Frank et al., 2019; Marcon et al., 2022). These procedures allowed for identifying distinct groups with similar ST characteristics in the sample (organizational, worker, and strategy-related variables), i.e., ST configurations. We used Ward's method in the clustering process for the hierarchical cluster analysis, with the Euclidean distance measure of similarity among respondents (Hair et al., 2009; Marcon et al., 2022). Based on the cluster memberships, we conducted a demographic investigation of the cluster composition. To this aim, we analyzed the company's distribution on demographic, market, technological, and performance aspects.

In Step 4, we analyzed the association between ST (clusters) configurations and Industry 4.0 (factors) through a series of ANOVAs to test for hypothesis 1. Finally, in Step 5, we investigated if ST configurations were associated with operational performance. To this end, we used a series of ANOVAs for the 5-point Likert scale variables. We ensured the data met the assumptions of normality by analyzing if the skewness and kurtosis values were below the threshold of 2.58 (α =0.01) (Hair et al., 2009). Equality of variance was also investigated, and the variables that did not meet this requirement were analyzed using a more robust analysis, i.e., Welch statistics, with post-hoc analyses using the Games-Howell test instead of the LSD method used on samples that had variance equality (Hair et al., 2009).

4.4 Results

4.4.1 Definition of ST clusters

The results presented in the dendrogram (Figure 6) show that companies can be clustered into 2, 3, 4, or 6 clusters. Since 2 or 3 clusters would represent very poorly the possible socio-technical configurations, and more than five resulted in non-representative and overly complex

configurations, we defined 4 clusters as ideal to obtain more differentiation among clusters and still be able to represent configurations of ST elements.



Figure 6 - Dendrogram for the selection of the number of ST clusters

We used these 4 clusters defined in the dendrogram to run the k-means (k= 4 clusters), which results are represented in Table 10. This step allowed us to label the clusters according to the ST characteristics that are represented in each cluster. All the ST variables allowed to differentiate statistically the clusters and they showed a ST pattern among the configurations. In this sense, we defined four groups: companies in the [Low] configuration reported having lower levels among all ST practices. Companies in the second cluster are more concerned with workers and customers and forms of improvement through upskilling their technical knowledge, engagement, training, and support. Hence, this cluster focuses on people management [PEOPLE]. Cluster 3 comprises companies with higher means for variables such as the definition of clear production, technology and leadership models, financial resources, and digital investments, i.e., it focuses on Organizational Design [ORGANIZATIONAL]. Finally, cluster 4 comprises companies with comparatively higher levels of all ST practices. Therefore, we named it [ST Masters].

				Clus	ter	
	1	2	3	4		
We have/own	[Low]	[People]	[Organiz	[ST	Welch	Pairwise comparison
			ational]	Masters]	statistic	
team_with_technical _knowledge	1.58	3.25	3.18	4.30	35.890	[1,2]***, [1,3]***, [1,4]***, [2,4]***, [3,4]***
skilled_workers	1.58	3.50	2.53	4.27	88.495	[1,2]***, [1,3]**, [1,4]***, [2,3]***, [2,4]***, [3,4]***
engaged_workers	2.08	3.61	3.35	4.52	74.816	[1,2]**, [1,3]**, [1,4]***, [2,4]***, [3,4]***
tech_supporting_tea m	1.08	3.03	2.45	4.20	33.740	[1,2]***, [1,3]***, [1,4]***, [2,3]*, [2,4]***, [3,4]**
techs_focused_on_c ustomers	2.67	3.67	3.53	4.55	28.479	[1,4]**, [2,4]***, [3,4]***
training_programs	1.17	2.31	2.15	3.98	16.288	[1,2]***, [1,3]***, [1,4]***, [2,4]***, [3,4]**
solid_production_mo del	2.25	2.50	4.05	4.39	72.722	[1,3]**, [1,4]***, [2,3]**, [2,4]***
defined_technology_ model	1.67	2.47	3.68	4.34	32.949	[1,2]**, [1,3]***, [1,4]***, [2,3]***, [2,4]***, [3,4]**
solid_social_preparat ion_model	1.33	2.19	3.25	4.05	97.009	[1,2]**, [1,3]***, [1,4]***, [2,3]**, [2,4]***, [3,4]**
prepared_leadership	1.92	2.78	3.25	4.14	164.545	[1,2]**, [1,3]***, [1,4]***, [2,3]*, [2,4]***, [3,4]**,
prepared_digital_cul ture	1.83	2.81	3.40	4.36	46.909	[1,2]**, [1,3]***, [1,4]***, [2,3]*, [2,4]***, [3,4]***

Table 10 - K-means results for ST cluster variables and pairwise comparison.

solid_digital_vision	2.17	3.06	3.73	4.70	64.344	[1,2]**, [1,3]***, [1,4]***,
financial_resources	1.33	2.75	3.55	3.98	40.286	[2,3]**, [2,4]***, [3,4]** [1,2]**, [1,3]***, [1,4]***,
Number of	12	36	40	44		[2,3]**, [2,4]***
companies						

4.4.2 Demographic analysis of the ST configurations

We used a series of ANOVAs to understand the association of ST configurations and company demographics, Industry 4.0 technologies, and performance. As **Table 11** depicts, the demographic analysis shows that [Low] and [ST Masters] configurations do not differ regarding their revenue, perception of foreign competition, and the level of business model change perceived in their sector. However, they differ in the level of technological acceleration demanded by their industry [techn_accel], which may indicate that [ST Masters] have a more advanced ST environment to cope with a fast-paced and competitive environment. [ST Masters] also perceive more technological acceleration than companies with a [Organizational]. Whereas for the foreign competition perception [foreign_comp], [ST Masters] perceive significantly more competition when compared to companies that focus on [People]. Market changes and BM changes do not differ based on the ST configuration.

Table 11 - Demographic analysis

	L	ow	Peo	ple	Organi	zational	ST Ma	sters	A	NOVA
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	f-value	Pairwise compariso n
size_revenue	2.666	.651	2.917	.604	3.250	.588	3.159	.914	3.587 (p=.021)	[1,3]*, [2,3]*
mkt_change s	3.583	.901	3.139	.833	3.350	.949	3.386	.841	.967 (p=.410)	Not sig.
techn_accel	3.167	1.029	3.361	.798	3.125	.791	3.659	.861	3.11 (p=.029)	[1,4]*, [3,4]**
foreign_com p	3.750	.7538	3.417	.996	3.425	1.083	3.818	.995	1.571 (p=.020)	[2,4]*,[3,4] *
bm_changes	3.333	.778	3.583	.874	3.475	.816	3.795	.954	1.372 (p=.254)	Not sig.

4.4.3 Technology analysis of the ST configurations

We analyzed also how Industry 4.0 technologies are adopted alongside the different ST configurations. This is shown in **Table 12.** As shown in this table, the average for the level of adoption of ST practices is statistically different among the four groups for all practices (see ANOVA F-values). Post-hoc analyses for this step showed that all clusters significantly differ regarding the ST variables. As **Table 12** depicts,

It is important to highlight that the Industry 4.0 factors presented range from -1 to 1 due to the EFA technique standardizing the scores by mean-centering them. Thus, a negative value does not mean a "negative amount of technology" implementation. The values should be interpreted as the extent to which each configuration deviates from the mean implementation for the technologies. Their correlation is also 0 due to the varimax orthogonal rotation method used to extract uncorrelated factors. Varimax rotation maximizes the sum of the variances of the

squared loadings for each factor while constraining the factors to be uncorrelated with each other, as also done by other Industry 4.0 studies such as Dalenogare et al. (2018). Other correlations and descriptive statistics are presented in **Appendix 3**.

The results of **Table 12** show no significant difference among the clusters for **Virtualization**, **Supply Chain Integration**, and **Advanced Manufacturing** in the sample studied. [Low] and [ST Masters] differ for all Industry 4.0 factors that are statistically significant. Also, **Traceability** showed statistically significant differences in adoption level between [People] and both [Organizational] and [ST Masters] (p<0.001), which indicates a tradeoff between people-related efforts and organizational. For the **Smart Products** factor, we found that [ST Masters] have more technologies implemented than all the other clusters, indicating that providing **Smart Products** with monitoring, maintenance, and autonomous operations demands more than only focus on people or organization, but a joint improvement on both, hence, [ST Master] higher implementation. Finally, **Vertical Integration**, a key concept for Industry 4.0, showed a significant difference for [Low] and all other ST configurations. This result indicates that **Vertical Integration** is expected to be more adopted in more advanced ST configurations, whether focused on people, organizational design, or both.

	Lo	w	Peo	ple	Organi	zational	ST Ma	asters		
	Std. Mean	S.D.	Std. Mean	S.D.	Std. Mean	S.D.	Std. Mean	S.D.	Welch statistic	Pairwise comparison Games- Howell
Traceability	451	.828	459	.662	.264	1.119	.270	1.010	7.205 (p<0.001)	[1,4]*[2,3]** *[2,4]***
Smart Products	398	.865	163	.816	234	.886	.443	1.129	4.073 (p=0.012)	[1,4]**[2,4]* *[3,4]**
Virtualizatio n	.172	.795	198	.534	105	.900	.206	1.347	1.588 (p=0.206)	Not significant
Supply Chain Integration	148	1.08 8	.023	.870	170	.947	.169	1.117	1.402 (p=0.504)	Not significant
Vertical Integration	809	.757	138	.811	.049	1.114	.290	.982	5.848 (p=0.002)	[1,2]*[1,3]** [1,4]**
Advanced Manufactur ing	113	1.11 3	113	.853	.041	1.017	.088	1.085	0.772 (p=0.788)	Not significant

Table 12 - Configurations' ANOVA for Industry 4.0 technologies

*Levene statistics were used since equal variances were assumed

The descriptive of Table 12 were also plotted in **Figure 7**. As seen in this figure, ST Masters have high differentiation from the other configurations in most of the Industry 4.0 domains, followed by a similar pattern between [People] and [Organizational].

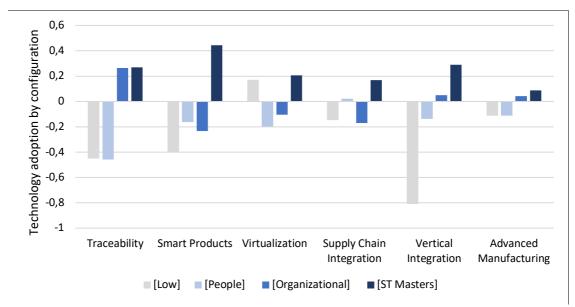


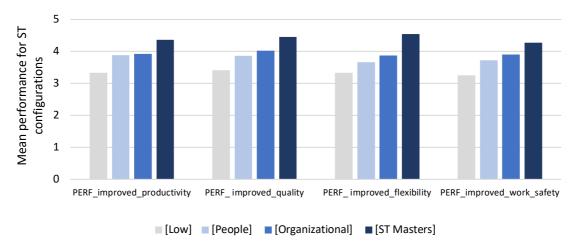
Figure 7 - ST configurations and Industry 4.0 implementation (mean-centered)

Finally, we analyzed how each ST configuration was associated with perceived gains in performance metrics due to digital technologies. For these performance metrics, companies responded how much they agreed that their Industry 4.0 journey was helping them achieve improvements in different metrics (5-point Likert scale). As our results show, [ST Masters] have the best performance in all metrics analyzed. [Low] showed lower performance than [Organizational] for all metrics but flexibility. Interestingly, [People] and [Organizational] showed no significant differences for all performance metrics, showing they are not necessarily tradeoff options. However, since the [Organizational] configuration has significantly better performance on productivity, quality, and work safety, this should interest companies searching for Industry 4.0 improvement.

	Lo	w	Peo	ple	Organiza	ational	ST Ma	sters		
	Std.	S.D.	Std.	S.D.	Std.	S.D.	Std.	S.D.	f-value	Pairwise
	Mean		Mean		Mean		Mean			comparison
PERF_impro	3.333	0.778	3.889	0.95	3.925	0.859	4.364	0.71	5.652	[1,2]**;[1,3]*
ved_produc tivity				0				8	(p=0.001)	*;[1,4]***;[2,4]**;[3,4]**
PERF_	3.417	0.900	3.861	0.86	4.025	0.832	4.455	0.73	6.658	[1,3]**;[1,4]*
improved_q uality				7				0	(p<0.001)	**;[2,4]**;[3,4]**
PERF_ improved_fl exibility	3.333	1.073	3.667	0.95 6	3.875	1.042	4.545	0.69 7	10.681 (p<0.001)	[1,4]**;[2,4]* **;[3,4]**
PERF_impro ved_work_s afety	3.250	0.965	3.722	1.00 3	3.900	0.900	4.273	0.92 4	4.606 (p=0.004)	[1,3]**;[1,4]* *;[2,4]**;[3,4] *

Table 13 - Configurations' ANOVA for performance metrics

Again, the descriptive results of Table 13 are also represented graphically in **Figure 8**. As shown in this figure there is a statistically advantage when companies are ST Masters regarding the operational performance achieved through Industry 4.0 technology implementation, followed



by a similar patter between People and Organizational (although the latter has some comparative advantage against the former).

Figure 8 - ST configurations and Industry 4.0 factors

4.5 Discussion

This section discusses the implications of these findings and how they contribute to Industry 4.0 literature. We divide our discussion into three sections. First, we discuss how ST masters are an important means for both technology implementation and performance improvement, then we discuss alternatives for companies that cannot improve both people and organizational aspects jointly, and finally, we propose the House of Industry 4.0, which depicts how companies should embrace their Industry 4.0 journey.

4.5.1 The Role of ST Masters in Technology Implementation and Performance Improvement

Both hypotheses were supported as ST Masters displayed higher technology implementation and performance levels than other ST configurations. Our results show that companies that invest in developing their organizational structure must also develop their people-related aspects. Thus, companies seeking increased Industry 4.0 technological maturity (especially for traceability, vertical integration, and smart products) and performance (productivity, quality, flexibility, and work safety) must develop a solid ST configuration jointly. This means investing jointly in clear and optimized processes, following a structured roadmap for building a digital culture, preparing leaders, upskilling workers, and engaging them in using Industry 4.0 technologies, having a supporting team for digitalization, and a structured training program. This view agrees with studies that propose that changes in organizational and administrative structures must precede Industry 4.0 implementation to be successful (Laubengaier et al., 2022; Marcon, Soliman et al., 2022). These changes and efforts are complex and involve many areas, but our results show they are essential for success. To this end, companies must seek a flatter hierarchy, develop digital skills at the operational and managerial levels (training and upskilling), assure top management commitment, and involve organizational functions (such as human resources) in technology implementation to ensure successful Industry 4.0 projects (Cagliano et al., 2019; Laubengaier et al., 2022).

However, our results show no significant difference among configurations for **Virtualization**, **Supply Chain Integration**, and **Advanced Manufacturing** for the sample studied. Such results may happen because these technologies are still not widespread in Brazil due to their costs and the higher interest in smart manufacturing technologies and technologies related to work that

companies have shown in Brazil (Frank et al., 2019). This is in line with the results in Brazil that showed that **Virtualization** technologies such as virtual commissioning equipment, simulation, and digital twins, as well as additive manufacturing, are more advanced and complex technologies in Brazilian company's Industry 4.0 journey, which explains their low adoption in general for our sample (Frank et al., 2019).

Regarding the second hypothesis, our findings align with previous literature that showed the organizational factors that contribute to operational performance. Tortorella et al. (2020) found that organizational learning significantly impacts the relationship between Industry 4.0 adoption and operational performance, whereas the technologies alone did not show this impact. Also, the lean literature has acknowledged that Industry 4.0 requires a well-organized system to become effective on performance (Tortorella et al., 2019). Our results support this perspective, showing that companies oriented toward a better organizational design can take more advantage from digital transformation. Our findings add to this scarce literature by showing that digital readiness and management support are also necessary. These aspects must be built with training, technical knowledge, production, technology, and people preparation models that subsidize the technological innovations and financial resources to enable these changes.

Our findings also align with those from Sony and Naik (2020), which showed how the ST perspective served as a guideline for implementing key principles of Industry 4.0 (vertical and horizontal integration and end-to-end engineering). In line with our configuration analysis, they show that technology, culture, processes, goals, and infrastructure need to be considered in integration with information systems for companies to develop a more mature Industry 4.0 implementation. To this end, designing end-to-end engineering systems in companies demands flexibility to customize products and production autonomously. For vertical and horizontal integration, managers should consider the changes in culture (decentralization), regulatory framework, stakeholders, and financial metrics posed by the technologies.

We also complement previous literature that analyzed how individual factors improve Industry 4.0 implementation by describing their configurations. In analyzing individual factors, companies with job standardization, employee engagement, training opportunities, continuous improvement programs, flow optimization tools, and clear strategic definitions showed higher Industry 4.0 implementation (Marcon et al., 2022). We complement their findings by showing that these factors are even more important when improved in integration, as companies should address people and organizational aspects in conjunction. This depicts an evolution in the Industry 4.0 literature that has departed from a technology-based centricity towards a view that is solidly built upon ST configurations between people and organizational factors that improve technology value (Bednar & Welch, 2020; Marcon, Soliman, et al., 2022; Sony & Naik, 2020). This change in perception is corroborated by research showing an increased focus on other aspects of Industry 4.0 than solely smart manufacturing technologies, such as the technologies that improve worker productivity and well-being (Dornelles et al., 2022; Meindl et al., 2021) and the ST factors enabling an improved implementation (Marcon et al., 2023).

Finally, we add to the analysis of configurations proposed by Cagliano et al. (2019) that proposes that companies advance towards a smart factory configuration composed of many integrated technologies, improved job autonomy and breadth, cognitively demanding tasks, social interactions, and decentralized decision-making. We depict a more complex scenario by demonstrating that ST configurations may show a non-balanced behavior between workers, organizational factors, and technology aspects. Companies can own different sets of technologies according to these configurations. For example, companies in ST Masters and Organizational configurations own more Traceability technologies than companies in the People configuration. In contrast, Vertical Integration implementation does not differ among all configurations except for companies in the Low configuration (which own fewer systems like ERP, MES, and SCADA). We show that this relationship between ST maturity and Industry 4.0

technologies does not occur so linearly and that some companies may even move towards configurations that do not lead to significant performance gains when compared to their current configuration.

4.5.2 Exploring Alternative Configurations for ST Implementation

We showed that ST Masters are associated with higher technology implementation and performance and that companies should improve both people and organizational aspects jointly, especially those in the Low ST configuration, which are expected to have poorer process standardization, fewer training programs, and a lack of strategic clarity (Cagliano et al., 2019; Marcon, Soliman, et al., 2022). Improving both people and organizational aspects is more important in the Industry 4.0 context since Industry 4.0 is increasingly dependent on these aspects and their intertwined interaction with the technologies. In the Industry 4.0 context, worker's roles are even more important since they are more independent and self-determined due to automation, access to information (ERP, MES), and supporting technologies (communication functionalities through chat, image, and video) at an operational level, and more analytical due to skills of data analytics, product, and project management, and process improvement at a managerial level(Lever et al., 2019). However, this Industry 4.0 context of fewer hierarchical levels brings challenges to companies that are required to build an environment that joins lean production principles of autonomation and operator empowerment to have the necessary engagement and learning opportunities for shopfloor and manageriallevel workers (Cimini et al., 2020; Dornelles et al., 2022; Leyer et al., 2019). Thus, companies in the Low configuration should balance their efforts into people and organizational improvements, such as developing a team with technical skills related to data analysis or cobots maintenance and structuring a long-term technology roadmap and a production model focused on diminishing waste to reach performance gains.

Companies in the Organizational or People ST configurations are already one step ahead as lower efforts are necessary to complement their ST configuration and achieve performance gains. However, even though People and Organizational configurations did not show significant differences among each other when they are compared to the Low configuration, the Organizational configuration is more associated with performance improvements than People. This indicates that companies that cannot jointly invest their efforts due to a lack of resources, staff, or time could first prepare their production model with proper layouts, lower process variation, and define clear digital and leadership strategies to reach performance gains earlier and then focus on People-related actions. However, an excessive focus on Organizational aspects without considering workers, their training, and how enriched their tasks become after Industry 4.0 implementation can risk companies developing a ST configuration where activities are monotonous, simplistic, and unchallenging, leading to a "Digital Taylorism" (Cagliano et al., 2019). This type of environment is the recipe for reducing morale, engagement, and productivity (Clegg, 2000; Trist & Bamforth, 1951).

Companies in the Organizational configuration aiming to achieve improved performance should employ people-related efforts. We show that these efforts are related to training and incorporating skilled employees, providing a support team, engaging them in the implementation process, and implementing technologies focused on customer needs. The technologies adopted should empower workers by providing access to information, and resources to make decisions, support workers by allowing synchronous and asynchronous communication, and give opportunities for them to innovate and solve recurring problems to increase production flexibility and competitivity (Leyer et al., 2019). To improve this aspect, companies should communicate with workers and prepare them not only to work with data, interact with machines, interpret graphs, or use wearables but also to be polyvalent and specialized, increasing their autonomy (Calış Duman & Akdemir, 2021; Cimini et al., 2020; Marcon, Soliman, Sturgeon, et al., 2023). In this context, training is fundamental, especially at a team level, to increase collaboration and integration and significantly improve performance (Tortorella et al., 2020). To this end, companies have invested in both internal and external training programs (i.e., from technology providers, technical schools, and internet platforms), involving multiple sectors and providing opportunities for workers to be part of the implementation process (Calış Duman & Akdemir, 2021; Cimini et al., 2020; Laubengaier et al., 2022). These actions can enhance aspects related to workers and make the ST configuration more balanced and enable the company to move towards a ST Masters configuration which is associated with most performance gains.

4.5.3 Embracing the Industry 4.0 Journey: The House of Industry 4.0

Based on our findings and the Industry 4.0 and ST theory literature, we propose the "House of Industry 4.0", a framework that depicts Industry 4.0 implementation principles through the ST tenets (see **Figure 9**). The House of Industry 4.0 is inspired by the House of the Toyota Production System and visually describes the lean philosophy and its principles. It starts with the foundations of heijunka, standardized work, kaizen, and stability, then the pillars of just-in-time and jidoka, and ends with the roof with the goals to be achieved (Liker, 2004). Similarly, the House of Industry 4.0 provides principles for companies implementing advanced technologies while considering the ST aspects necessary for technology's operation.

The foundation of the House of Industry 4.0 is the company's strategic definition, which is fundamental to guiding the technologies and the ST changes necessary. This is still a major barrier to technology adoption since companies struggle to have clear objectives with them (Laubengaier et al., 2022; Marcon et al., 2022). To fulfill these aspects, Industry 4.0 roadmaps and maturity models help companies by depicting the long-term strategic support for the Industry 4.0 journey based on the current technologies, objectives, and future demands (Ghobakhloo, 2018; Mittal et al., 2018; Schuh et al., 2017). Otherwise, companies risk spending significant financial resources without attaining the intended objective (Sony & Naik, 2020), following trends without understanding their impacts on the organization, and even generating boycotts for future initiatives (Mittal et al., 2018; Schuh et al., 2017).

The pillars of the house are composed of **people** and **organizational** aspects that support the technologies being implemented, as demonstrated in our results. People aspects are related to workers, their training, upskilling, support, and engagement, in addition to the necessary focus on customers and their experience (Dornelles et al., 2022; Kadir & Broberg, 2021; Leyer et al., 2019). The Organizational pillar is composed of the operation's management optimization and digital definitions that provide long-term delineations about the digital culture developed, management support, and financial resources necessary, as well as the tools for continuous improvement proposed by the lean philosophy that is important for operational improvements through Industry 4.0 technologies (Marcon et al., 2022; Srivastava et al., 2022; Tortorella et al., 2019).

Finally, Industry 4.0 technologies are placed on the roof since they depend on the ST pillars' balance. The ST configuration supports the base and specific technologies providing the structure for their implementation and uses (Marcon et al., 2022; Mittal et al., 2018; Schuh et al., 2017). To this end, the definition, adoption, and implementation of base technologies (related to IoT, big data, analytics, and AI) or specific technologies (Traceability, Virtualization, Vertical Integration, and Smart Products) should be grounded on the foundation and pillars of the House of Industry 4.0, which in turn, increase performance (top part) when these aspects are aligned and in balance.

The House of Industry 4.0 framework provides a visual and summarized ST structure to help ensure that the company's Industry 4.0 journey is not limited to investing in technologies in

islands. However, more importantly, it prevents the technologies from being the center of the journey, setting aside or ignoring the ST changes necessary for their use and consequent gains.



Figure 9 - The House of Industry 4.0: A sociotechnical view of Industry 4.0 implementation

4.6 Conclusion

This article provides a view on how ST configurations and Industry 4.0 implementation are related and which ST configurations allow more performance through digital technologies. We add to the literature that generally considers these aspects in isolation or that mostly describes the impact of technologies on the work system, people, and operations, without looking at how these aspects provide more welcoming settings for Industry 4.0 technologies. Our results support the joint optimization premise between ST aspects of people, organization, and technology as a determinant for performance gains through Industry 4.0 technologies. We also show which Industry 4.0 technologies are mostly associated with ST configurations. ST Masters implement the most technologies and achieved higher performance improvements with Industry 4.0. We also show that companies of the Organizational and ST Masters configurations implement more Traceability technologies. All configurations implement similar Vertical Integration levels except those in the Low configuration. Smart Products technologies seem to be mostly adopted by ST Masters, which could be explained by their complexity and servicerelated characteristic (Marcon et al., 2022). Our findings evidence that companies with configurations of lower maturity are also associated with less technology implementation and performance. Whereas companies at more mature ST configurations have increased performance gains, companies that balance their efforts related to people and organizational improvements are the ones that leverage technologies the most. To the extent of our knowledge, no prior study has analyzed these aspects; thus, we bring more depth to this field.

4.6.1 Practical Implications

The insights provided in this paper can be leveraged by practitioners implementing Industry 4.0 since we provide guidelines related to technological implementation and their efforts inside the company to materialize investments in performance improvements. Managers can use the findings related to the ST configurations to map how their companies fit into this classification

and plan actions to balance their efforts. For example, a company centered around manufacturing improvements that are mature in lean and technical aspects can move its focus towards more actions related to engaging, training, and communicating with workers about Industry 4.0. Similarly, a company that has worked with employees to develop technical skills, involving them in the process and qualifying them for the Industry 4.0 implementation but that lags behind on the production management maturity, leadership preparation, clarity of their technology roadmap, and lacks financial resources will have to direct more efforts to these areas.

Our findings show that these configurations with both aspects had more performance improvements than those that see them as tradeoffs or that focused more on one of them. Moreover, we provide managers and decision-makers with a framework that provides guidelines and a visual representation based on our results and the literature on ST environments and Industry 4.0. To this end, companies should build their Industry 4.0 strategy in 3 steps. First, revisiting their strategy and operational goals to ensure the actions and technologies are in line with their long-term view, mission, and values. Then, diagnose their ST configuration to understand the efforts necessary to balance the inconsistencies between people and organizational aspects proactively rather than reactively. Finally, they should map, research, and define the base and specific Industry 4.0 technologies that match and complement their systems and technologies. To this end, the frameworks proposed by Frank et al. (2019) with base and smart technologies can guide companies for the technologies they might implement in different functional areas. The House of Industry 4.0 framework helps companies in this definition by showing the technologies associated with each configuration to match both.

4.6.2 Limitations

Our research has limitations that future studies could address. The first limitation is related to the practical use of the configurations in industries interested in Industry 4.0 implementation. We propose the configurations based on cluster analysis and show how they relate to ST practices. However, we do not provide forms and methods that companies can use to map and classify their ST environment into one or another configuration and use this diagnosis to make investments. Even though this was not our goal from the start, we acknowledge this is a limitation of our research for practical applications. Thus, we suggest future studies develop metrics and maps to diagnose the ST readiness and configurations for companies implementing Industry 4.0.

We also highlight that the configurations found in this article may differ in other contexts, such as developed countries. Despite the configuration analysis being valuable due to its specificity and the fact that the configurations emerge from the data and its characteristics, researchers and practitioners should be aware that different contexts, digitalization levels, and cultural aspects may give rise to a different set of configurations, resulting in particularities in the relationship between configurations, technologies, and performance. For example, Nordic countries have historically been more concerned with social aspects (Marcon, Soliman, et al., 2022; Stentoft & Rajkumar, 2019). Configurations, technologies, and performance in these countries might present different relationships. We also propose future studies to address how these configurations (or new emergent configurations) are related to Industry 4.0 technologies in the context of small and medium enterprises (SMEs). SMEs are known to own fewer organizational and financial resources but have more resilient and motivated leaders (Marcon & Ribeiro, 2021). Researchers could analyze if ST configurations impact performance differently and if a configuration is more recommended than others for SMEs starting their Industry 4.0 journey.

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APPENDIX 2 – EFA matrix	

Factor	Variables	Mean	S.D.	1	2	3	4	5	6	Communalities
Traceability	TRAC _materials	2.848	1.356	.816	.280	.007	.086	.080	.085	.710
	TRAC _integrate_supply_chain	2.394	1.131	.810	.074	.157	.125	.150	.106	.736
	TRAC_improved_planning	2.695	1.258	.806	.220	.206	.123	.202	010	.786
	TRAC _plant	2.500	1.293	.794	.041	.043	.133	.104	.118	.604
	TRAC_prod_line	2.803	1.367	.783	057	.181	.169	.146	.061	.738
	TRAC _defects	2.523	1.207	.739	.183	.102	.081	.212	.081	.772
	TRAC _supply_stock	2.909	1.438	.708	042	.048	.380	.122	028	.675
	TRAC _horizontal	2.023	1.007	.692	.047	.240	.148	069	.150	.698
Smart Products	SP_remote_operation	2.492	1.401	038	.875	.203	.098	.111	006	.752
	SP_maintenance	2.667	1.429	.118	.850	.205	.128	.168	068	.601
	SP_monitoring	2.765	1.413	.096	.836	.218	.048	.209	083	.661
	SP_autonomous_operation	2.061	1.259	.128	.789	.244	.087	.047	.062	.800
	SP_monitoring_service	2.909	1.411	.132	.721	.044	.065	.218	.227	.834
	SP_ai_delivery	1.841	.956	.208	.591	026	.281	.109	.371	.813
Virtualization	VIRT_sim_plant	1.962	.911	.150	.039	.827	.226	.141	019	.829
	VIRT_sim_process	2.220	1.107	.230	.136	.775	.206	.178	.053	.708
	VIRT_sim_equip	2.424	1.267	.142	.235	.732	.132	.246	.106	.645
	VIRT_VR_operation	1.909	.928	.048	.224	.705	087	.111	.315	.643
	VIRT_AR_checklist	2.038	.944	.191	.279	.569	.001	.162	158	.698
	VIRT_digital_twin	1.697	.864	.127	.212	.565	.255	.156	.342	.756
Supply Chain	SC_distrib_asynchronous	2.288	1.293	.231	.008	.254	.793	.036	.066	.665
Integration	SC_supplier_asynchronous	2.667	1.352	.258	.083	.056	.753	.057	078	.756
	SC_distrib_realtime	2.015	1.011	.239	.274	.206	.732	.009	.184	.572
	SC_supplier_realtime	2.038	1.007	.166	.309	.057	.596	.166	.275	.738
Vertical	VI_mes	3.030	1.348	.126	.221	.249	.019	.811	013	.706
Integration	VI_clp	3.598	1.370	.131	.065	.120	.067	.781	.245	.839
	VI_scada	2.840	1.446	.233	.227	.185	.085	.754	.042	.836
	VI_mes_erp	3.311	1.261	.177	.200	.188	.069	.590	059	.573
Advanced	AM_cobot	1.705	.889	.084	.055	.327	012	.009	.689	.566
Manufacturing	AM _3D_prototype	2.356	1.415	.308	.038	053	.280	.137	.654	.625

% of variance explained (cumulative)	34.389	46.309	53.558	59.900	64.649	68.732
Cronbach's alpha	0.925	0.909	0.868	0.807	0.818	0.842
Composite reliability (CR)	0.912	0.901	0.850	0.794	0.820	0.578

APPENDIX 3 – Correlation and descriptive statistics

		1	2	3	4	5	6	7	8	9	10	11
1	Traceability	1										
2	Smart Products	.000	1									
3	Virtualization	.000	.000	1								
4	Supply Chain Integration	.000	.000	.000	1							
5	Vertical Integration	.000	.000	.000	.000	1						
6	Advanced Manufacturing	.000	.000	.000	.000	.000	1					
7	ST Configuration	0.308***	0.274**	.095	.080	0.291***	.084	1				
8	PERF_improved_productivity	0.275**	0.199**	0.183**	.060	0.161*	.012	0.32***	1			
9	PERF_ improved_quality	0.314***	0.216**	.068	.095	0.189**	081	0.36***	0.772***	1		
10	PERF_ improved_flexibility	0.25**	0.263**	.084	001	0.306***	001	0.404***	0.661***	0.696***	1	
11	PERF_improved_work_safety	0.312***	0.263**	.112	.068	.102	.008	0.307***	0.736***	0.68***	0.746***	1
	Mean	.000	.000	.000	.000	.000	.000	2.879	4.008	4.068	3.992	3.917
	Standard Deviation	1.000	1.000	1.000	1.000	1.000	1.000	.981	.878	.867	1.000	.981
	Skewness	.650	.552	.808	.415	.060	.429	344	358	276	589	373
	Kurtosis	.040	077	1.507	145	531	.737	994	893	-1.277	603	805

APPENDIX 3 – Questionnaire

	Question	Variable Name
General	Company name	company name
questions	Company revenue	size revenue
	In your opinion, what is the level of market changes in your	market_changes
	industry in terms of preferences and demand?	
	In your opinion, what is the level of technological acceleration	techn_accel
	in your industry?	
	In your opinion, what level of foreign competition does your	foreign_comp
	company face in the market?	
	In your opinion, what level of change companies in your	bm_changes
	industry face regarding business model?	
ndicate the	We have a competent technical team for Digital	team_with_technical
degree of	Transformation	_knowledge
agreement	We have qualified employees to deal with Digital	skilled_workers
with the	Transformation	
ollowing	We have open and engaged employees to adopt Digital	engaged_workers
statements	Transformation technologies	
indicate from	We have a support team to accompany Digital Transformation	tech_supporting_team
L to 5)	Our Digital Transformation actions are developed with a focus	techs_focused_on
	on the customer	_customers
	We have education and training programs on Digital	training_programs
	Transformation	
	We have a well-implemented production management model	solid_production_mode
	We have a well-defined technology implementation model	defined_technology
		_model
	We have a well-defined model for preparing employees for	solid_social_preparation
	Digital Transformation	_model
	We have leaders trained in aspects of Digital Transformation	prepared_leadership
	We have a culture favorable to Digital Transformation	prepared_digital_culture
	We have a strategic vision to adopt the Digital Transformation	solid_digital_vision
	We have financial resources for investments in Digital	financial_resources
	Transformation	
ndicate the	Online tracking the receipt of materials or stocks of finished	TRAC _plant
degree of	products	
online	Tracking of inputs and components on the production line	TRAC_prod_line
raceability of	Plant-wide tracking of inputs and components	TRAC _supply_stock
our plant	Track all stages of the production chain, including the external	TRAC_integrate_supply_
(indicate from 1 to 5)	stages of the supply chain (e.g. using blockchain or platforms)	chain
	Materials and components location	TRAC _materials
	Detection and track of defects	TRAC _defects
	Production planning	TRAC_improve_planning
	Integration with other stages of the chain	TRAC _horizontal
ndicate the	Connected products for fault detection and maintenance	SP_maintenance
degree of	Connected products for performance monitoring	SP_monitoring
digitization of	Connected products for remote operation	SP_remote_operation
he products	Connected products for autonomous operation	SP_autonomous_operat
offered		on
	Product monitoring and performance services	SP_monitoring_service
	Service delivery with artificial intelligence	SP_ai_delivery
ndicate the	Equipment operation simulation	VIRT_sim_equip
degree of	Simulation of production processes	VIRT_sim_process
	Simulation of all plant operations	VIRT_sim_plant
virtualization	Simulation of all plant operations	
virtualization of	Plant's digital twin Activity checklists with augmented reality	VIRT_digital_twin VIRT_AR_checklist

	Production operations with interactions via Virtual Reality	VIRT_VR_operation
Indicate the	Asynchronous data from distributors	SC_distrib_asynchronous
degree of	Asynchronous data from suppliers	SC_supplier
digitization of		_asynchronous
your supply	Integration of real-time product availability data from	SC_distrib_realtime
chain	distributors	
	Real-time supplier product availability data integration	SC_supplier_realtime
Indicate the	The equipment is operated using a local computer (e.g., via	VI_clp
degree of	PLC/PLC)	
integration of	Equipment data is captured through supervisory devices (e.g.,	VI_scada
information	through SCADA)	
systems	Devices are connected for data integration (e.g., via MES)	VI_mes
	Production data is integrated with other levels of the company	VI_mes_erp
	(e.g., MES-ERP integration or in	
Indicate the	Collaborative robots	AM_cobot
level of use of	Additive manufacturing/3D printing for prototyping	AM _3D_prototype
advanced		
manufacturing		
technologies		

5. Final considerations of the thesis

More than providing an extensive view of the necessity of considering social, technical, work organization, and strategic aspects when implementing Industry 4.0, this thesis has contributed to empirically showing how the impact of Industry 4.0 and the interactions between these aspects that contribute to organizations that want to leverage Industry 4.0 technologies. Literature showed that companies implementing Industry 4.0 technologies tend to be more interested in the technical aspects and productivity gains than in how technologies will fit their organizational environment, especially at the beginning of their journey. Unlike, we showed that this technology-centered approach is not indicated since companies that improve their sociotechnical environment can implement more Industry 4.0 technologies and reach more performance than those that rely only on technologies and their technical requirements. To this end, companies can improve their socio-technical environment by training employees, engaging them in technology implementation, integrating the new technologies with other systems and equipment, reducing process variability, and developing a clear strategy and digital culture. Through the three articles, this thesis reached its aim: to identify how socio-technical factors impact the implementation of Industry 4.0 and contribute to improved performance. Together, the studies draw a comprehensive picture of the interrelationships between ST factors related to the companies' internal and external environments and empirically provide evidence of the importance of taking a holistic approach to Industry 4.0 implementation, which considers the interplay between people, technical, work organization and external environment factors. This thesis answered the proposed research question through these articles and met its general and

specific objectives. The findings contribute to a still scarce and mostly theoretical literature by providing evidence and unique insights into the dynamics between socio-technical factors and Industry 4.0, providing valuable contributions to academia, decision-maker, system designers, and governmental policies. By utilizing qualitative and quantitative methods, we have conducted detailed and comprehensive analyses of the interactions between these factors, which have not been previously explored in such depth.

5.1 Theoretical contributions

This thesis contributes to both the socio-technical and, more importantly, the Industry 4.0 body of knowledge. Regarding the former, this thesis highlights the importance of the socio-technical approach to Industry 4.0 implementation, which recognizes the interdependence of technology and social systems and the need to consider both dimensions to ensure successful adoption. This thesis shows that the theory proposed by Trist and Bamforth in 1951 and its principles remain no matter how adaptable, flexible, and cutting-edge the technologies are. Also, this thesis adds to the socio-technical literature by discussing established constructs (Article 1), identifying emerging socio-technical enabling factors that research can build on, and proposing a configuration view that had not been done previously (Articles 2 and 3). The methodological approaches used in this thesis are important contributions to the socio-technical theory since it shows how ST complexity and holistic approach can be operationalized using qualitative and quantitative methods, especially the configuration approach using cluster analysis from Article 3. This approach can aid researchers in moving beyond the predominant qualitative approach used in the field while still providing a comprehensive understanding of the socio-technical relationships among its components.

Additionally, this study operationalizes the holistic analysis called for research in socio-technical articles. Previous studies have analyzed specific aspects of the implementation process, such as the impacts of work design, employee engagement, or integration of technologies on the implementation of technologies (Cagliano et al., 2019; Cimini et al., 2020; Laubengaier et al., 2022; Schuh et al., 2017). However, this doctoral thesis takes a systemic and broad view of the implementation process by analyzing the interfaces and interactions between the socio-

technical subsystems that make up the organizational environments and their external environment.

Additionally, this thesis contributes to the growing and evolving Industry 4.0 body of knowledge. This thesis makes significant contributions by challenging the preconceived view around maturity models or roadmaps designed to guide Industry 4.0 implementation. It emphasizes the need to consider non-technological steps, including actions focused on developing sociotechnical factors to enable a successful Industry 4.0 adoption. The findings provide theoretical contributions on how companies are changing their approach toward Industry 4.0 implementation, highlighting the importance of a holistic approach that considers both technical and social dimensions. Industry 4.0 requires the alignment of technology with the organization's goals and strategies, as well as changes in the organizational culture and structure. Therefore, the contributions of this doctoral thesis go beyond technological aspects, which have been the biggest concern from literature, to consider the socio-technical aspects necessary for Industry 4.0 implementation and success.

In this regard, the articles contribute to the theory by showing that Industry 4.0 will not deliver the expected performance gains unless they focus on improving both their people and organizational aspects (Dalenogare et al., 2018; Sony & Naik, 2020). More importantly, to gain performance, companies must jointly engage, train, and communicate with workers, involving them in the process of Industry 4.0 implementation, as well as develop lean maturity, leadership preparation, clarity of their technology roadmap, and financial resources. While existing studies have focused on one or two dimensions, such as worker's interaction with human-machine interfaces in smart factories or lean production practices and technologies (Cagliano et al., 2019; Kumar & Lee, 2022; Tortorella et al., 2019), this study identifies the ST configurations that bring the best results for Industry 4.0. By doing so, the study emphasizes that the type of configuration a company fosters is crucial to improve Industry 4.0 implementation and gain optimal benefits, as it was similarly proposed by Flynn et al. (2010) in the supply chain context. This contribution expands the understanding of the role of configurations of ST dimensions in Industry 4.0 and provides insights for performance gains.

Finally, this thesis adds to the literature on the socio-technical theory and Industry 4.0 by exploring and providing more specificity to the socio-technical factors related to the implementation of technologies. The literature discusses higher-level factors such as people, culture, goals, processes, and infrastructure (Sony & Naik, 2020) and lower-level factors such as job breath, control, cognitive demand, social interaction, and decision-making centralization (Cagliano et al., 2019). However, the literature lacked a thorough and broad mapping of these factors that researchers can explore and discuss. Moreover, the thesis depicts the importance of non-technical enabling factors, such as empowering operators, developing digital leaders, knowledge management, technology funding, and developing a digital culture. This theoretical contribution expands the understanding of Industry 4.0 implementation beyond technical considerations and highlights and considers the well-being of the workers as a critical factor for successful Industry 4.0 implementation.

5.2 Practical contributions

Industry 4.0 is a complex and broad concept that companies struggle to implement and manage. As the concept and technologies spread, misconceptions in communication and definitions led to more complexity and an excessive focus on technologies. Despite technologies, their integration, and patterns being important subjects, this thesis provides insights for managers, system designers, and policymakers on conducting the implementation process considering more than only the technical aspects. First, managers should focus on socio-technical aspects before beginning their Industry 4.0 journey, as organizational conditions must be prepared for new technologies before their adoption. Evaluations, readiness evaluations, and roadmaps can help companies assess if aspects within socio-technical dimensions present gaps between

current and future states. We contribute to this evaluation by providing decision-makers with a framework (proposed in **Table 8**) that can serve as a basis for assessing and improving the necessary enabling factors and elements to increase technology's socio-technical maturity and acceptance. In addition, we propose the House of Industry 4.0 framework, which provides a visual and summarized structure to help companies implement advanced technologies while considering the ST aspects necessary for technology's operation.

The framework can guide decision-makers in defining their company's Industry 4.0 implementation process. It shows that the company's strategy is the foundation of the Industry 4.0 journey. Then, managers should consider the pillars of people and organization. The thesis shows that workers' development programs must be created to ensure that their workers are prepared and engaged in digital transformation. Managers should consider involving employees in idea generation, training them, and promoting the exchange of experience between teams. The second pillar is related to organizational aspects, which highlights that managers should apply continuous improvement tools, provide leadership support to employees, technology sponsoring, and develop a digital culture. These pillars support Industry 4.0 technologies and provide the basis for performance gains. Otherwise, the company risks implementing isolated technologies or automating problematic processes.

Finally, policymakers can benefit from this study when designing policies to support companies implementing Industry 4.0. first, they should design programs that assess and increase the maturity of processes and people within the companies' socio-technical. This thesis shows that although funding and training programs for workers are essential, policymakers should also evaluate if the socio-technical configuration of the companies is prepared for the technologies. This thesis provides analytical and practical frameworks to help them assess and develop policies for funding for Industry 4.0, considering what organizational aspects antecede technology implementation. Policymakers should also promote the development of partnerships and alliances between companies and external actors, such as universities, research institutions, and technology centers, to develop ecosystems for knowledge and experience exchange related to Industry 4.0 technologies. The insights and discussions in this thesis can help managers and policymakers develop strategies encompassing more than technologies alone, but the whole set of factors impacting Industry 4.0 success.

5.3 Limitations and recommendations for future research

Although this thesis brings insights and findings on the role of socio-technical systems in Industry 4.0 implementation, it presents some limitations that can be explored by future research. The first limitation of this thesis is that it does not evaluate the relationship between the socio-technical factors of a company and how successful and used the Industry 4.0 technologies are. This response variable was partly addressed in Article 3, where companies responded if they noticed performance gains due to Industry 4.0. However, future studies should evaluate the success of Industry 4.0 implementation using metrics that can be translated for different technologies. A method of measuring form could be developed to measure how different socio-technical factors or configurations led to more use and satisfaction.

Studies should also study the role of leadership in the socio-technical aspects and how they enable or hinder Industry 4.0 implementation. Literature has analyzed the impact of leaders and leadership styles in other contexts and showed that senior managers were negatively associated with lean manufacturing implementation (Tortorella & Fettermann, 2018) and that leaders with great concern for people and technology implementation in the Industry 4.0 context should be cross-hierarchical, team-oriented, and cooperative, with a focus on innovation. However, further studies are necessary to analyze how the leadership style and the socio-technical aspects interact and contribute to gains in Industry 4.0 (Oberer & Erkollar, 2018). To address this limitation, future studies should investigate how leadership styles, strategies, and behaviors affect the adoption and success of Industry 4.0 initiatives. Specifically, researchers should

investigate how leaders can enable or hinder technology integration and human factors, such as workforce skills and organizational culture, to achieve optimal socio-technical performance. Understanding the impact of leadership on Industry 4.0 implementation is critical to developing effective management practices that promote organizational innovation and competitiveness in the digital age.

Finally, studies should discuss how Industry 4.0 impacted and changed the socio-technical system after they were implemented and used for a considerable time and what unexpected changes appeared. Studies could also analyze which socio-technical subsystem or factors were most impacted and changed. This could contribute to the findings of Article 2, which showed the enabling factors for Industry 4.0 but did not address the changes that arose after the technologies were integrated and matured in the company. Moreover, studies could analyze if these challenges and changes appeared in order or more intensely in particular socio-technical factors within the subsystems so that managers and leaders can be more prepared for the upcoming changes from Industry 4.0.

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