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THE CONTRIBUTION OF INDUSTRY 4.0 TECHNOLOGIES TO INCREASE INTERNAL AND EXTERNAL OPERATIONAL FLEXIBILITY OF PRODUCTION SYSTEMS

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A contribuição das tecnologías da Industria 4.0 para o incremento da Flexibilidade Operacional dos Sistemas Produtivos

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DEDICATÓRIA

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RESUMO

A flexibilidade da manufatura é reconhecida como um fator competitivo essencial na estratégia operacional das empresas, como resposta a necessidades do mercado, especialmente diante de incertezas e turbulências. A Industria 4.0 surge como um novo paradigma industrial que permite atender esse tipo de necessidades das empresas manufatureiras, sendo seu foco a criação de um sistema inteligente ao longo de toda a cadeia de valor que possibilita a obtenção de processos flexíveis e adaptativos. Contudo, a literatura acadêmica ainda não tem apresentado evidências empíricas sobre a forma como cada tecnologia específica da Indústria 4.0 pode contribuir para os requisitos de flexibilidade operacional. Embora Industria 4.0 seja apresentada como uma solução para essa necessidade, é sabido que existem diferentes tipos de implementação da Indústria 4.0 que dependem dos objetivos operacionais almejados e das características das empresas. Portanto, os conjuntos tecnológicos da Indústria 4.0 podem ter diferentes formas de contribuição para alcançar uma maior flexibilidade dos processos de produção. O objetivo desta tese é criar um framework para auxiliar as empresas na implementação de operações flexíveis no contexto da Indústria 4.0. O estudo seguiu uma abordagem mista, combinando métodos qualitativos e quantitativo. Em termos quantitativos, a tese apresenta duas pesquisas *survey*. A primeira foi conduzida com 94 empresas do setor de máquinas e equipamentos, através da qual se analisa o efeito que diferentes objetivos operacionais – dentre eles a flexibilidade – possuem sobre a definição de arranjos tecnológicos da Indústria 4.0. A segunda foi conduzida com 379 empresas, com objetivo de analisar como o conceito de *smart supply chain* contribui para a flexibilidade da cadeia de suprimento, principalmente no contexto de incertezas. Por outro lado, em termos qualitativos, a tese apresenta um estudo multicasos em 11 empresas de manufatura líderes na implantação de tecnologias 4.0, visando entender a forma como essas tecnologias são implementadas para alcançar diferentes requisitos de flexibilidade operacional. A presente tese demonstra que, de fato, as tecnologias 4.0 contribuem para a flexibilidade operacional, mas também explora as limitações e nuances dessas contribuições em diferentes situações. A principal contribuição deste estudo é fornecer evidências empíricas da efetividade de diferentes tecnologias utilizadas de forma combinada para incrementar a flexibilidade operacional nos seus diferentes níveis.

Palavras Chaves: Flexibilidade da Manufatura, Flexibilidade da Cadeia de Suprimento, Industria 4.0, Tecnologias digitais

ABSTRACT

Manufacturing flexibility is recognized as an essential competitive factor in the company's operational strategy as a response to market uncertainties and turbulence. Industry 4.0 emerges as a new industrial paradigm that allows meeting these types of needs of manufacturing companies, focusing on the creation of an intelligent system along the entire value chain that allows the achievement of flexible and adaptive processes. However, the academic literature has not yet presented empirical evidence on how each specific Industry 4.0 technology can contribute to operational flexibility requirements. Although Industry 4.0 is treated as a solution to this need, it is known that there are different types of implementations of Industry 4.0 depending on the operational objectives pursued and the characteristics of the companies. Therefore, the technological sets of Industry 4.0 can have different forms of contribution to achieve greater flexibility in production processes. The aim of this thesis is to create a framework to help companies implement flexible operations in the context of Industry 4.0. The study followed a mixed approach, combining qualitative and quantitative methods. In quantitative terms, the thesis presents two survey research. The first was conducted with 94 companies in the machinery and equipment sector, through which the effect that different operational objectives – including flexibility – have on the definition of technological arrangements in Industry 4.0, is analyzed. The second was conducted with 379 companies, with the objective of analyzing how the smart supply chain concept contributes to the flexibility of the supply chain, especially in the context of uncertainties.. On the other hand, in qualitative terms, the thesis presents a multi-case study in 11 leading manufacturing companies in the implementation of 4.0 technologies, aiming to understand how these technologies are implemented to achieve different operational flexibility requirements. The present thesis demonstrates that, in fact, 4.0 technologies contribute to operational flexibility, but also explores the limitations and nuances of these contributions in different situations. The main contribution of this study is to provide empirical evidence of the effectiveness of different technologies used in a combined way to increase operational flexibility at its different levels.

Keywords: Flexible Manufacturing, Supply Chain Flexibility Industry 4.0, Digital technologies

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1. INTRODUCTION

The proliferation of digital technologies and cyber-physical systems has brought a new revolution to manufacturing, commonly known as Industry 4.0 (KAGERMANN *et al.*, 2016; WANG *et al.*, 2016). Arising as an initiative of the German government to increase the competitiveness of organizations, Industry 4.0 (I4.0) has attracted the attention of the most recent academic studies (LU, 2017; PEREIRA; ROMERO, 2017) and is considered by many authors the fourth industrial revolution (LU, 2017; WANG *et al.*, 2016; DALENOGARE *et al.*, 2018).

Industry 4.0 may be understood as the result of the increasing digitization of companies, especially regarding manufacturing processes (SANTOS *et al.*, 2018; ISSA *et al.*, 2018; LI *et al.*, 2018). Several authors have related I4.0 with advanced digital technologies such as Internet of Things (IoT), cyber-physical system (CPS), information and communication technology (ICT), Enterprise Architecture (EA), Enterprise Integration (EI), Cloud Computing, and Big Data (WANG *et al.*, 2015; LU, 2017; JESCHKE *et al.*, 2017; GIUSTOZZIA *et al.*, 2018).

Nevertheless, the concept is much broader than the simple use of digital technologies (DALENOGARE *et al.*, 2018). Frank *et al.* (2019) state that Industry 4.0 considers the integration of different dimensions of the business, such as smart products/services, smart supply chain, smart energy, and smart working, focusing mainly on smart manufacturing (LIAO *et al*., 2017; LU, 2017; DALENOGARE *et al*., 2018).

Companies can take different paths to employing I4.0 technologies (AHMAD *et al.*, 2018). In order to guide them through the implementation of digital technologies, studies have aimed to create models to measure the maturity level of Industry 4.0 (for example, SCHUMACHER *et al.*, 2016; MITTAL *et al.*, 2018) and to supply roadmaps for the implementation (for instance, GHOBAKHLO, 2018; LU; WENG, 2018). However, these studies do not consider operational performance objectives that companies seek to achieve, which are seen as one of the main factors that influence the adoption of technologies (WANG *et al.*, 2010; ABOELMAGED, 2014).

In this sense, studies have associated the implementation of Industry 4.0 mainly with benefits related to increased productivity and quality (LEE; BAGHERI, 2015; ZHONG *et al.*, 2017; DALENOGARE *et al.*, 2018). Nonetheless, it is noteworthy that one of the main objectives of implementing these technologies is to achieve a highly customized supply, which reflects the need for greater production flexibility (WANG *et al.*, 2016; LONG *et al.*, 2017; ZHONG *et al.*, 2017; ZHONG *et al.*, 2017).

Manufacturing flexibility is defined as the organization's ability to precipitate intentional changes and continually respond to unforeseen changes based on the reconfiguration of resources (PEREZ *et al.,* 2016; EYERS *et al.*, 2018). The literature has focused on various aspects of the topic such as the definitions of manufacturing flexibility, dimensions, classifications and taxonomies, the measurement of flexibility, the relationship between uncertainty, flexibility and performance, as well as the dimension of supply chain flexibility (BRETTEL *et al.*, 2016). However, it is still a great challenge to design and optimize production systems to obtain a highly flexible and efficient production system (SREEDEVI; SARANGA, 2017; LONG *et al.*, 2017).

Sethi and Sethi (1990) described manufacturing flexibility as a complex and multidimensional concept that is difficult to synthesize, which makes its implementation difficult. Moreover, the study by Frank *et al.* (2019) on the adoption of Industry 4.0 technologies demonstrated that operational flexibility is one of the most difficult and lacking aspects in companies that implement concepts of Industry 4.0. Furthermore, at the industrial level, Dalenogare *et al.* (2018) point out that industries still have difficulty associating technologies that enable operational flexibility with benefits for the development of new products and for the operational performance. These studies show that in practice, although plant flexibility is preached in the context of I4.0 as one of the main objectives, managerial and strategic implications and their results are still challenging for many companies. Consequently, there is a need to understand flexibility in the context of Industry 4.0 in order to reduce the risk of failure and optimize the production system (BRETTEL *et al.*, 2016; LONG *et al.*, 2017).

Traditionally, two types of manufacturing systems to ensure levels of flexibility are seen in the literature: Flexible manufacturing system (FMS) and reconfigurable manufacturing system (RMS) (BROWNE *et al.*, 1984; GUPTA; SOMERS, 1992; JIMENEZ *et al.*, 2015; GUPTA; SOMERS, 1992; JIMENEZ *et al.*, 2015; HUETTEMANN *et al.*, 2016). According to several authors, intelligent systems are necessary to effectively implement flexible production systems (ELMARAGHY, 2006; BALOGUN; POPPLEWELL, 2010; WANG *et al.*, 2016; BRETTEL *et al.*, 2016). Regarding the implementation of Industry 4.0, Qin *et al.* (2017) analyzed the stage of these manufacturing systems and others that already existed. The authors concluded that companies with flexible or reconfigurable manufacturing systems are a step closer to implementing Industry 4.0 technologies. Nevertheless, there is still much to be explored regarding the real-time responsiveness, self-organization, and self-reconfiguration of these systems that could only be achieved with the implementation of I4.0 technologies (QIN *et al.*, 2017).

Furthermore, flexibility has been studied mainly from the point of view of the internal manufacturing system (ZHANG *et al.*, 2002; LIAO, 2020). Nowadays, however, it is not enough to be competitive as an individual company. Instead, competitiveness involves all channels in the supply chain (KUMAR *et al.*, 2006). Consequently, the operational challenges associated with flexibility objectives depend heavily on the internal changes in the company, the mix and flexibility of new products, as well as on the flexibility of the supply chain (MALHOTRA; MACKELPRANG, 2012). All participants and functional areas of the chain must participate and share responsibility for achieving supply chain flexibility. In other words, the analysis of flexibility must be seen from the point of view of the theory of Complementarity (MALHOTRA; MACKELPRANG, 2012).

According to Sanchez and Perez (2005), companies that considered flexibility from both internal and supply chain perspectives have a greater ability to be flexible and, therefore, increase the company's performance. Nonetheless, it is already complex to implement flexible manufacturing processes at the internal level, thus, achieving flexibility at the supply chain level is extremely difficult, for it is a complex system which is influenced by inherent internal and external uncertainties that arise from intra-and inter-organizational relationships (SEEBACHER; WINKLER, 2015).

Considering the scenario described, the following research questions arise: *(i) Which I4.0 technologies can drive the implementation of flexible manufacturing? (ii) How does the implementation of I4.0 technologies influence a company's ability to become flexible at both internal and supply chain levels?*

1.1 DISSERTATION TOPIC AND OBJECTIVES

The present study focuses on Operations and Technology Management. The general objective of this dissertation is *to create a framework to assist companies in implementing flexible operations in the context of Industry 4.0*. In order to achieve the general goal of this work, the following specific objectives are proposed:

1. To analyze the specific Industry 4.0 technologies adopted by these companies when looking for productivity, quality and/or flexibility as operational goals;

2. To analyze the main strategies aiming to implement Industry 4.0 to obtain internal manufacturing flexibility;
3. To identify which Industry 4.0 technologies influence the supply chain flexibility.

These objectives aim to develop a framework that can help decision-makers in the implementation of the I4.0 concept to make their production more flexible and increase offer customization.

1.2 JUSTIFICATION OF THE TOPIC AND OBJECTIVES

This dissertation is justified by the lack of theoretical and practical works. Regarding theoretical aspects, it is important because Industry 4.0 is a new paradigm and, therefore, brings different questions to be researched. In this sense, despite increasing academic studies on the subject in recent years, there are still gaps in the research on the implementation paths of Industry 4.0 and the impact of the use of these technologies in companies (KAMBLE *et al.*, 2018; BÜCHI, CUGNO; CASTAGNOLI, 2020).

This study addresses specifically the implementation of I4.0 and its impact on manufacturing flexibility. Flexibility has been considered an important competitive capability for companies, especially those with mass customization and make-to-order production systems (DEY *et al.*, 2019). For this reason, manufacturing flexibility is a widely studied topic, and different technological systems such as FMS and RMS have been suggested to achieve it. However, the concept of flexibility is still considered complex to implement because it is multidimensional and depends on a large set of variables (SETHI; SETHI, 1990; DEY *et at.*, 2019).

Moreover, intelligence concepts, which are the main objective of the development of Industry 4.0, are still difficult to enforce in flexible manufacturing systems, thus, being one of the main goals of research on the development of I4.0 (QIN *et al.*, 2017). In this sense, according to several authors, there is a need to understand the role of Industry 4.0 in achieving different levels of flexibility (BRETTEL *et al.*, 2016; EYERS *et al.*, 2018; FRANK *et al.*, 2019).

From a practical point of view, although several studies claim that flexibility is one of the main objectives of Industry 4.0, it still seems to be far from reality for companies, especially in developing countries such as Brazil (DALENOGARE *et al.*, 2018; LUTHRA; MANGLA, 2018). Furthermore, achieving flexibility at both internal and supply chain levels still requires great effort (LONG *et al.*, 2017; SEEBACHER; WINKLER, 2015). This may be due to the fact that companies still do not have enough knowledge to reach high levels of implementation of Industry 4.0 (FRANK *et al.*, 2019). Another possibility is that they see flexibility as something that requires a very advanced level of implementation, as it involves an expensive process and its benefits are difficult to perceive immediately (SREEDEVI; SARANGA, 2017).

1.3 STUDY DESIGN

In this topic, the research and work methodology for achieving general and specific objectives within the topic of implementing Industry 4.0 for manufacturing flexibility are detailed.

1.3.1 Research Methodology

According to the procedures, this can be classified as mixed-method research (CASTRO *et al.*, 2010). It presents both qualitative and quantitative stages, as there are mainly data from literature reviews and case studies and statistical analyzes of data collected through questionnaires and the literature.

Each of the articles that make up the dissertation can be classified differently due to their research approach. Article 1 can be classified as deductive since it is based on hypotheses that were tested using statistical tools. On the other hand, Article 2 presents an inductive approach as it seeks to generalize results from the study of several cases (MARKONI; LAKATOS, 2003).

1.3.2 Work Methodology

The work methodology is based on the theory building by Van de Ven (2007). This theory aims to construct conceptual models by combining theory and practice and includes four main steps that all research must have: (i) problem definition, (ii) theory building, (iii) definition of an explanatory model, and (iv) proposal of solutions from the results found (VAN DE VEN, 2007).

The problem definition was developed throughout this introduction. Therefore, the following sections focus on the theory-building stage. The subsequent stages, model definition and solution proposition, are not part of this work as the primary attention of this work was to the theory construction process. Therefore, this work is composed of three articles, each achieving a specific goal to meet the general objective of this study, as shown in Table 1.

Table 1. Work structure according to specific objectives.

	RESEARCH QUESTION	AIM	METHOD
ARTICLE 1	Which Industry 4.0 technologies can be adopted by manufacturers to achieve specific production targets such as productivity, quality, and operational flexibility?	To analyze the specific Industry 4.0 technologies adopted by these companies when looking for productivity, quality and/or flexibility as operational goals	Quantitative Research Survey 1. Exploratory factor analysis (EFA) 2. Test-T
ARTICLE 2	How can Industry 4.0 technologies enable internal manufacturing flexibility?	To analyze how different Industry 4.0 technologies can contribute to reaching internal dimensions of the manufacturing flexibility concept	Qualitative Research – Case Studies 1. Interviews 2. Technical Visits 3. Document review
ARTICLE 3	How can the implementation of the Smart Supply Chain concept contribute to the external flexibility of the supply chain and companies' operational performance in the context of uncertainty?	Understand how the implementation of Industry 4.0 contributes to the external flexibility in the context of uncertainties	Quantitative Research-Survey 1. Confirmatory factor analysis (CFA) 3. Linear regression with moderating and mediating effects test

Article 1 - "*Implementing Industry 4.0 for flexibility, quality, and productivity improvement: Technology arrangements for different purposes.*" This article aimed to identify which Industry 4.0 technologies companies implement depending on their operational objectives. A quantitative approach to the subject was adopted because a survey was conducted. The data were analyzed through exploratory factor analysis for the development of constructs and using the t-test.

Article 2 - "*Industry 4.0 enabling manufacturing flexibility: technology contributions to individual resource and shop floor flexibility levels.*" This stage analyzed case studies aiming to understand how Industry 4.0 technologies enable different internal levels of manufacturing flexibility. As the main result, this article presents a framework which explains how companies seek internal flexibility through the adoption of Industry 4.0 technologies and different contingency factors that influence the adoption of flexibility technologies.

Article 3 - "*Being digital and flexible to navigate the storm: How digital transformation enhances supply chain flexibility in turbulent environments.*" This article focused on understanding how the implementation of Industry 4.0 technologies contributes to flexibility at the supply chain level, aiming to reduce the effects of uncertainties that companies face on operational performance. In other words, it addresses aspects of *external* operational flexibility. This study is even more relevant in the current context in which companies and supply chains have been affected by COVID-19. A quantitative approach was used with the application of a survey and subsequent statistical data analysis.

1.4 STUDY DEFINITION

For the development of the research, the practical context of Brazil was considered, since developing countries often have difficulties in industrializing and gaining a competitive advantage over others. Thus, with the implementation of Industry 4.0 aimed at flexibility, the country can accelerate its development and digital transformation. However, other countries may have different contexts and levels of technological development. Therefore, the territorial space is considered a limitation of this work.

Furthermore, this study does not intend to address all the technologies, but to consider the main ones cited in the literature as being the most used in practice. Nonetheless, companies may require different types of flexibility over time. In this sense, this research considers aspects that demand flexibility but does not follow companies to see changes in the profile of the need for flexibility.

Finally, this study assumes that operational flexibility is a desired operational aspect to be achieved by companies but does not question whether the choice of flexibility is the best strategic option for the companies studied. In other words, the impacts of the operational flexibility on the company's financial performance are not considered and neither are more strategic levels of flexibility.

1.5 STRUCTURE OF THE DISSERTATION

This dissertation is organized in five chapters. This first chapter discussed the research problem, its objectives, and their respective justifications, in addition to the study methodology, structure, and definition. Subsequently, in chapters 2, 3, and 4, the articles on each of the specific objectives are presented, as detailed in Figure 1. Finally, the fifth chapter is dedicated to the conclusions and contributions of this dissertation.

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2. IMPLEMENTING INDUSTRY 4.0 FOR FLEXIBILITY, QUALITY, AND PRODUCTIVITY IMPROVEMENT: TECHNOLOGY ARRANGEMENTS FOR DIFFERENT PURPOSES

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Productivity, quality, and flexibility are key production targets pursued by companies that adopt Industry 4.0. However, it is unclear how Industry 4.0 technologies can help achieve these different and sometimes competing targets. This study investigates this relationship through a survey of 92 manufacturers. The study employs Exploratory Factor Analysis to define four main technology arrangements based on 18 Industry 4.0 technologies: Vertical Integration, Virtual Manufacturing, Advanced Manufacturing Processing Technologies, and Online Traceability. Then, independent samples tests were conducted to compare the implementation status of these arrangements when manufacturing flexibility, process quality, and productivity are (or are not) pursued as the main production targets. The results show that Vertical Integration is a general-purpose technology arrangement because it supports all targets. On the other hand, Virtual Manufacturing and Online Traceability are specific-purpose arrangements, adopted especially for flexibility and productivity targets, respectively. Advanced Manufacturing Processing Technologies, in turn, is an integrative-purpose technology arrangement since it is adopted when two competing targets are pursued: productivity and manufacturing flexibility. The study ends with a decision model to implement Industry 4.0 based on the production targets a company may pursue. It shows the interconnection and trade-offs between these production targets and the Industry 4.0 technologies adopted.

Keywords: Industry 4.0, production targets; smart manufacturing; technology adoption.

2.1 INTRODUCTION

Mass production and lean manufacturing are mainly concern with improving productivity and quality of production systems (MARODIN *et al.*, 2017). On the other hand, production flexibility has often been considered an production target that odds with productivity. The trade-off between flexibility and productivity was depicted in Hayes and Wheelwright's (1979) Product-Process matrix, which shows that highly flexible systems operate with lower productivity. Thus, a reduction in flexibility is needed to increase productivity. For instance, universal machines, multitask workers, and a wider product mix – to the detriment of large-scale production – will better cope with changes in the market and the supply chain (PÉREZ, BEDIA, LÓPEZ, 2016). While these are different production targets, Industry 4.0 has been proposed as a new industrial maturity stage in which these targets can converge in the same system (MOEUF *et al.,* 2017). Industry 4.0 considers the use of cutting-edge technologies supported by the Industrial Internet of Things (IIoT) to create smart manufacturing environments, also called cyber-physical systems (LI, 2018; ZHANG; CHEN, 2020; BUENO *et al.,* 2020). According to a company's specific needs, these new environments will be based on different technology arrangements (BENITEZ *et al.,* 2021). Such technology arrangements are expected to provide more productive and flexible manufacturing systems following high-quality standards (SCHUH *et al.*, 2020).

Prior empirical studies have considered relationships between Industry 4.0 and operational performance (e.g., LEE, BAGHERI; KAO, 2015; BRETTEL, KLEIN; FRIEDERICHSEN, 2016; ZHONG *et al.,* 2017), or with production targets and expected benefits that drive the decision-making for investing in Industry 4.0 technologies (DALENOGARE *et al.,* 2018; FRANK *et al.,* 2019). A detailed description of these studies is provided in Appendix A. Most of these studies acknowledge that Industry 4.0 can make general contributions for production targets (GILLANI *et al.*,2020), while some studies suggest that different targets will be achieved with specific Industry 4.0 technologies (MOEUF *et al.,* 2017; DALENOGARE *et al.,* 2018). However, when the literature considers Industry 4.0 technology adoption, it usually follows rigid technology roadmaps that do not consider the nuances of different production targets aimed with these sets of technologies. The priority among these technology sets must not necessarily follow a single roadmap but can be adopted differently according to the production target pursued.

Moreover, when production targets are considered in the Industry 4.0 literature, the debate mainly concentrates on increasing productivity and quality, probably due to the legacy of mass production and lean manufacturing concerns (SCHUMACHER *et al.,* 2016; ALEKSANDROVA, VASILIEV; ALEXANDROV, 2017; MITTAL *et al.,* 2018; ASIF, 2020). Paradoxically, although the aim of obtaining more flexible operations has been at the core of the Industry 4.0 concept (SCHUH *et al.,* 2020), few empirical studies have considered how companies adopt Industry 4.0 technologies to achieve this production target, which remains a theoretical gap in the literature (ENRIQUE *et al.,* 2022; DALENOGARE *et al.,* 2018). Flexible operations gained importance in turbulent environments when industries face uncertainties and need to respond quickly to changes in the market and supply chain (SREEDEVI; SARANGA, 2017; KAMALAHMADI *et al.,* 2021), but the answer on which specific Industry 4.0 technologies can better support such flexibility is still open. In this context, more balanced analysis of productivity, flexibility, and quality becomes necessary for manufacturing companies to adopt Industry 4.0-related technologies to ensure a technology-target alignment and avoid a lack of effectiveness due to the wrong implementation of Industry 4.0 technologies. Although it is well known that Industry 4.0 can help companies to achieve quality, productivity, and flexibility, there is a lack of understanding on which specific technologies are adopted when each of these three specific targets is pursued or when companies want to achieve some of them simultaneously. Thus, the study proposes the following research question: *Which Industry 4.0 technologies can be adopted by manufacturers to achieve specific production targets such as productivity, quality, and operational flexibility*? By answering this question, the contribution of this study relies on exploring the trade-offs between such targets when companies follow different Industry 4.0 technologies to achieve them.

Thus, this study investigates which technologies of the Industry 4.0 concept are adopted by manufacturers when they pursued productivity, quality, or flexibility (or a mix of them) as the main production target. The aim is to identify sets of Industry 4.0 related technology (technology arrangements) that are organized and adopted around specific production targets to provide a better understanding of how Industry 4.0 is conceived when manufacturers look for different goals. To this aim, this study performed a quantitative survey with 92 manufacturers from the machinery and equipment industry. The study analyses the specific Industry 4.0 technologies these companies adopt when they pursue productivity, quality, and/or flexibility as production targets. Exploratory Factor Analysis (EFA) was first used to define sets of technology arrangements that these companies implement together. These arrangements were categorized into four main groups: Vertical Integration technologies, Advanced Manufacturing Processing technologies, Virtual Manufacturing technologies, and Online Traceability technologies. Then, an independent sample test was used to assess the relationship between the production targets pursued by these companies and the Industry 4.0 technology arrangements adopted by them. The results show that these Industry 4.0 technology arrangements make different contributions to production targets. Some of them can be considered general-purpose technologies because they are adopted to achieve all of these three production targets; others can be considered specific-purpose technologies because they are adopted to increase productivity or flexibility targets; finally, another arrangement of Industry 4.0 technologies was named as integrative-purpose technologies because these technologies are used to reconcile the productivity vs. flexibility trade-offs, helping to balance both production targets. The main contribution of this study is that it explores the trade-offs between production targets showing how different sets of Industry 4.0 technologies can contribute to them either by supporting each of them or helping to balance such targets better. In this sense, this study advances the debate of driving Industry 4.0 adoption by production targets instead of considering a mandatory set of technologies that must be necessarily implemented step-by-step independently of the target being pursued. The study shows that some Industry 4.0 technologies are dependent on specific targets pursued, while others are always necessary as the initial ground of Industry 4.0 implementation. As a final contribution, the study proposes a decision model to implement Industry 4.0 technologies according to the expected production targets a company may pursue. The findings help operations managers understand which technology to adopt based on the operations strategy they want to follow.

The remaining sections are organized as follows. First, the study begins with a theoretical background section, where the conceptual framework and the proposed hypotheses are introduced. In Section 3, the data and the measurements used to test the hypotheses are described. In Section 4, the analysis and findings are presented. Finally, in Sections 5 and 6, theoretical implications and managerial insights are discussed, and future research directions are proposed.

2.2 INDUSTRY 4.0 AND PRODUCTION TARGETS

Industry 4.0 is considered a new industrial maturity stage represented by several technologies that consolidate cyber-physical systems based on the Industrial Internet of Thinks (FRANK *et al.,* 2019). Industry 4.0 comprises several technology applications, including Smart Manufacturing, Smart Products and Services, Smart Supply Chain, and Smart Working (FRANK *et al.,* 2019; MEINDL *et al.,* 2021). This paper considers only the Smart Manufacturing dimension, which comprises the technologies associated with the manufacturing production system (MEINDL *et al.,* 2021). Since the initial concept was developed in Germany and then disseminated worldwide, some authors have considered it an international technology diffusion-adoption process, in which countries and companies consolidate a set of technologies to increase performance and, consequently, their competitiveness (DALENOGARE *et al.,* 2018). Such a view is based on the innovation diffusion theory proposed by Rogers (1995), which considers five main factors that influence the adoption of technological innovation: relative advantage, compatibility, complexity, reliability, and observability. The relative advantage is how new technology is considered beneficial for companies and can be measured in terms of costs, productivity, market opportunities, convenience, and satisfaction. This view has been addressed in different technology adoption studies that have shown that the expected targets to be achieved with technology adoption are factors that impact the decision to adopt such technologies (WANG *et al.*, 2010; ABOELMAGED, 2014).

Studies in the Industry 4.0 literature have followed the diffusion-adoption view when considering the technology adoption process (ALMEIDA *et al.,* 2022). For instance, Ghobakhloo and Ching (2019) showed that small companies are more prone to adopt smart manufacturing technologies when they realize potential gains in productivity, agility, and improve response. Dalenogare et al. *(*2018) identified which Industry 4.0 is most adopted in the Brazilian industry when companies want to increase operational goals based on productivity metrics. Moreover, Simões et al. (2020) investigated the main reasons companies adopt collaborative robots and showed the importance of speed in executing tasks and cost benefits as main determinants. These are some examples of studies that address adoption levels of the disseminated technologies based on targets that companies may want to achieve in the production system. As shown in these studies, managerial objectives and expectations are the driving force behind the adoption of Industry 4.0 technologies (HORVÁTH; SZABÓ, 2019). This study calls these objectives as production targets, representing the main goal the manufacturing system should achieve by implementing technologies and process execution (GRÖßLER; GRÜBNER, 2006).

One of the most discussed concepts in the literature regarding production targets is the manufacturing trade-offs suggested by Skinner (1969). According to this concept, unless there is slack in the system, improving one of the generic capabilities (targets) is only possible at the expense of the others (DA SILVEIRA; SLACK, 2001; GRÖßLER; GRÜBNER, 2006). On the other hand, through the implementation of manufacturing methods and technologies, modern manufacturing systems should allow improvements in more than one production target simultaneously. This is known as the cumulative view, according to Ferdows and Meyer (1990). A cumulative view of production trade-offs focuses on continuous changes in performance. The cumulative view does not deny the trade-off challenge between production targets, but it suggests that companies could achieve a balance, maybe with lower but more balanced results.

The literature review presented in Appendix A analyses how the Industry 4.0 literature has considered the adoption of Industry 4.0 technologies, targets that lead companies to adopt such technologies, and the performance that companies have achieved with such technologies. As it is possible to see, the literature has been more focused on performance measurement, which does not necessarily represent the main production target that triggers the technology adoption. Some authors have considered motivations, drivers, or expected benefits (e.g., BÜCHI *et al.*, 2020; CUGNO *et al.*, 2021), but when such aspects are considered, Industry 4.0 technologies are not differentiated. This present study aims to address such a gap in two different ways: firstly, by considering, through the innovation diffusion-adoption theory (ROGERS, 1995), the main production targets that trigger the adoption of different types of Industry 4.0 related technologies. This study hypothesizes that specific production targets will make companies more prone to invest in *some sets of* Industry 4.0 related technologies, creating different nuances of adoption patterns. Secondly, by considering the cumulative view of production targets trade-offs (FERDOWS; DE MEYER, 1990), this study acknowledges that some targets can be pursued simultaneously (or not) by adopting Industry 4.0 related technologies.

2.2.1 Hypotheses development

The hypotheses of this study are built around three production targets defended as the core of the Industry 4.0 implementation: productivity, quality, and operational flexibility (SCHUH *et al.*, 2020). Although other production targets could be present, these three metrics are the most common alongside the Industry 4.0 literature (Appendix A). In this sense, this study follows Boyer and Lewis' (2009) perspective on competitive priorities that define the operations strategy model, including the technology that should be implemented. According to them, the main competitive priorities (i.e., production targets) can be divided into cost, delivery, quality, and flexibility. Productivity can be used as an alternative to summarize costs and delivery since it represents the rate between total output (product delivery) and total input (cost reduction) (HUANG *et al.*, 2010). Any other production target should derivate from these three essential priorities of manufacturing decision-making (BOYER; LEWIS, 2009). Next, the study provides evidence about the reasons for such connection and the hypotheses derived from such production targets.

2.2.2 Industry 4.0 and Productivity

Productivity is generally related to the effort necessary to produce goods using fewer resources (DE LA FUENTE-MELLA *et al.*,2019; KIRAN, 2019). Productivity gains can be associated with several resources, such as labor productivity, space utilization, inventory turnover, energy costs, and equipment utilization (BACKHAUS; NADARAJAH, 2019; DE LA FUENTE-MELLA *et al.*,2019). Prior studies have shown that increased industrial computerization and automation have generated stable productivity growth in companies using fewer workers (AUTOR *et al.*,2020). Industry 4.0 thus considers a set of technologies aiming to increase resource consumption and autonomy to execute tasks and complete operation cycles, which should result in productivity gains (SCHUH *et al.*, 2020). Sensing capabilities help machines better utilize materials, combined with optimization algorithms and the intensive use of data to learn the best way to use production resources (DALENOGARE *et al.*, 2018). Moreover, Industry 4.0 also considers smart production planning and control based on advanced technologies and real-time data, which helps the manufacturing system organize its schedule and save time (BUENO *et al.*, 2020). Workers can also become more productive with the aid of smart devices supported by Augmented Reality (AR), Virtual Reality (VR), and other digital tools that can help them improve focus on their tasks or provide additional skills to support their decision-making processes (PEREIRA; ROMERO, 2017; REALYVÁSQUEZ-VARGAS *et al.*, 2019; FARERI *et al.*, 2020).

The Industry 4.0 literature provides several examples of specific technologies that are suggested to increase productivity. For instance, intelligent systems can optimize manufacturing processes, especially in terms of resources and energy consumption, representing the second-highest production cost in many sectors (FATORACHIAN; KAZEMI, 2018). Moreover, additive manufacturing maximizes the use of materials and the manufacture of a wide variety of parts, also permitting scalability (ALCÁCER; CRUZ-MACHADO, 2019). Adopting Manufacturing Execution Systems (MES) and other information systems with real-time data collection can support process monitoring and production planning to better use production resources (CHIARINI; KUMAR, 2020; BÜCHI *et al.*,2020). Robots are another important technology in the Industry 4.0 context. They are associated with productivity gains, especially in highly repetitive tasks in the production environment, including processing, material handling, and inspection systems (FRANK *et al.*, 2019; DALENOGARE *et al.*, 2018). In sum, the Industry 4.0 literature mentions a wide range of technologies for productivity. However, many of them are only assumed to be important to this production target without the backing of empirical tests. Therefore, the following hypothesis is proposed:

H1: Companies that pursue productivity as an important production target are more likely to have a higher level of use of some specific Industry 4.0 technologies than companies that do not.

2.2.3 Industry 4.0 and Quality

Quality of products and processes can become the main competitive target of the company. While product quality is associated with product design requirements, the quality of the process is related to the production system activities, which is the focus of this study. This is a production target related to how the manufacturing system should work to reduce process variability and non-conformities in the final product (FLYNN, SCHROEDER; SAKAKIBARA, 1994; GOYAL, AGRAWAL; SAHA, 2019). Process quality considers implementing best practices and technologies to standardize processes, improve and maintain equipment operation, and check for potential failures and non-conformities in the production line (FLYNN, SCHROEDER; SAKAKIBARA, 1994; ASIF, 2020).

According to Dutta et al. (2021), the available literature on integrating quality practices in a digital environment is limited, deserving more attention in the Industry 4.0 domain. Nonetheless, some studies have mentioned how Industry 4.0 technologies can support process quality in different ways. According to Markulik, Sinay, and Pačaiová (2019), Industry 4.0 technologies in three main areas of process quality: digital quality management, advanced process control, and statistical process control. The intensive adoption and use of sensors in the production line ensures better control of quality parameters, and machine connectivity allows monitoring such parameters in real-time (WANG *et al.*, 2016; ALEKSANDROVA *et al.*, 2019). Sensing capabilities on the shop floor enable the tracking of materials, supporting product components' traceability to identify non-conformities (RAMADAN, AL-MAIMANI; NOCHE, 2016). An online check of equipment conditions is also an important maintenance tool, contributing to improvements in predictive models of equipment failure and preventive maintenance that will ensure process quality (SHIVAJEE, SINGH; RASTOGI, 2019). Moreover, the intensive use of automated machines and robots helps implement standardized processes that reduce potential quality problems due to high operations variability (DALENOGARE *et al.*, 2018). On the other hand, when production tasks are manual-intensive, tools such as AR and VR can help better execute repetitive operations and reduce the chance of workers' mistakes. (ELIA, GNONI; LANZILOTTO, 2016; TZIMAS, VOSNIAKOS; MATSAS, 2019; URBAS, VRABIC; VUKASINOVIC, 2019). These technologies can also be useful in training workers to ensure a certain quality standard in their activities (ROLDÁN *et al.*, 2019). Furthermore, according to the results of Závadská and Závadský (2018), smart devices such as smartwatches and smart glasses have the greatest presence in processes such as non-compliance management, quality control, and change management, and visual management Quality managers and their future technological expectations related to Industry 4.0. These are some examples of the use of Industry 4.0 technologies when companies have process quality as a main target of the manufacturing system. These are evidence reported in the literature suggesting that there are different arrangements of Industry 4.0 technologies that can improve process quality. Therefore, the following hypothesis is proposed:

H2: Companies that pursue quality as an important production target are more likely to have a higher level of use of specific Industry 4.0 technologies than companies that do not.

2.2.4 Industry 4.0 and Manufacturing Flexibility

Flexibility can be developed at different levels in the company. The operations management literature has considered some levels, such as supply chain flexibility, organizational flexibility, and operational flexibility (PÉREZ-PÉREZ *et al.,* 2018). This paper focuses on operational flexibility, which is the level of flexibility a company may pursue in the shop floor through adaptation of its manufacturing process and activities to different types of orders (KOSTE; MALHOTRA, 1999). This level of flexibility considers the production system's ability to handle changes in the product mix and production volumes, as well as dealing with uncertainties related to manufacturing resources, with a minimum impact in terms of time, costs, and performance (GERWIN, 1993; PEREZ *et al.*, 2016).

Operational flexibility has been identified as one of the main targets of Industry 4.0 (LONG, ZEILER; BERTSCHE, 2017; FATORACHIAN; KAZEMI, 2018). The Industry 4.0 literature highlights that cyber-physical systems can improve a company's ability to introduce new products rapidly and/or change its product mix, both key characteristics of manufacturing flexibility (PÉREZ-PÉREZ *et al.,* 2018). In this sense, smart production planning and control systems are expected to be one of the main drivers for introducing flexibility in the production system because they can quickly reconfigure the production schedule (BUENO *et al.*, 2020). However, this could also require the complement of flexible machines. Additive manufacturing is considered the extreme in this flexibility concept since such technology would ideally allow a company to produce any product component in the same machine (KIM, LIN; TSENG, 2018; HALEEM; JAVAID, 2019). Smart and reconfigurable machines facilitate new products, as they are much more flexible than fixed automatic systems (WANG *et al.*, 2016). Assembly lines can also be benefited by the combination of the labor force and collaborative robots (cobots), which, when combined, can boost flexibility by allowing workers to focus on the most value-added and flexible work while a cobot handles the repetitive tasks previously performed by human workers (LIU; WANG, 2017; ZOLOTOVÁ *et al.*,2020). Other technologies, such as AR and VR systems, improve the information exchange process and train operators to quickly adapt to changes (MOURTZIS *et al.*, 2017). In terms of product mix flexibility, Robots with Artificial Intelligence (AI), which are both adaptive and flexible, can more quickly learn how to produce new products, thus adding the flexibility component to the already known benefit of reducing production costs (ZHONG *et al.*, 2017; ALCÁCER; CRUZ-

MACHADO, 2019). In addition, process simulation tools and virtual commissioning can be used to view, analyse and control the state of a part or process and to build different scenarios before introducing real changes in the production system (MOURTZIS, ZOGOPOULOS; VLACHOU, 2017; CORONADO *et al.*, 2018; SCHAMP *et al.*,2019; ZHUANG, GONG, LIU, 2020). However, although several Industry 4.0 technologies are proposed to increase flexibility in the production system, Frank et al. (2019) and Dalenogare et al. (2018) showed that this is usually one of the biggest challenges of manufacturing companies. As they suggested, more research is needed to understand which technologies effectively contribute to this concept in companies' real environments. Therefore, the literature suggests this association, but it still lacks empirical evidence on what specific Industry 4.0 technologies are pursued when operational flexibility is the company's main target. Thus, the following hypothesis is proposed: *H3: Companies that pursue flexibility as an important production target are more likely to have a higher level of use of specific Industry 4.0 technologies than companies that do not.*

2.2.5 Summary of the conceptual research model

Figure 1 shows the conceptual research model that summarizes the three hypotheses proposed. As the figure shows, it is assumed that companies can pursue different production targets (Productivity, Process Quality, and Manufacturing Flexibility). Such targets may drive to the adoption of different Industry 4.0-related technologies to facilitate their achievement. However, since Industry 4.0 solutions can be represented by a combination of different technologies (technology arrangements), the study aims to define these arrangements to understand how they are adopted based on the production targets pursued.

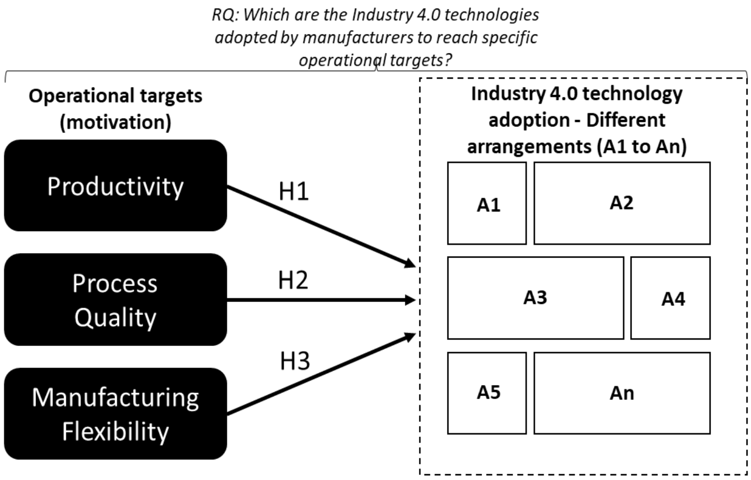

Figure 1. Conceptual research model

2.3 Research method

2.3.1 Sample and Data Collection

This study performed a cross-sectional survey of manufacturing companies associated with the southern chapter of the Brazilian Machinery and Equipment Builders' Association (ABIMAQ-Sul)[1]. This association was chosen due to its relevance in the Brazilian industry and for Industry 4.0 in the country: it is one of the most representative manufacturing sectors in the country, and it is engaged with the Industry 4.0 platform promoted by the Brazilian Chamber of Industry 4.0, which is part of the Brazilian Federal Ministry of Science and Technology. The questionnaire was sent by e-mail to the 143 companies that are member of ABIMAQ's southern chapter and obtained a return of 92 useable questionnaires, representing a response rate of 64.33%. The questionnaire was addressed to the CEOs or Operations Directors or equivalents with knowledge on the company's operations management activities, including technology investments and performance metrics. The research obtained a high engagement rate among the target public because the industry association promoted the research in business seminars on Industry 4.0 and because the survey was distributed through the associations' mailing channels. Therefore, although the absolute number of the sample size may not seem too large, it is focused on a single industry and represented by a high response rate (65% of the

[1] Other variables from this survey were used in Frank et al. (2019). This other study focused on investigating the implementation patterns of Industry 4.0 technologies through cluster analysis. Frank et al. (2019) did not consider production target variables. They focused on other "smart dimensions" like smart products, smart working, and smart supply chain complementary to smart manufacturing. In this sense, while this present study deepens the manufacturing technology variables and connects them with production targets (motivations), the one from Frank et al. (2019) has a broader scope and focuses on the breath of Industry 4.0 technologies complementary to the manufacturing technology variables. Therefore, both studies are complementary in their research focus.

representatives). The final sample was composed of 41% of small enterprises (<100 employees), 37% of medium enterprises (100 to 500 employees), and 22% of large enterprises (>500 employees). The companies representing this industry sector serve a high diversity of markets, including the agricultural, chemical, furniture, and food industries. Table 2 shows the characteristics of the sample.

Table 2. Demographic characteristics of the sample

Sectors	**(%)**	**Category**	**Description**	**(%)**
Agriculture	48%	Company's size	Small(<100 employees)	**41%**
Biotechnology	1%			
Chemicals	24%		Medium (100 - 500 employees)	**37%**
Construction	10%			
Energy	15%		Large (>500 employees)	**22%**
Food products	29%			
Leather products	3%	Respondent's profile	Managers or directors	**78%**
Mining	21%		Supervisors	**10%**
Furniture	10%			
Pharmaceutical	10%		Analysts	**4%**
Pulp and paper	16%			
Software and technology	17%		Other	**8%**
Steelworks	18%			
Transport	13%			
Metal products	34%			
Other manufacturing	24%			

2.3.2 Definition of the variables

The questionnaire (see Appendix A) aimed to assess the level of adoption of a set of Industry 4.0-related technologies and three production targets pursued by companies when the implement Industry 4.0 technologies and concepts. The list of technologies related to the Industry 4.0 concept was adapted from previous industry surveys on this topic conducted by the National Confederation of Industries (CNI, 2016), as well as by other previous studies from the literature (LU; WENG, 2018; FRANK *et al.*, 2019). This survey also considered production targets from which the three most representative ones were selected, namely productivity, manufacturing flexibility, and process quality. These three targets were included because most of the studies presents them as the key targets in the Industry 4.0 concept (DALENOGARE *et al.,* 2018; TORTORELLA *et al.,* 2019; SCHUH *et al.*,2020; SZÁSZ, *et al.,* 2020) while other targets and performance metrics described in Appendix A, such as costs reduction, time-to-market improvement, among others, can be directly or indirectly related to them (DALENOGARE *et al.*, 2018). A five-point Likert scale was used for technology adoption varying from 1 - Very low implementation to 5- Advanced implementation. The production targets were assessed through the following question: "Which of the following production targets do you pursue with the implementation of Industry 4.0 technologies?". A list of targets was provided with binary options: 0-Not a competitive priority or 1- competitive priority. The questionnaire was pretested and refined using interviews with 15 scholars and seven CEOs that compose the board of directors of ABIMAQ-Sul. The full questionnaire is provided in Appendix B.

2.3.3 Sample and common method variance bias

To check response bias, the t-test for equality of means and Levene's test for equality of variance were used when early and late respondents are compared; 63 companies represented the early respondents, i.e., those that answered in the first wave of data collection. In comparison, 29 companies composed the group of late respondents that answered in the following rounds of data collection. None of the 18 technologies investigated showed statistical differences between these waves of respondents (<0.05), suggesting that there is no significant difference of populations between samples (ARMSTRONG; OVERTON, 1977).

Some strategies proposed by Podsakoff et al. (2003) were adopted to deal with potential common method variance. Firstly, the procedure was to randomized the technologies list to avoid any intentional correlation between them by respondents. It was also highlighted in the questionnaire introduction that the answers were anonymous and free from judgment. The questionnaire was also sent to specific respondents, namely CEOs and Operations Directors, and explained that they should deeply understand technical issues pertaining to the operations of their companies. Furthermore, a statistical remedy was adopted by running Harman's single-factor test (PODSAKOFF *et al.,* 2003). This test with all variables resulted in a first factor that comprehended only 40% of the observed variance. Therefore, there was no single factor accounting for the majority of the variance in the model.

2.3.4 Data analysis

Data analysis was performed in two main stages. Firstly, it was proceeded with the technology clustering in order to define subsets of Industry 4.0 technology arrangements. Therefore, Exploratory Factor Analysis (EFA) was used to summarize the 18 Industry 4.0 technologies in the technology arrangements, following Hair et al.'s (2009) procedures. The EFA technique is used when researchers need to find common underlying patterns between variables from exploratory analysis to synthesize new factors representing those variables with similar characteristics (Hair et al., 2009). A similar approach has been used in other studies in the operations management field when technologies or practices are grouped based on similar implementation profiles (e.g., MARODIN *et al.*, 2017; DALENOGARE *et al.*, 2018). This study adopted such an approach to group Industry 4.0 technologies in common groups of technologies with similar profiles of implementation, as previously done by Dalenogare et al. (2018). A qualitative analysis of the sample size was performed before conducting the EFA feasibility tests (reported in the Results Section). The common practice on the use of EFA technique recommends that (HAIR *et al.*, 2009, p.101): a) there should be not used less than 50 observations to conduct this technique; b) the sample must have more observations than variables, and c) a good minimum sample for EFA should use five or more observations per variable. This study used 92 observations, exceeding the criteria (a) and (b). Regarding criteria (c), the study analyses 18 variables (technologies) in the EFA model, which would demand a minimum size of 18 (variables) x 5 (minimum size per variable) = 90 observations. Therefore, based on these criteria, the sample used is above the minimum recommendation for a reliable EFA.

The technology arrangements were defined based on those technologies with high factor loading on the same factor, which means that those technologies were usually implemented jointly. In this sense, the labels of the factors (technology arrangements) were defined by considering the technologies' main characteristics of the group and contrasting them with prior studies with similar arrangements (HAIR *et al.*, 2009). The average of these technologies was used to represent the new constructs used as new dependent variables for the second stage of the analysis. The reliability of the constructs was also assessed using Cronbach's alpha with a required threshold higher than 0.7, as recommended in the literature (HAIR *et al.*, 2009). Data validity was also assessed qualitatively, based on similar profiles of technology arrangements found in the literature. In this sense, the results did not define technologies arrangements that present significant differences from those used in other studies (e.g., DALENOGARE *et al.*, 2018; FRANK *et al.*, 2019).

In the second stage of analysis, which aimed to test the hypotheses, a series of independent samples t-tests for two groups were conducted. Independent tests allow differentiating levels of adoption of the Industry 4.0 technology arrangements when different production targets are set as priority, a similar approach to the one used by Marodin et al. (2016) when they compared levels of implementation of lean practices. In this sense, the present study compared whether companies prioritizing each of the three production targets (productivity, process quality, or manufacturing flexibility) showed levels of implementation of each Industry 4.0 technology arrangement different from those of companies that did not prioritize the same target. For the comparison of means, Levene's test was used to define whether the t-test should assume equal variance at $p<0.05$.

2.4 RESULTS

2.4.1 Industry 4.0 technology arrangements

The data analysis synthesized 18 technologies in the main categories using an Exploratory Factor Analysis (EFA). The EFA technique allowed to obtain broader technologies implementation arrangements based on the partial contribution of different but correlated measures (HAIR *et al.*, 2009). Based on Hair et al. (2009), the procedure was divided into two steps: validation of EFA adequacy to the sample and reduction of variables using the EFA technique.

For the EFA validation, the Kaiser-Meyer-Olkin (KMO) test was used to measure sampling adequacy and Bartlett's test of sphericity. These tests allowed us to assess whether the EFA would suit this sample (HAIR *et al.*, 2009). Both tests indicated that the dependent variables could be reduced using EFA: KMO's test was 0.821 (i.e., much above the threshold value of 0.5), and Barlett's test of sphericity showed a p-value < 0.001 (i.e., lower than the suggested $p < 0.05$ significance level) (HAIR *et al.*, 2009).

The technology arrangements containing different Industry 4.0 technologies were defined using a Varimax orthogonal rotation factor solution for the EFA since it reduces ambiguities related to non-rotated analysis (HAIR *et al.*, 2009). The optimal number of components was selected using the latent root criterion, which includes factors only when they show an eigenvalue higher than 1.0, and it was also supported by the percentage of variance criterion, which considers only factors that exceed 60% of the total variance (HAIR *et al.*, 2009). The results obtained four main factors that accounted for 64.37% of the total variance (Table 3). The four main factors were defined according to the variables with high factor loading (>0.5) represented in them. Only one item (AI for PPC) showed a slightly lower factor loading, but it was strongly distributed in two factors. It was accounted for it in the first factor (Virtual Manufacturing) because it is theoretically more strongly associated (BUENO *et al.*, 2020). The average of the technologies with high factor loadings was used to represent each arrangement's final score in the independent sample tests. Table 3 also shows the reliability analysis for the three constructs using Cronbach's alpha, all above 0.75 (Hair et al., 2009).

Table 3. Rotated Factor-Loading Matrix from EFA

Industry 4.0 technologies	**Factor loadings [a]**				
	Digital Manuf.	**Vertical Integ.**	**Advanced Manuf.**	**Online traceability**	**Commu -nalities**
Process control (PLCs and sensors)	0.265	**<u>0.730</u>**	0.143	0.159	0.649
SCADA	0.263	**<u>0.813</u>**	0.029	-0.042	0.733
MES	0.325	**<u>0.556</u>**	0.355	0.336	0.654
Real-time monitoring	0.307	**<u>0.706</u>**	0.216	0.141	0.581
Virtual commissioning	**<u>0.674</u>**	0.336	0.044	0.111	0.566
M2M communication	**<u>0.585</u>**	0.286	0.338	0.164	0.544
AI for maintenance	**<u>0.582</u>**	0.373	0.259	0.000	0.543
AI for PPC	**<u>0.444</u>**	**<u>0.455</u>**	0.219	0.301	0.514
Process simulation	**<u>0.530</u>**	-0.005	0.382	0.295	0.635
Automated failure detection	**<u>0.706</u>**	0.084	0.165	0.321	0.903
Remote operation	**<u>0.687</u>**	0.261	0.134	-0.069	0.900
AR for maintenance	**<u>0.655</u>**	0.341	0.266	-0.007	0.789
AR for workers training	**<u>0.722</u>**	0.254	0.085	0.057	0.584
Raw material online traceability	0.058	0.145	0.127	**<u>0.929</u>**	0.558
Product online traceability	0.133	0.096	0.091	**<u>0.930</u>**	0.658
Robots	0.107	0.292	**<u>0.815</u>**	0.170	0.563
Collaborative robots	0.241	0.218	**<u>0.681</u>**	0.116	0.616
3D printing	0.188	-0.003	**<u>0.723</u>**	0.012	0.596
Eigenvalue	7.496	1.794	1.250	1.047	
% of variance (cumulative)	22.214	38.662	51.829	64.368	
Cronbach's alpha	0.869	0.830	0.725	0.924	

[a] High factorial loadings are represented in bold and underlined

As a result, the four factors labels were defined based on the items representing them. The first factor, named *Virtual Manufacturing*, is the group with the largest number of technologies, nine in total. This dimension includes a set of AI and simulation technologies designed for simulation, virtual validation, and system self-configuration. AI technologies enable companies to achieve intelligent functions at all stages of industrial value, from customer demand, R&D design, operations management, production and processing, and other activities (ZHANG *et al.*, 2019). Within AI technologies, computer vision, machine learning, and AR are included. Furthermore, simulation technologies comprise a set of tools and technological methods to experiment and validate the design and configuration of products, processes, and systems (MOURTZIS, DOUKAS; BERNIDAKI, 2014) and the virtual validation of automation equipment through commissioning virtual.

The second factor, technologies for *Vertical Integration*, comprises the set of technologies used in the Industry 4.0 context to integrate several information layers in the company. This begins at the machines with process control through PLCs and sensors, then the collection of data through Supervisory Control and Data Acquisition (SCADA), and this being integrated from different work stations in the Manufacturing Execution System (MES), which finally provides real-time monitoring of the production system (DALENOGARE *et al.*, 20218). These real-time monitoring systems include tools for quick production (re)scheduling, helping to define production routes and redistribution of activities according to the current situation of the factory and equipment (BUENO *et al.*, 2020; TABIM *et al.*, 2021). In this sense, the technologies included under this label have been broadly considered as components of the vertical integration process necessary in the Industry 4.0 domain (DOTOLI *et al.*, 2018).

The third factor was named *Advanced Manufacturing Processing Technologies* and integrates robots, cobots, and additive manufacturing (3D printing) as a single construct focused on manufacturing processing. This name was given because the technologies included only comprise hardware tools that are part of the Industry 4.0 domain and used for manufacturing processing purposes. This refers to the creation of interconnected and modular processing systems that guarantee automated industrial plans. These technologies include automatic material-moving systems and advanced robotics, the latter of which are now on the market as “cobots” (collaborative robots) or automated guided vehicles (BUCHI *et al.*, 2020). They are processing tools because in the case of robots and collaborative robots (cobots), they can execute processing activities like welding, machining, handling or packing (LEE; MURRAY, 2019; COHEN *et al.*, 2021), and 3D printers can print products components through additive manufacturing (MANI *et al.*,2017). Several studies consider such tools as part of the Industry 4.0 context, even robots, because they are becoming more usual and integrated with data and machine-to-machine communication, to operate in an integrated process in the factory (FRANK *et al.*, 2019).

The final factor is *Online Traceability,* which refers to automatic identification technologies that can track raw material and products, and components along the value chain, enabling and transferring data with limited human intervention (USTUNDAG; CEVIKCAN, 2017; SCHUITEMAKER; XU, 2020, EICHSTÄDT *et al.*, 2021). Online Traceability in the Industry 4.0 context is mainly based on RFID solutions applied in materials and products to better track them in the factory (MEINDL *et al.*, 2021).

2.4.2 Production targets and Industry 4.0 technologies

Table 4 provides the correlation matrix for the final variables used in the second stage of analysis, including means, standard deviation, and normality checks using the Skewness and Kurtosis of the data.

Table 4. Correlation matrix and descriptive analysis

	Mean	S.D.	Skewness	Kurtosis	1	2	3	4	5	6
1- Vertical_integration	2.984	.999	0.202	-0.897	--					
2-Digital_manufacturing	2.278	.705	1.170	1.747	.709***	--				
3- Online Traceability	3.076	1.183	0.114	-1.347	.332***	.336***	--			
4-Advanced manuf.	2.359	.924	0.607	-0.160	.486***	.555***	.294***	--		
5-Manuf.flexibility	2.315	1.157	0.789	-0.246	-.053	-.087	-.090	-.097	--	
6-Produtivity	4.217	.767	-0.842	0.548	-.189**	-.169*	.054	-.003	.206**	--
7-Product quality	4.250	.909	-1.506	2.619	-.165*	-.083	-.018	.071	.091	.488***

*p < 0.1; **p<0.05; ***p<0.01

Table 5 presents the independent samples t-test for comparison of means. The means differences were compared between the technology arrangements when each of the three production targets was or was not a priority.

For *productivity* as a production target (H1, Model 1), it was found that Vertical Integration (t= -3.557, p=002), Online Traceability (t= -1.922, p= 0.058), and Advanced Manufacturing Processing Technologies (t= -2.436, p=0.017) were statistically significant as technology arrangements adopted for this target, supporting H1. Regarding H2, which considers *process quality* targets and its relationship with Industry 4.0 (Model 2), the results showed statistical support for Vertical Integration (t= -2.311, p=0.023) presented a significant difference between groups, supporting the hypothesis, but only for one of the technology arrangements. Finally, for *manufacturing flexibility* (H3, Model 3), the results indicate that companies pursuing this target are more likely to have increased adoption of Vertical Integration (t= -4.238, p<0.001), Virtual Manufacturing (t= -2.246, p=0.025) and Advanced Manufacturing Processing Technologies (t= -2.082, p= 0.05). Consequently, the results support the three hypotheses and provide further refinement, showing that different technology arrangements are adopted depending on the specific production target pursued. As shown in this table, although the results support all the three hypotheses, several nuances are shown in these results that deserve more exploration, especially those related to technologies that attend to production targets that compete in a trade-off, as explained in the theoretical section. Therefore, such differences are discussed in the next section.

Table 5. Independent Samples T-Test for comparison of means

Industry 4.0 technology arrangements	**Model 3**			**Model 2**			**Model 1**		
	Technology adoption levels (Mean±S.D) for **Productivity**			Technology adoption levels (Mean±S.D) for **Process Quality**			Technology adoption levels (Mean±S.D) for **Manufacturing Flexibility**		
	Target is a low priority	Target is a high priority	t-test⁺ (dF)	Target is a low priority	Target is a high priority	t-test⁺ (dF)	Target is a low priority	Target is a high priority	t-test⁺ (dF)
Vertical Integration	2.21 (0.822)	3.11 (0.972)	**-3.557****** **(18.01)**	2.40 (1.023)	3.08 (0.969)	**-3.311**** **(90)**	2.78 (0.922)	3.80 (0.883)	**-4.238***** **(90)**
Virtual Manufacturing	2.14 (0.552)	2.30 (0.728)	-0.776 (90)	2.03 (0.655)	2.31 (0.710)	-1.349 (90)	2.16 (0.603)	2.72 (0.920)	**-2.426**** **(20.69)**
Online Traceability	2.50 (1.080)	3.17 (1.179)	**-1.922***** **(90)**	2.846 (1.297)	3.11 (1.168)	-0.754 (90)	3.00 (1.170)	3.38 (1.219)	-1.254 (90)
Advanced Manufacturing Processing Technologies	1.79 (0.701)	2.45 (0.928)	**-2.436***** **(90)**	2.10 (1.074)	2.40 (0.898)	-1.079 (90)	2.22 (0.770)	2.88 (1.288)	**-2.082**** **(20.05)**
Subsamples (n)	13	79		13	79		74	18	

*p<0.1, **p<0.05, ***p<0.01, ⁺ underlined values report equal variances not assumed (i.e. Levene's test p<0.05)

2.5 DISCUSSIONS

The discussions are divided into two main sections. First, a conceptual discussion about the findings is provided, explaining the reasons why Industry 4.0 technology arrangements from the findings are connected to the production targets observed. Then, the second part of the discussion shows how these technology arrangements can be organized in a decision model that can enable manufacturers to choose and adopt Industry 4.0 technologies that would serve their strategic needs the most.

Connecting Industry 4.0 technology arrangements to production targets

The main empirical findings are summarized in the conceptual framework of Figure 2. This framework represents the relationships between the three production targets and the main Industry 4.0 technology arrangements adopted to achieve such targets. Results indicate that companies implement complementary technologies that configurate clusters or technology arrangements, as previously suggested also by other studies (e.g., DALENOGARE *et al.*, 2018;

FRANK *et al.*, 2019). Four main arrangements were identified: *Vertical Integration, Advanced Manufacturing Processing Technologies*, *Virtual Manufacturing, and Online Traceability*. Although they have a primary objective (e.g., online traceability is to track components and materials, or vertical integration is to integrate information layers to provide real-time data flow), the results showed that the adoption of these arrangements depends on the type of production target pursued. This means that instead of pursuing the full implementation of Industry 4.0-related technologies, as usually presented in some Industry 4.0 technology roadmap models (e.g., FRANK *et al.,* 2019), companies should first consider which production target they want to improve to then adopt the most appropriate technology arrangement. In this sense, the innovation diffusion-adoption view of Industry 4.0, which was adopted as theory lens of this study, needs to be based on production targets that companies aim to achieve rather than on prescriptive linear models of technology diffusion and adoption in which technologies are proposed to be implemented in a prescriptive order independently of the production target pursued.

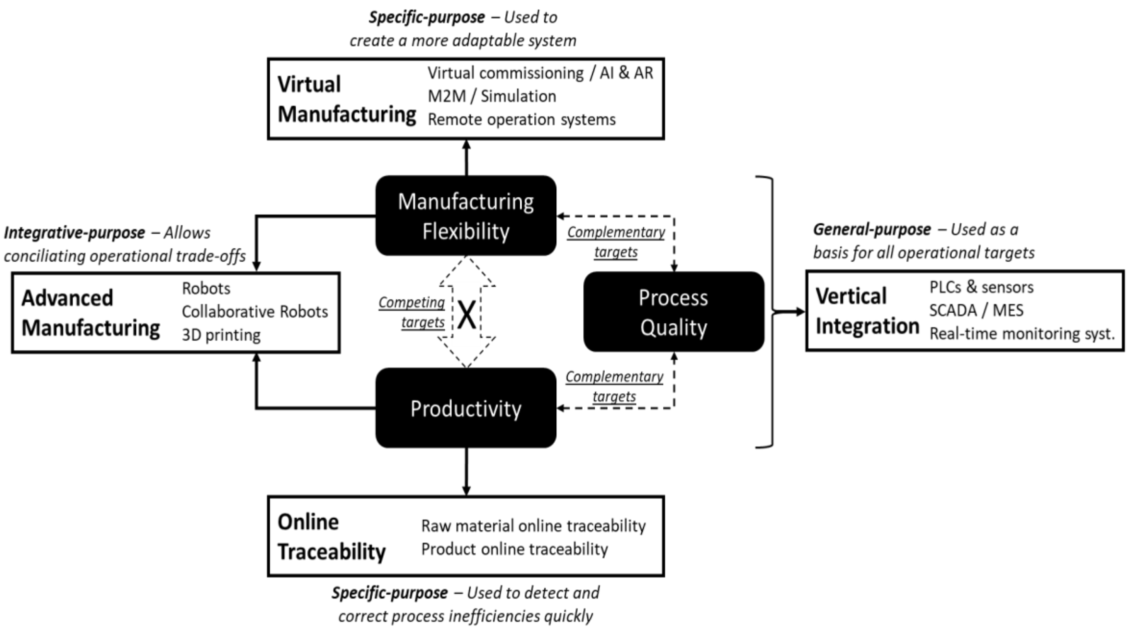

Figure 2. Conceptual framework of the empirical findings

The study also helps to explore the trade-offs between these three production targets. The findings showed that some technologies are implemented for specific targets, and others are adopted in more than one of the production targets. In this sense, if there are technologies adopted by companies independently of the target pursued, although such targets can compete with each other, such technologies should contribute to the cumulative view of production trade-offs explored in the theoretical background (FERDOWS; MEYER, 1990). In this sense, the conceptual framework of the results evidence which technologies contribute to the cumulative view of the targets helping the pursued goals achieve a balance, maybe with lower but more balanced results between such targets with specific technologies (FERDOWS; MEYER, 1990). Next, it is explained how the different technology arrangements are adopted according to trade-offs and complement between production targets shown in Figure 2.

Regarding *Vertical Integration*, the results show that this is a *general-purpose technology arrangement* (Figure 2) because it is adopted by companies independently on the production target pursued. This means that *Vertical Integration* is a primary focus of companies when adopting an Industry 4.0 approach, being always present in the Industry 4.0 journey. Vertical Integration helps to achieve the first objective of Industry 4.0, which is the visibility and transparency of the manufacturing processes (TABIM *et al,* 2021; SCHUH *et al.,* 2020). Visibility means that decision-makers will be able to 'realize' what is happening in different stages of the process, while transparency means that they will be able to 'understand' relationships between different process parameters (SCHUH *et al.*, 2020). Although it is known that such objectives are only achieved when information layers supported by PLCs, SCADA, MES, and other systems are integrated (TABIM *et al.*, 2021), the results provide empirical evidence that the basic integration of information provided by this technology arrangement is necessary for all these production targets. This result also clarifies why Dalenogare et al. (2018) did not find support for a positive association between *Vertical Integration* and the expected benefits they can produce for operational performance. In that study, the authors considered a single construct for operational benefits in which many other production targets were also included (and may not be correlated to these technologies). By deploying expected operational benefits in only three main production targets, the results showed that there is, in fact, a strong association of the three targets investigated with *Vertical Integration* adoption. Therefore, the lack of analysis on trade-offs by Dalenogare et al. (2018) might confound this correlation.

Moreover, the results showed that *Vertical Integration* is the only technology arrangement highly adopted when companies pursued process quality as the main production target (Table 3). *Vertical Integration* allows one to visualize and analyse what is happening in the different stages of the production process (CHIARINI, 2020). Consequently, decision-makers can quickly detect and correct non-conformities and improve process parameters based on the resulting analysis of the data (MISHRA *et al.,* 2018; SOUZA *et al.,* 2020). Furthermore, the theoretical view adopted in this study on cumulative production targets argues that companies can pursue some complementary targets (FERDOWS; MEYER, 1990). In this sense, manufacturing studies have shown that quality and productivity, or quality and flexibility are complementary targets in production systems (MARODIN *et al.,* 2019).

Consequently, process quality and *Vertical Integration* are shown in the results as highly correlated contributing for the whole Industry 4.0 system, independently whether the company may pursue additional manufacturing flexibility or productivity, as represented in Figure 2.

The findings suggest that two technology arrangements – *Virtual Manufacturing* and *Online Traceability* – are *specific purposes technologies* because they are adopted when two different *competing targets* are pursued (DA SILVEIRA; SLACK, 2001; GRÖßLER; GRÜBNER, 2006). The findings show that when companies pursue productivity as the main production target, besides implementing *Vertical Integration*, they also implement *Online Traceability*. This latter helps companies track raw materials and product components on the shop floor using technologies such as RFID, allowing them to reduce the time of supporting material handling activities (such as material identification, product allocation, production routing of material inputs, etc.) and, consequently, reduce process inefficiencies (GUO *et al.,*2014; RAMADAN *et al.,* 2016). The combination of *Online Traceability* with *Vertical Integration* should allow companies to achieve a fully integrated, real-time data flow in the manufacturing activity, one of the advantages proposed by the Internet of Things concept to increase productivity (WANG *et al.*, 2016; TAO *et al.*, 2018). The real-time data flow helps companies understand and make decisions to improve manufacturing indicators such as overall equipment efficiency (OEE), take times, or downtimes (LEE *et al.,* 2015; ROSIN *et al.*, 2019).

On the other hand, when companies pursue manufacturing flexibility as the main production target, the findings show that they implement *Virtual Manufacturing*, besides *Vertical Integration*. The literature has acknowledged that digital tools such as simulation, virtual commissioning, and augmented reality help operations managers to make complex decisions before taking the risks of physical changes in the manufacturing layout or production scheduling (BAYKASOGLU; GORKEMLI, 2017; TAO *et al.,* 2019; BUENO *et al.,* 2020). Advanced applications of the Industry 4.0 domain comprehend the creation of cyber-physical systems by combining *Virtual Manufacturing* with *Vertical Integration*, which allows simulating changes in real-time based on the information collected from the integrated systems from vertical integration (DALENOGARE *et al.,* 2018). Consequently, the findings show that *Virtual Manufacturing* is not mainly adopted when companies aim for productivity as a production target but when they look for flexibility. The literature has usually included *Virtual Manufacturing* as a contribution to productivity (AUTOR *et al.,*2020; BUCHI *et al.,* 2020), but this is because such studies have not addressed trade-offs between targets as different main options that decision-makers can take when adopting Industry 4.0.

The results also show that, while there are two specific-purpose technologies for the competing targets, there is also a technology arrangement that should be considered *integrative-purpose* because it is adopted for the two competing targets (productivity vs. flexibility). This is the case with *Advanced Manufacturing Processing Technologies*. This arrangement allows reconciling two trade-offs. Thus, it is useful to balance manufacturing flexibility and productivity, i.e., contribute to the cumulative production targets view of Ferdows and Meyer (1990). From a practical perspective, this means that EFA results pointed out that robots, collaborative robots, and 3D printing are more prone to be implemented by the same type of companies and that such companies are pursuing both competing production targets together. In this sense, the literature has acknowledged that 3D printing is still limited for high productivity, but it contributes to high flexibility (MELLOR *et al.*, 2013; NIAKI; NONINO, 2016) and that robots may sometimes be too 'rigid' for flexible operations, but help for productivity (AUTOR *et al.*, 2020). Nevertheless, manufacturing processes using a technology arrangement that combines these characteristics can help achieve an integrative purpose of such targets. For example, the literature has reported factories with high join adoption of different advanced hardware for Industry 4.0, including robots, collaborative robots, and additive manufacturing (3D printing). Such factories would be those pursuing a better balance for a cumulative perspective of production targets (SZÁSZ *et al.*, 2020).

Organizing the Industry 4.0 technology arrangements in a decision model towards different production targets aimed

Considering the discussions on the conceptual framework of Figure 2, the last step to understanding the Industry 4.0 technology arrangements obtained is organizing the different technologies into a decision path that connects such technologies with the production targets they can contribute to. This is represented in the decision model in Figure 3. The model describes three main decision paths based on the production target aimed. In the horizontal axis, the implementation steps *between* the different technology arrangements are represented. In the vertical axis, the implementation steps *within each* technology arrangement are represented. Next, the rationale behind these steps is explained.

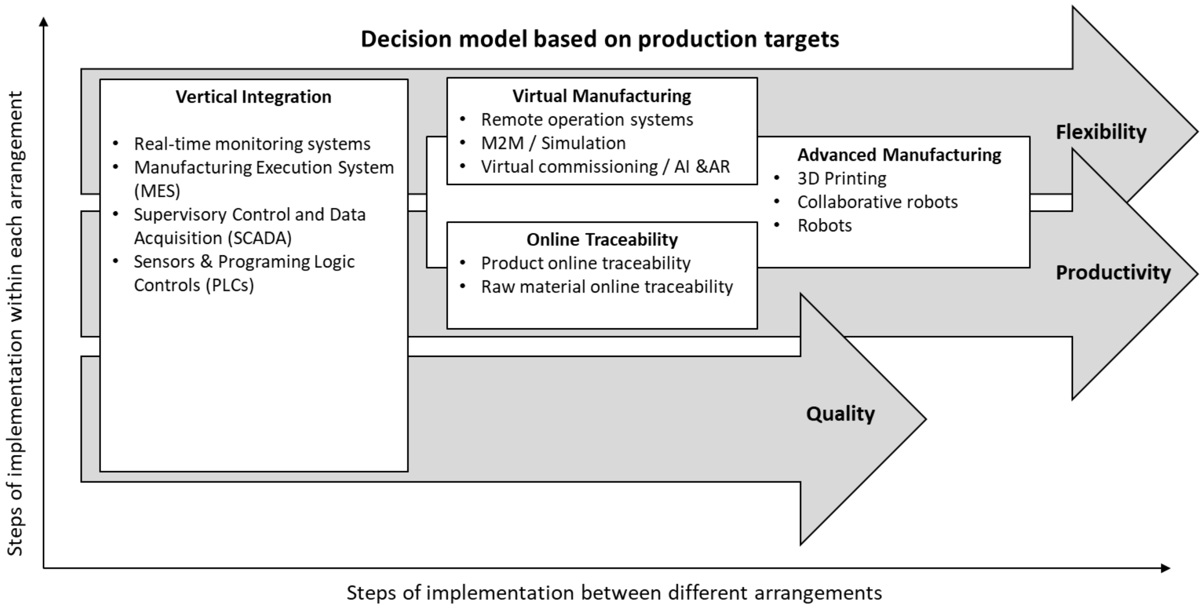

Figure 3. Decision model to implement Industry 4.0 technologies according to the expected production targets

First, the model (Figure 3) shows that companies could start with *Vertical Integration*, as usually considered in the maturity models. This start points out visibility and transparency (i.e., characteristics of vertical integration) as the first aims (SCHUMACHER *et al.*, 2016; MITTAL *et al.*, 2018; SANTOS; MARTINHO, 2019) since this is a general-purpose technology arrangement useful to any target. Considering previous studies on *Vertical Integration* (e.g., DALENOGARE *et al.*, 2018; TABIM *et al.*, 2021), it is well established that such implementation should start with the usage of sensors and PLCs at the manufacturing stations. This will be followed by adopting a SCADA to integrate the data and then adopting an MES that allows organizing the activities based on the information flow from the manufacturing stations (TABIM *et al.*, 2021). Finally, this will enable achieving a real-time monitoring system that can provide scheduling, i.e., an advanced planning and scheduling (APS) based on (quasi)real-time operations (BUENO *et al.*, 2020).

As discussed in the previous subsection, the next step will depend on the specific target pursued. Therefore, different paths will be followed depending on each company's needs (Figure 3). The decision model shows that there are no necessary further technology arrangements for the Quality target to be adopted. Quality can be controlled through data acquisition and monitoring, which is already comprised in *Vertical Integration*. Still, other technologies can serve specific quality purposes, such as using collaborative robots to execute quality measures (DORNELLES *et al.*, 2021). In this sense, the model only describes the main functions to which such technologies can contribute. On the other hand, for *Productivity* and *Flexibility* targets, further steps of implementation must be considered. Therefore, Quality is represented as a primary target with a shorter process of implementation that will create the base for the other two targets, as represented in Figure 3 with the shorter arrow in the horizontal axis.

The model of Figure 3 shows that when *Productivity* is the target, *Online Traceability should be the next step of implementation,* following Vertical Integration. This is because it requires data acquisition from sensors and data distribution from information systems provided by the technologies involved in the first step (ENRIQUE *et al.*, 2022). Regarding the steps within *Online Traceability,* the model emphasizes that raw material traceability would be the first necessary step to be monitored to increase shop floor productivity, followed by the finished products that will be sent to the inventories. Besides, *Advanced Manufacturing* can be implemented concurrently with *Online Traceability,* but the model highlights that these are more complex technologies that will require greater changes and adaptations of the manufacturing production line, being, therefore, one of the last steps of implementation, as previously demonstrated by Dalenogare et al. (2018) and Frank et al. (2019). A similar sequence of steps is proposed when companies aim *for Flexibility* (Figure 3). In such a case, *Vertical Integration* is followed by *Virtual Manufacturing* because the virtualization of the manufacturing (e.g., virtual commissioning, simulation, etc.) requires first visibility and transparency of the process through the integration of systems (SCHUH *et al.,* 2020). Again, Advances in Manufacturing can be implemented concurrently. Still, the benefits should be better when there is a virtualization of the factory that allows simulation and organization of the way robots and 3D printers will operate (ENRIQUE *et al.,* 2022). Thus, as previously discussed, *Advanced Manufacturing* technologies can be used either for Productivity, Flexibility, or even for both combined. This will depend on how such technologies are configurated, which demands higher complexity of the implementation (FRANK *et al.,* 2019; DALENOGARE *et al.,* 2018).

2.6 CONCLUSIONS

This study investigated the relationship between Industry 4.0 technology adoption and production targets. The study surveyed 92 manufacturers and analysed which Industry 4.0 technologies they adopted when pursuing three different targets: productivity, manufacturing flexibility, and process quality. It was shown that manufacturers tend to adopt 18 technologies analysed in four different arrangements represented by technology clusters: Vertical

Integration, Virtual Manufacturing, Advanced Manufacturing Processing Technologies, and Online Traceability.

Theoretical contribution

Industry 4.0 has been presented as a concept that should be implemented to achieve several performance metrics such as productivity, quality, and flexibility (see Appendix A). This present study shows that the concept needs to consider different technology arrangements according to the different production targets that are aimed to achieve. This study opens a new perspective for Industry 4.0 theory by showing the interconnection between specific targets and technologies. Firstly, scholars should study the variety of Industry 4.0 technology roadmaps that can be implemented based on specific production targets. The message of the findings is that Industry 4.0 technologies should be configurated according to the production targets pursued by the companies. Therefore, generic models can fail when they do not consider the variety of production targets pursued. Secondly, this study showed that production targets could compete or be complementary. Therefore, Industry 4.0 arrangements can also be combined and configurated to different multi-target approaches. A third theoretical contribution of this study is that it provides evidence of how each technology arrangement is associated with the pursued production targets. In this sense, Vertical Integration acts as a *general-purpose* technology arrangement for companies to implement any of the production targets investigated. On the other hand, *Virtual Manufacturing* and *Online Traceability* are *specific-purpose* technology arrangements adopted when companies aim for flexibility or productivity. *Advanced Manufacturing Processing Technologies* (robots, cobots, and 3D printing) are useful as *an integrative-purpose* technology arrangement since they are adopted for two competing targets, either for *manufacturing flexibility* or *productivity*. Such understanding is important for the advance of theory. For instance, flexible operations have become the main requisite in companies due to the pandemic impacts (LIU *et al.*, 2021). In such a case, the present findings enlighten which technologies are seen as more promising in Industry 4.0 adoption to achieve such flexible operations. Scholars can find in these results a starting point for investigation of the detailed implementation of such technologies to attend the pursued production targets.

Practical implications

The decision model proposed (Figure 3) helps operations and technology managers to understand which technology arrangement they should choose based on the production target pursued. The main message to practitioners is that they need to consider the production targets they aim with the implementation of Industry 4.0 technologies because this will guide the adoption of different types of technology arrangements. Practitioners need to question such targets to look at the broad picture of Industry 4.0 technologies before adopting specific technologies. Then, technologies can be grouped around targets, as shown in the conceptual framework that summarizes the findings (Figure 2). From a practical perspective, the study shows what technologies are more prone to be implemented together and to attend to the specific target expected. This can provide insights for managers that aim to develop their Industry 4.0 journey of their factories.

Limitations and future research

The research method presented some limitations that should be considered for the reading of the obtained findings. Firstly, this study analysed a single industry sector with particularities. This sector is mainly focused on lower volumes and high added value. However, the study lacks an analysis of manufacturing sectors with large economies of scale, such as the automotive or fashion industries. In such sectors, the considered technologies can present other behaviour than those considered here.

Second, the study only considered what we call the first generation of technologies in the Industry 4.0 domain, which are focused on obtaining a smart and interconnected factory. Recent literature has emphasized the social aspects of the factory, showing that workers should be better integrated and enhanced by the Industry 4.0 technologies (MARCON *et al.,* 2021; MEINDL *et al.,* 2021). In this vein, Dornelles et al. (2022) showed that AI and AR technologies should also be applied to workers' manufacturing activities like assembly or processing, which were not included in our study. As Industry 4.0 technologies and their focus are constantly evolving in this emerging field, future studies should address other new technologies in this field.

A third aspect is that the study only considers independent samples t-tests, presenting limitations for deeper conclusions. Larger samples would allow other multivariate techniques such as regression models that would help obtain explanatory power on the targets pursued when different technologies are adopted. The used method helps to detect differences between groups but not to know how much each target explains the technologies adopted. Future studies could advance in such a direction.

Regarding future opportunities for research, this study discussed the relationship between technology and production targets, which allows understanding why companies implement some specific types of Industry 4.0 technologies. However, this study did not consider performance metrics from such technology adoption. Future studies can advance in this direction by applying regression models to analyse how the combination of such arrangements may increase the different production targets. To this aim, future research should ideally consider longitudinal data to verify effects during a longer period since technology adoption can require time to become effective. Moreover, the study did not consider the necessary investments for the different technology arrangements analysed. Prior research has considered technology investment frameworks (e.g., FRANK *et al.*, 2013; ALMEIDA *et al.*, 2022). Such studies could be adapted to investigate how companies prioritize their investments in the set of technologies that comprise each technology arrangement. For instance, adopting Advanced Manufacturing Processing Technologies to integrate flexibility with productivity requires investments in robots, cobots, and 3D printing. Thus, a financial appraisal is necessary to ensure that such investments are feasible. Besides, technology adoption is a complex process that depends of a large number of contingency factors such as company size, demand characteristics, corporate strategy, among others (MARCON *et al.*, 2021; ENRIQUE *et al.*, 2022) that must be analyzed in future studies.

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APPENDIX A – LITERATURE REVIEW

Authors	**Aim**	**Method**	**Industry 4.0 implementation**	**Operational Target/ Performance**
Fatorachian and Kazemi	This study investigated the academic research and industrial reports in the industry 4.0 area and smart Manufacturing to	Literature Review	-Industrial Internet -Internet of Things -Cyber-physical-Sytems -Information Network -Software Sytems -Cloud Computing	**Drivers and benefits of industry 4.0** -Meeting individual customer demands

	provide insights on the execution of Industry 4,0			-Flexible and agile engineering and Manufacturing -Improved information sharing and decision-making -Improved integration and collaboration -Improved Resource Productivity -Mass customization
Dalenogare et al., 2018	This study analysed the potential benefits for product development, operations, and side-effects aspects of the Brazilian industry when implementing the Industry 4.0 related technologies.	OLS regression Sample Size: Aggregated data from 2225 companies	The authors used single variables to measured Industry 4.0 implementation: -Computer-Aided Design integrated with Computer-Aided Manufacturing -Integrated engineering systems -Digital automation with sensors -Flexible manufacturing lines -MES and SCADA systems -Big data -Digital Product-Services -Additive manufacturing -Cloud services	**Expected benefits:** **Product:** Improvement of product customization, Improvement of product quality, Reduction of product launch time **Operational:** Reduction of operational costs, Increase productivity, Increase processes visualization, and control **Side-Effects:** Improving sustainability (externalities), Reduce of labor claims (worker satisfaction)
Tortorella et al., 2019	This study aimed to examine the moderating role of Industry 4.0 technologies on the relationship between lean production (LP) and operational performance improvement within Brazil, a developing economy context.	OLS regression-(Moderation test) Sample Size: 147	Industry 4.0 was measured using two Constructs: **Process-related:** Digital automation without sensors, Digital automation with process control sensors, Remote monitoring, flexible lines **Product/Service-related:** Integrated engineering systems for product development, 3D printing	**Performance construct:** -Productivity, -Delivery service level, -Inventory level, -Quality (scrap and rework) and -Safety (accidents).
Szász, et al., 2020	This study investigated the performance impact of implementing Industry 4.0 and how important contingency factors (plant size, multinational status, country context) affect	Structural equation modeling Sample Size: 705	The Industry 4.0 implementation construct was developed using three individual items: -Use of advanced processes - Development of “the factory of the future” - Engaging in process automation programs	Four constructs measured operational Performance. **Quality:** Conformance quality, Product quality and reliability **Flexibility:** Volume flexibility, Mix flexibility

	implementation efforts.			**Delivery:** Delivery speed, Delivery reliability **Cost:** Manufacturing cost, Ordering costs, Manufacturing lead time
Tortorella et al., 2020	This study aimed to understand the effect of the interaction between Healthcare 4.0 technologies and barriers on hospitals' Performance?	One-Way - ANOVA Sample Size: 181	Two constructs measured industry 4.0 implementation: **Sensing Communication:** Biomedical/digital sensors, IoT, Big data, Cloud computing, Remote control or monitoring **Processing–Actuation:** 3D printing, Collaborative robots, Machine/deep learning, Augmented reality/simulation	**Performance Construct:** Cost, Productivity, Quality, Patient satisfaction, Patient safety
Büchi et al., 2020	This study analysed the causal relationship between this degree of openness to Industry 4.0 and Performance.	OLS-Regression Sample Size: 231	The degree of openness to Industry 4.0 was investigated using two indicators: breadth, the number of technologies used, and depth, or the number of value chain stages involved. **The breadth of Industry 4.0**: This indicator was measured by the sums of 10 Industry 4.0 enabling technologies. Each technology is a dummy variable, coded as zero to indicate these were not implemented, while one indicates these were implemented. **Depth of industry 4.0:** Is a single indicator measured by the sum of the frequency of use in the value chain of 10 Industry 4.0 technologies.	**Perceived opportunities:** It was measured by a single indicator obtained through the sums up the six opportunity variables, each of which is a dummy variable coded as zero and one to indicate no opportunities and perceived opportunities, respectively: -Less time from prototype to production, -Greater productivity through shorter set-up times, -Reduction of errors and machine downtimes, -Better quality and less waste, -Greater product competitiveness due to greater product functionality.
Chauhan et al., 2020	This study analysed how the intrinsic and extrinsic barriers to digitalization affect Industry 4.0 adoption by the firms. The paper also evaluates how these barriers influence the linkage	Structural Equation Modeling Sample Size: 143	Industry 4.0 Adoption Construct: -Digital automation but no sensors -Sensors in place for process control -Remote monitoring with production control -Sensors for identification of operating conditions, products, and flexible production lines	**Operational Performance:** -Decrease in operating costs, -Decrease in time required for creating and delivery of new products,

	between digitalization and the firm's Performance regarding its supply chain competency and operational Performance.		-Integrated engineering systems for development and production -Additive manufacturing and rapid-prototyping -Designing and commissioning by simulations and analysis of virtual models -Gathering and analysing huge datasets (big data) -Linking product to cloud and using cloud services -Incorporating digital services such as IoT in products	-Successful launches of new products, -Improvement in the quality of products, -Rise in product innovativeness Improvement in product capability and Performance
Stentoft et al., 2020	This study aimed to investigate the drivers and barriers for Industry 4.0 readiness and practice among Danish small and medium-sized manufacturers.	A mixed-method approach that combines elements of quantitative and qualitative research approaches Quantitative Approach: Mediation test Sample Size: 308	Industry 4.0 implementation was measured using 12 technologies grouped into five sub-categories: (1) Data, computational power, and connectivity (Big Data and Analytics, IoT, Cloud Computing, Horizontal and Vertical System Integration, Mobile Technologies and RFID and RTLS systems); (2) Analytics and intelligence (Artificial Intelligence and Simulation); (3) Human-machine interaction (Augmented Reality); (4) Digital-to-physical conversion (Autonomous Robots and Additive Manufacturing) and (5) Cybersecurity (Cybersecurity).	Performance variables as drivers for Industry 4.0: -To meet the Customer requirements -To reduce costs -To improve time-to-market
Lia et al., 2020	How digital technologies influence economic and environmental Performance in the new era of Industry 4.0.	OLS regression-(Mediation test) Sample Size: 188	**Digital technologies Construct:** -Cloud computing, -Big data, -Analytics, -Internet of Things	**Economic Performance Construct:** Growth in return on sales, Growth in profit Growth in return on investment, Growth in sales, Growth in market share **Environmental performance Construct:** Reduction of air emission, Reduction of wastewater, Reduction of solid wastes, Improvement of the firm's environmental situation
Gillani et al., 2020	This paper studied the role played by technological context, organizational context, and environmental	Structural equation modelling Sample Sizes: 931	**DMT construct:** -Use of advanced processes, such as laser and water cutting, 3D printing, high precision technologies	**Operational Performance Construct:**

	context of firms in the implementation of the digital manufacturing technologies (DMT)		-Development towards "the factory of the future" (e.g., smart/digital factory, adaptive manufacturing systems, scalable Manufacturing) -Engaging in process automation programs (e.g., automated machine tools and handling/transportation equipment, robots) -Engaging in product/part tracking and tracing programs (bar codes, RFID)	**Flexibility:** Mix Flexibility, Volume Flexibility **Delivery:** Delivery Speed Delivery Reliability **Design:** New Product Introduction Ability Product Customization Ability **Quality:** Product Quality, Conformance Quality
Cugno et al., 2021	This paper explores the impact of barriers and incentives on the relationship between openness to Industry 4.0 and Performance.	Mixed-Method: Qualitative and quantitative approach Quantitative Approach: OLS regression Sample Size: 500	The breadth of Industry 4.0: This indicator was measured by the sums of 10 Industry 4.0 enabling technologies. Each technology is a dummy variable, coded as zero to indicate these were not implemented, while one indicates these were implemented.	The performance variable is a single indicator measured by the sum of seven variables, where each is a dummy variable coded as 1 to indicate perceived opportunities. -Production Flexibility, -Speed of serial prototypes, -Greater output capacity, -Reduced set-up costs, -Fewer errors and shorter machine downtimes, -Higher product quality and fewer rejected products, -Customers' improved opinion of products, -Improved productivity of human resources

APPENDIX B - QUESTIONNAIRE

1. Indicate which of the following production targets your company want to achieve with the adopted Industry 4.0 technologies:
    - Productivity
    - Process quality
    - Manufacturing flexibility
2. Indicate the degree of implementation of the following technologies from Industry 4.0 in your company. Likert scale varying from 1-Not implemented to 5-Advanced Implementation

- Process control (PLCs and sensors)
- Supervisory Control and Data Acquisition (SCADA) systems
- Manufacturing Execution Systems (MES)
- Real-time monitoring tools
- Virtual commissioning tools
- Machine-to-Machine (M2M) communication systems
- Artificial Intelligence tools for maintenance
- Artificial Intelligence tools for Production Planning and Control
- Process simulation tools
- Automated failure detection systems
- Remote operation systems
- Augmented Reality tools for maintenance
- Augmented Reality tools for workers training
- Raw material online traceability in the shop floor
- Product online traceability in the shop floor
- Robots for processing activities
- Collaborative robots
- 3D printing (additive manufacturing)

3. INDUSTRY 4.0 ENABLING MANUFACTURING FLEXIBILITY: TECHNOLOGY CONTRIBUTIONS TO INDIVIDUAL RESOURCE AND SHOP FLOOR FLEXIBILITY

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This paper focuses on understanding the contribution of Industry 4.0 technologies to manufacturing flexibility. A multiple-case study was conducted through interviews and complementary data from 12 adopters of Industry 4.0 technologies from the industrial sector. To enable a broad perspective, cases from 5 industry sectors with different technological intensity levels were studied. The findings show that Industry 4.0 technologies are mostly used to improve machine flexibility since there is a major focus on technological approaches rather than on wider flexibility. The results also showed that cloud services, IoT, and data analytics provide the basis for flexible operation, and collaborative robots, ERP/MES/PLM, AGVs, and traceability devices are the most commonly implemented technologies for flexibility. However, inherent contingency factors such as production complexity and product life cycle need to be considered. This article expands the research on manufacturing flexibility, considering new capabilities introduced by Industry 4.0.

Key Words: Digital Technologies, Industry 4.0, Manufacturing Flexibility, Production Flexibility; Smart Manufacturing

3.1 INTRODUCTION

Industry 4.0 has been leveraged by the exponential growth of digital technologies based on the industrial internet of things (IIoT) and other emerging technologies that constitute cyber-physical systems (CPS) (MEINDL *et al.*, 2021; DALENOGARE *et al.*, 2018). These technologies enable manufacturing systems to monitor physical processes and make smart decisions through real-time communication and cooperation with humans, machines, and sensors (ZHONG *et al.*, 2017). They also help to offer more customized products through an advanced and intelligent system, capable of adapting shop floor operations for fluctuating demands, producing a different mix of products, and responding to unexpected events (LU; WENG, 2018). This often implies a need for more flexible production lines, capable of adapting to changes in demand and customer specifications (i.e., customization and change of production mix) without compromising productivity (BRETTEL *et al.*, 2016). However, even though manufacturing flexibility is considered one of the pillars of the Industry 4.0 concept (BRETTEL *et al.*, 2016; LONG *et al.*, 2017), the empirical results of Dalenogare *et al.* (2018), at the industry level, and (FRANK *et al.,* 2019b), at the firm level, have shown that companies struggle to set up a flexible production system when implementing Industry 4.0 technologies.

Although flexibility has been widely recognized as a vital competitive priority in manufacturing strategy, even before the Industry 4.0 concept was coined, the meaning and actual implementation of flexibility remain diffuse, especially when the Industry 4.0 context is considered (LONG *et al.,* 2017; PÉREZ-PÉREZ *et al.,* 2018). As compared to traditional technologies, Industry 4.0 brings new reconfiguration features, providing new possibilities for more flexible manufacturing. Therefore, exploratory studies are needed to better understand how companies can take advantage of Industry 4.0 technologies, as well as the best ways of implementing and managing these technologies according to their needs (DALENOGARE *et al.*, 2018). Additionally, internal and external contingency factors such as product type, size, variety, production volume, product complexity, local legislation, and union demands can impact how technologies may drive performance and flexibility within a company (LUCIANETTI *et al.,* 2018; MARCON *et al.,* 2021). Thus, the contingency view considers the impact of such inherent factors on how the company's strategy is implemented. It states that there is no better way to organize and manage an organization because strategy depends on contingency factors (DONALDSON, 2001). This is also expected for flexibility strategies; thus, this article also considers these factors in the analysis due to the need to understand their relationship with technological and non-technological resources to achieve flexibility (PEREZ *et al.,* 2018).

In this sense, some studies have focused on implementing Industry 4.0 technologies as a strategy to increase flexibility (BRETTEL *et al.,* 2016; EYER *et al.,* 2018). Nevertheless, these are not in-depth studies, nor do they focus on specific dimensions of flexibility. Thus, this study addresses the following research question: *How do Industry 4.0 technologies enable internal flexibility in manufacturing firms?* Aiming to answer the research question, this article employs multiple-case studies with twelve technology adopters of these technologies. Different concepts of manufacturing flexibility are considered through the analyses of the two main levels of internal flexibility, namely individual resource, and shop floor flexibility.

3.2 THEORETICAL BACKGROUND

3.2.1 Manufacturing Flexibility – conceptualization and types

The concept of flexibility has been traditionally seen as the organizational capability to adapt to changing circumstances or instability in the environment (EYERS *et al.*, 2018; MISHRA, 2020). This capability focuses on reconfiguring manufacturing resources and processes using minimum time, effort, and resources (URTASUN-ALONSO *et al.*, 2014). In general, manufacturing flexibility is considered a complex, multidimensional concept that is difficult to synthesize (SETHI; SETHI, 1990) because it can exist in several different forms in a manufacturing firm (KOSTE; MALHOTRA, 1999).

The various concepts describing flexible manufacturing result in overlaps, duplications, and, sometimes, contradictions between studies (EYERS *et al.*, 2018; PÉREZ-PÉREZ *et al.*, 2018). Nevertheless, several authors have tried to reach a consensus on some classifications for flexibility (e.g., SETHI; SETHI, 1990; JAIN *et al.*, 2013), which are generally classified from two different perspectives: strategic and hierarchical (PEREZ-PEREZ *et al.*, 2016). The strategic perspective refers to the relationship between company and environment, and how customers perceive its capabilities. It classifies flexibility into two types, *internal* and *external*. In general, internal flexibility is understood as the competences of the production system to deal with resources and production management uncertainties (MENDES; MACHADO, 2015; EYER *et al.*, 2018). On the other hand, external flexibility is related to customers' perception of a company and comprises market uncertainties and external aspects that directly affect the company's strategic positioning (SUAREZ *et al.*, 1996; MENDES; MACHADO, 2015). From this point of view, this article focuses on *internal flexibility* since it addresses technology adoption and the competences of the manufacturing line and their impacts on the shop floor level. In contrast, external flexibility addresses the capabilities that are achieved due to internal flexibility (EYERS *et al.*, 2018). Proposed by Koste and Malhotra (1999), the *hierarchical perspective* states that flexibility is composed of layers, hierarchically organized from the most basic *individual resource* and *shop floor levels* up to the highest flexibility levels, such as *plant flexibility*. This perspective implies a necessary “flexibility path”, organized from individual resources up to a broad, business unit flexibility. Since the focus is on internal flexibility from the strategic perspective, this article considers only the individual resource and shop floor flexibility levels in the hierarchical perspective. We use these two dimensions, strategic and hierarchical, to summarize the most relevant flexibility types cited in the literature and discussed next, as shown in Table I.

Table 6. Manufacturing Flexibility types

Strategic Dimensions	Hierarchical Dimensions	Flexibility Type
Internal Flexibility	Individual Resource Level	Machine Flexibility
		Material Handling Flexibility
		Labor Flexibility
	Shop Floor Level	Operation Flexibility
		Routing Flexibility
External Flexibility	Plant Level	Process Flexibility
		Product Flexibility
		Volume Flexibility
		Expansion Flexibility

(i) Machine Flexibility refers to a machine's capability to execute various operations without incurring high effort from one operation to another or great changes in performance outcomes to produce a given set of parts (KOSTE; MALHOTRA, 1999). This type of flexibility depends on the existing hardware in the manufacturing line, and it is measured by the number of operations that a workstation performs and the changeover time needed to switch from one operation to another (JAIN *et al.*, 2013).

(ii) Material Handling Flexibility is the capability of moving different materials effectively through the manufacturing facility, including the loading and unloading of parts, inter-machine transport, and storage of parts under various conditions in the manufacturing facility (SETHI; SETHI, 1990; EYERS *et al.*, 2018; PÉREZ-PÉREZ *et al.*, 2018). Material Handling flexibility also includes the number of possible routes within the factory to transport the parts (EL MARAGHY, 2006).

(iii) Labor flexibility is related to the number and heterogeneity of the tasks that workers can perform (KOSTE; MALHOTRA, 1999). According to Tsourveloudis and Phillis (1998), two variables influence labor flexibility: level of training, in which flexibility can be achieved through education and cross-training programs, and job rotation.

(iv) Routing Flexibility is an inherent property of the manufacturing system to produce products through alternative routes without incurring high transition penalties or expressive changes in performance outcomes (KOSTE; MALHOTRA, 1999; PÉREZ-PÉREZ *et al.*, 2018). The number of potential routes and the backup machinery during breakdowns determines this type of flexibility (TSOURVELOUDIS; PHILLIS, 1998).

(v) Operation Flexibility is related to the number of potential production plans for the same product (KOSTE; MALHOTRA, 1999; EL MARAGHY, 2006). It means that a part can be produced using alternative process plans, i.e., different sequences of operations to produce the same part. An alternative process plan may be obtained by exchanging or replacing certain operations with others (SETHI; SETHI, 1990).

3.2.2 The link between Industry 4.0 and flexible production systems

In general, prior studies have proposed production technologies as the driving factor to achieve manufacturing flexibility (URTASUN-ALONSO *et al.*, 2014; PÉREZ-PÉREZ *et al.*, 2018). Although the literature relating production technologies to manufacturing flexibility concepts is large, the emerging concept of Industry 4.0 has intensified the discussion on how to achieve manufacturing flexibility when this set of emerging digital technologies is considered (DALENOGARE *et al.*, 2018; FRANK *et al.*, 2019). Industry 4.0 is related in many studies with manufacturing technologies that are autonomous, capable of self-controlling and self-configuring in response to different situations, sensor-equipped and spatially dispersed, and that also incorporate the relevant planning and management systems to enhance production based on data analytics (LU; WENG, 2018).

Industry 4.0 considers three main principles that should contribute by implementing digital technologies to flexible production systems. First, vertical integration considers the integration of the different information layers of the shopfloor and corporate environments, allowing real-time decision making (TABIM *et al.*, 2021). In this environment, technologies should help connect and integrate machines, materials, production planning and control activities (BUENO *et al.*, 2020). Second, horizontal integration refers to the capability of cooperating with other entities, companies, suppliers, and customers, creating an ecosystem through the use of digital technologies (DOS SANTOS *et al.*, 2021; BENITEZ *et al.*, 2020). Technologies for integration with external actors should provide more flexibility regarding the plant and supply chain activities (BENITEZ *et al.*, 2021). Third, end-to-end engineering integration is associated with all activities that add value to a product during the development phase, integrating different functional activities of the company related to the manufacturing system (WANG *et al.*, 2016a). Industry 4.0 technologies should allow for on-time verification and quick incorporation of design decisions into engineering and production processes through end-to-end transparency and visibility of required design elements (DALENOGARE *et al.,* 2018).

These three principles provide capabilities that can enhance integration and collaboration between different businesses and manufacturing processes and improve responsiveness and decision-making. Moreover, according to several authors, operators are the most flexible component of a manufacturing system (EL MARAGHY, 2006; MENDES; MACHADO, 2015; DORNELLES *et al.,* 2021). In this sense, different Industry 4.0 technologies can support the work of operators (smart working) (FLORES *et al.,* 2020). Dornelles et al. (2021) conducted a comprehensive analysis on Industry 4.0 technologies and showed how 18 different technologies could provide workers with enhanced capabilities to make their tasks more productive and flexible.

3.3 RESEARCH METHOD

A multiple-case study approach based on collecting and analyzing qualitative data from manufacturing companies utilizing Industry 4.0 technologies was adopted. This research approach is useful for building theories based on deep field analysis when researchers need to understand how a specific phenomenon happens (YIN, 2009). The guideline proposed by Voss et al. (2002) was employed, which is divided into the following main steps discussed next.

3.3.1 Research Design

The research was designed following the categories of analysis presented in Table I and described in detail in Section 2.1. Manufacturing contingency factors and other challenging factors that may affect the contribution of Industry 4.0 technologies to the flexibility concepts studied were considered. According to Perez et al., 2018, studies that analyze the relationship between contextual variables and technological and non-technological resources are necessary to achieve flexibility. Therefore, this aspect was also considered in this article since some recent studies on the adoption of advanced manufacturing tools have demonstrated the impact of contingency factors on the adoption of advanced technologies and their impact on performance (MARCON *et al.,* 2021). Thus, this broad approach allowed for consideration of the complex and broad impacts that Industry 4.0 technologies may have on flexibility.

3.3.2 Research sampling

Considering that flexibility could vary by uncertain factors (YU *et al.*, 2015), a multiple-case study approach was followed to understand different manufacturing firm contexts and the factors that lead them to invest in different flexibility strategies. Using a multiple-case approach allowed to increase external validity and reduce bias from potential observers (VOSS *et al.*, 2002). For sample selection, leading companies in the implementation of Industry 4.0 concepts were chosen. To that end, the researchers asked representatives of the Brazilian Federation of Industries to list such companies and their respective contacts. These industry representatives work in the Brazilian Chamber of Industry 4.0 and follow most of the initiatives for Industry 4.0 technology adoption in companies. From an initial list of 60 companies, researchers refined the selection to those aiming at manufacturing flexibility as one of their operational targets, which resulted in a final sample of 12 companies. These procedures are aligned with those suggested when a theoretical sample is selected (YIN, 2009). The companies studied were all large companies. Table II presents more details about the cases. A sample of companies from different sectors was selected in order to enable a broader view of manufacturing. Relevant features such as market characteristics and production system are also presented to better characterize the companies. As shown in this table, the cases present a maximum variance approach, which means that the study aims to investigate differences in the selected cases.

Table 7. Case study description

Description	Sector/ Market	Data Source
1. American vehicle manufacturer, and provider of financial services	Automotive/ Multinational	Engineering Manager
2. American company that manufactures automotive seating and automotive electrical systems	Automotive/ Multinational	Process Engineer
3. German company in automotive technology, steel and tube production, and engineering	Automotive/ Multinational	Plant Operation Manager
4.Swedish manufacturer of commercial vehicles (heavy lorries and buses)	Automotive/ Multinational	Executive Manager
5. Swiss food and drink processing conglomerate	Foods/ Multinational	Continuous Improvement Coordinator
6. Brewing company	Foods/ Multinational	Industrial Manager
7. Manufacturer and marketer of home appliances	Electric Machinery/ Multinational	Process Engineer

8. Technology company that sells personal computers, tablet, smartphones, servers, and storage devices	Electric Machinery/ Multinational	Engineering Manager
9. German manufacturer of chainsaws, trimmers, blowers and other handheld equipment	Metal-Mechanical/ Multinational	Vice President of Operations
10. Brazilian conglomerate in the transport solutionssector	Metal-Mechanical/ National	Process Engineer
11. Brazilian textile company of adult’s clothing	Textile/ National	Industrial Manager
12. Brazilian textile company of children's clothing	Textile/ National	Continuous Improvement Coordinator

Table 8. Manufacturing characteristics of the selected cases

Case	Production Characteristics	Industry 4.0 Technologies	Flexibility dimensions
1	Volume: High Product mix: Medium New Products: Low	Robots and AGVs Vertical Integration (sensors, MES System, ERP System) Traceability Technologies (RFID) Simulation Technologies	Machine Flexibility Routing Flexibility Material Flexibility
2	Volume: Low Production mix: Low New Product: Low	Virtual Guide Systems Virtual Training Room	Labor Flexibility
3	Volume: Low Production mix: Low New Product: Low	Augmented Reality Traceability technologies (RFID) to guide workers	Labor Flexibility
4	Volume: High Production mix: High New Product: Low	Vertical Integration Autonomous Robots Machine learning, IoT, and sensors	Machine Flexibility
5	Volume: High Production mix: Medium New Product: Medium	Collaboratives Robots and AGVs Vertical Integration Drones for smart logistic	Machine Flexibility Material Flexibility
6	Volume: High Production mix: Low New Product: Low	Vertical Integration for machine connection and flexibility Mobile application to guide workers for task variation	Machine Flexibility Labor Flexibility
7	Volume: High Production mix: High New Product: Medium	Robots, Collaborative Robots and AGVs Vertical Integration Cloud Computing	Machine Flexibility Material Flexibility Routing Flexibility
8	Volume: Low Production mix: High	Robots and AGVs Vertical Integration	Machine Flexibility Material Flexibility

	New Product: Medium		Labor Flexibility
9	Volume: High Production mix: Low New Product: Low	Virtual Reality Robot Vertical Integration	Machine Flexibility Labor Flexibility Material Flexibility
10	Volume: Low Production mix: Low New Product: Low	Vertical Integration Cloud Computing	Machine Flexibility Routing Flexibility
11	Volume: High Production mix: High New Product: High	Machine to Machine Vertical Integration PLM	Machine flexibility
12	Volume: High Production mix: High New Product: High	Augmented Reality Cloud Computing, Vertical Integration and PLM AIV 3D Printing	Labor Flexibility Material Flexibility

3.3.4 Data collection

An interview guideline was developed based on the manufacturing flexibility and Industry 4.0 literature (see **Appendix A**). The instrument was composed of open questions addressing the types of internal flexibility cited in the literature and the Industry 4.0 technologies defined by Frank et al. (2019). The instrument was designed to explore the organizational context, technology adoption criteria, flexibility results, manufacturing strategies, successful actions to enhance flexibility and identify adoption problems. Data collection was then performed by semi-structured interviews with the participation of two researchers. Interviews were conducted by videoconference, and the average time of each meeting was 45 minutes.

3.3.5 Data Analysis – Validity, Reliability and Interpretation

To ensure reliability and construct validity, multiple sources of evidence were consulted as secondary data (VOSS *et al.,* 2002). Thus, chains of evidence from data provided in the interviews were established with other means. Results were validated by a fellow researcher who did not participate in the interviews to avoid bias and misinterpretations and were presented in a research seminar with other researchers from the operations management and Industry 4.0 field, which allowed to validate the coherence of results according to an external perspective. Reliability was also ensured by a study protocol validated in a meeting with other researchers and tested before case collection (see Appendix A) (YIN, 2009).

For data organization, first, the theoretical basis for the categories was chosen, which served as input for coding. Second, coding rules were defined for each category. In this stage, it was defined that information on Industry 4.0 technologies should be grouped according to the types of flexibility achieved. After these definition phases, data was compiled and organized in the relevant categories. Finally, the blocks of information regarding each type of flexibility, the technologies related to them, the company's contingency factors, and challenges for implementation were analyzed. Then, the categories and codes to ensure data reliability and validity were reviewed, as the constructs needed to be different from each other (VOSS *et al.*, 2002).

3.4 RESULTS

3.4.1 Industry 4.0 enabling Individual Resource Flexibility

Machine Flexibility

The results show that the implementation of Industry 4.0 technologies related to machine flexibility has the main objective to reduce setup times and enable the manufacturing of a greater variety of products. Companies with high production volumes and a smaller variety and variability of products, such as Company 1, tend to see robots as an important strategy because they allow for greater repeatability and low setup times, producing more units of each type. In such a case, the interviewees highlighted that flexibility is not expressed in a high variation of items produced but rather by a quick setup when changes are needed. As explained by the interviewee, "*advanced robots allow for changing the painting system much faster than we were able to do manually years ago, and this has given us more flexibility to introduce more options in the production line*". However, in the case of Companies 11 and 12 – where soft materials are used, the variety of products is wide, and the introduction of new products is frequent –, the implementation of robots is not considered viable. As the interviewee from Company 12 described: "*We produce a huge variety of products. The machines would need to learn how to make 10,000 new products every 3 to 4 months. Automation works best when the product is not malleable, when it is less variable, and has longer life cycles*". Therefore, the use of advanced robots for flexibility is highly dependent on the type of production system and its requirements. In high-volume production systems, it can facilitate some operations, introducing some levels of flexibility, but this is not the type required when more customization and adaptation is needed.

Moreover, companies have invested in *collaborative robots* for two main reasons: ergonomic aspects and replacing manual activities that do not add value to the process. According to the interviewees, collaborative *robots* bring flexibility as they can perform various actions and are easy to be reconfigured. In addition, the interviewee from Company 6 stated that, through hybrid (human-machine) work, manufacturing lines achieve a higher quality of process while keeping flexibility. However, the interviewee affirmed that collaborative *robots* are still expensive and challenging to use because they frequently stop due to safety triggers. The execution of tasks is slow, causing problems in other indicators, including productivity.

Companies have also invested in other technologies such as *Additive Manufacturing* and *Modular Machines* to achieve higher machine flexibility. *Additive Manufacturing* technologies offer a great variety of products and low manufacturing costs. However, its application is still limited to the manufacture of spare parts and prototypes because manufacturing large volumes of parts using this technology is still difficult, given its production throughput. Besides, a contingency factor associated with its adoption is the rather high price of acquiring the equipment, and most companies still lack the necessary knowledge to operate them. Company 7 avoided facing these problems by implementing *machine flexibility* through modularity with flexible mold machines that automatically change the molds according to the product through *PLC*. This approach guarantees fast setup times, as described by the interviewee from Company 7: "*We decided to have a machine capable of producing 100% of the models requiring no configuration time, with total flexibility and with a quality verification system provided by the machine".*

One of the most commonly implemented initiatives is systems and devices that allow for *traceability, vertical integration,* and *artificial intelligence* applications. These technologies are essential to achieve machine intelligence, as they can identify products and materials, adjust machine parameters, and allow automatic intelligent configuration. Some companies employed them as a first stage in the implementation of Industry 4.0 to make equipment more intelligent and flexible. Companies 5 and 6 (both from the food sector) have implemented software to monitor machine parameters and adjust processes and operations depending on the product. The interviewees from Companies 4 and 11 emphasized the importance of systems such as *ERP*: *"we can have two families of products (and their variations) at the same time; thus, ERP is an essential tool to organize production".*

In addition to the aspects of *ERP* use, automation linked to data collection was also considered important, as it enables machine adaptations without which the systems might become more rigid rather than flexible (Company 10). The interviewee from Company 4 noted that these technologies contribute to vertical integration since: *"the ERP sends the orders, then MES manages the execution of the manufacture. Supervising systems report what is happening on the line, and this whole system is enabled by equipment connected using IoT".* Company 10's sensing strategy started with *IoT* technologies such as *RFID* and beacons, aiming to reach a stage of automatic machine adaptation based on *Artificial Intelligence* that would allow for faster and easier exchange between products. According to the interviewee: "*instead of having a specific oven for painted products, an adaptation of this oven could automatically 'understand' the product being manufactured and, based on its characteristics, select the appropriate paint, temperature, etc.".* Complementarily, some companies have opted for a *cloud computing service* to operate the *ERP* and *MES* systems. Even though they do not reckon the cloud itself to be a direct driver of flexibility, it does enable higher system availability, ensuring that it is constantly operational, and thus resulting in faster response times, visibility, and lower costs, as the server is not inside the company (Company 10).

On the other hand, contingency factors hinder the adoption of cloud and ERP systems. Company 1 finds cloud storage too susceptible to data security concerns, which has led them to adopt internal servers instead of cloud servers. Also, some companies do not implement or use the *MES* system because they face very high product variation that makes the system hard to adapt to the process flow (Company 5). As stated by one of the interviewees, "*the production flow needs a minimum standard of production sequence for the current MES systems; otherwise, the system is not able to provide new configurations for each order that manufacturing receives*".

Furthermore, interviews have shown that *machine flexibility* is closely related to *labor flexibility*. According to the interviewees, investments in digital technologies focusing on machine flexibility bring additional challenges related to worker adaptability. In this context, Company 7 reports difficulty in using technologies such as *collaborative robots* and *machine vision* due to worker knowledge gaps leading to technology underutilization. According to the interviewee from Company 9, automation initiatives that aim to support workers with a *robot* require workers trained to program the *robot*. Thus, it is necessary to change the operators' mindset and develop new digital capabilities to adapt to new ways of working with digital technologies, which is not a common capability to be found. Thus, we propose:

Proposition 1.1: *Machine flexibility can be supported by technologies that ensure fast setup times and easy machine reconfiguration, including advanced robotics, additive manufacturing, and vertical integration.*

Besides this technical proposition related to Industry 4.0 technologies, the exploratory qualitative approach allowed to identify contingency factors related to each company's production characteristics, as explained above. Thus, a complementary proposition is also proposed:

Proposition 1.2*: The implementation of smart machines for flexibility depends on some contingency factors such as product variety, product variability, production volume. For example, the implementation of robots is a challenge for companies with production systems characterized by high variability and short product life cycles due to the necessary reprogramming, which is time-consuming and costly.*

Proposition 1.3: *The adoption and use of machine flexibility technologies demand workers' flexibility to acquire new digital skills.*

Labor Flexibility

Regarding *Labor Flexibility*, the results show that assembly processes in manufacturing are generally labor-intensive due to the complexity of these tasks. In the automated stages, labor intensity decreases, and operators mainly supervise the machines, making a few interventions and reprogramming the equipment. Production volume was also an important factor driving companies to invest in *labor flexibility* or automation. In this sense, companies with lower production volumes usually rely on manual activities, mainly due to the cost of investing in hard automation, which demands constant reprogramming and setup, implying a longer return on investment.

Some interviewees mentioned focusing on Industry 4.0 technologies that will assist in training workers and supporting their tasks, mainly for human error reduction. Interviewer 11, said: *"In terms of people, a lot of training is needed for workers to be able to manufacture a high variety of products with the same productivity."* Company 12 has been researching *Augmented Reality* to improve worker training processes and enable employees to produce more types of clothes. A similar approach has been adopted by Company 3, a supplier of axles for the automotive sector. According to the company, this technology allows "(…) *to identify defects in the production cell, and improve operator selection based on their compliance with safety, quality, and delivery standards. And we can see the ones who will have more difficulties".* Thus, by understanding operators' skills and profiles, the company can select the best operators to perform complex tasks and build the capacities of those that cannot yet meet the standards.

Company 2 is similar to Company 3 in production characteristics, and it has invested in implementing *Augmented Reality* software for quality inspection and visual workflow, with an operator-controlled camera that maps the product. The company is also planning to implement a virtual training room. These initiatives aim at building operators' skills and adding more flexibility to the workforce through the adoption of advanced technologies. This is the case of Company 7, which has a project for using smart technologies in maintenance activities. In this case, the technology acts as a personal assistant in complex activities.

Nevertheless, for operational tasks, the use of *Augmented Reality and Virtual Reality* still seems rather limited. The interviewee from Company 9 explained these technologies are still not fully adapted for shop floor use, needing some enhancements in their design: "*We did some tests with Augmented Reality on the production line, and we did not adopt it because the glasses are not comfortable, and workers did not get used to them. I think it is still a technology for training only. In our company, it is used for product development*." *Traceability Systems* are also used in combination with other tools such as automated poka-yoke devices to avoid problems in product assembly. According to Company 3, the just-in-time system combined with traceability supports worker flexibility since the company manufactures several models of different parts, and this technology allows workers to identify the product being manufactured in real-time.

Proposition 2.1: *Advanced technologies for training (e.g., Augmented Reality and Virtual Reality) and digital technologies that support workers' activities allow for labor flexibility since they enable operators to adapt to new tasks more quickly and easily.*

Proposition 2.2*: The development of more ergonomic technologies, adapted for use in production, is an important factor for the work of operators. Thus, these technologies can have their use extended from training to other manufacturing areas as well.*

The analysis of technologies adopted for labor flexibility revealed complementary aspects in terms of the contingency factors required to supplement them. This is especially true for companies with low production volumes and products comprising several parts and requiring numerous assembly processes. These companies require great labor flexibility, which can be achieved by training workers and also by the adoptions of technologies to support them in the production line. For instance, these companies could focus on technologies such as *Augmented*

Reality for a better visualization of processes and activities in training sessions. Besides, they can invest in technologies such as pick-by-light, cobots, and tablets to assist workers in assembly activities. On the other hand, companies with high production volumes should focus more on *robotics*, as explained in the previous section.

Proposition 2.3*: Labor flexibility can provide better results in low-volume production systems demanding numerous assembly processes and several parts. This type of flexibility makes it easier to switch between products and processes and can be supported by cobots and smart devices.*

Material Flexibility

Material flexibility is considered a fundamental capacity of systems because, when the product mix changes, material transport systems need to guarantee the provision of the right inputs to each workstation. According to the interviewee from Company 6, current investments in Industry 4.0 technologies for logistics will enable high *material flexibility*. In fact, Companies 1, 8, and 11 have invested in technologies to automate material transportation, including *AGVs* (*automated guided vehicles*), *traceability systems*, as well as material management using production management systems. The interviewee from Company 2 describes the importance of AGVs in logistical processes: "*AGVs take finished products to a specific storage unit along an assigned path. They know in which position to place them due to the identification tag in each batch"*. The interviewees from Companies 2 and 8 state that investments in *AGVs* are not necessarily linked to flexibility, but rather to a reduction in labor and energy costs due to the reconfigurability of these technologies. However, they also offer a level of flexibility in the transport of materials. In fact, Company 11 also tested an *AIV* (*automated intelligent vehicle*) which does not require markings on the factory floor since it defines optimal transport routes. However, the company's products were heavier than the *AIV's* maximum load capacity.

Finally, companies emphasize the use of production management systems, such as *ERP* systems and *traceability systems* for material management. Company 9 implemented an *electronic Kanban system* connected to the *ERP* system. While defining the routes, the *ERP* system is fed back and notifies the logistics sector on how much material is missing in a certain workstation. In the case of Company 1, material programming and supply chain are also linked in the *ERP* system. The integration of suppliers into the company's system ensures that production orders are automatically sent to the suppliers' systems, which will then manufacture and supply the auto parts in the same order as needed by the assembler. According to the interviewees from Companies 1 and 3, nowadays, variations in companies' production planning considerably impact the whole supply chain, especially when the company-supplier relationship is closer. Thus, companies need to have greater *horizontal digital integration* for more efficient material and service provision.

Proposition 3.1: *The use of advanced technologies to transport materials, as well as vertical and horizontal integration, supports material flexibility as they all optimize operations and automate logistics.*

Proposition 3.2*: As customer-supplier relationships become more closely connected, companies should invest in technologies that provide the horizontal integration required to improve flexibility in material supply.*

Besides the technological aspects described in the two propositions above, contingency elements were also identified, as described in the following proposition:

Proposition 3.3: *Contingency factors related to physical restrictions of a product (e.g., weight, rigidity, volume) can pose difficulties to transportation technologies linked to material flexibility.*

3.4.2 Industry 4.0 enabling Shop Floor Flexibility

Operation flexibility

Operation flexibility refers to the number of different production plans for the same product. According to the interviewees, one of the main tools used to define their sequencing plans is simulation software, as it allows to digitally test different sequencing plans without having to change the production line. In addition, other technologies assist in expediting product design. Company 7 uses *3D printing* for rapid prototyping, which helps quickly test new components and parts that need to be assembled in the plants. Moreover, Company 9 reported the use of *PLM systems* to support the integration between product development and manufacturing, with real-time data making integration between the two functional activities faster and more effective.

By asking the interviewees about the characteristics of technologies that will enable operation flexibility, we also identified product design as a contingency factor deeply interrelated with Industry 4.0 technologies. First, this type of flexibility will depend on product design, i.e., whether the products are designed to be flexibly manufactured or not. Even if the company has a high level of flexibility in terms of resources, it will find difficulties changing the sequence of operations if the product follows a rigid manufacturing process. According to the interviewees from Companies 1 and 10, the production sequence is usually specified based on the technical structuring requirements of products and on the resources necessary for their production. In this sense, the interviewee emphasizes the importance of *design for manufacturing*, that is, a reduction in product complexity leading to a reduction in setup times. As argued by one interviewee: *"Digital technologies will not significantly impact sequence flexibility if the products were not designed considering flexibility aspects, such as modularity. Thus, we must think more systemically and consider product design together with the manufacturing technology*".

Product modularity was highlighted as another key contingency factor in product design. Modularity aims at designing more products with fewer components, by using "modules" that can be integrated into several different products. Such an approach contributes to better use of Industry 4.0 technologies in processing a high mix of components. For instance, an interviewee from Company 11 explained that "major retailers in the textile sector standardize the shape of each piece of clothing, which is then distributed to all suppliers. This concept of modularization should be explored, as our collections are becoming more complex, and variety is increasing". Company 10 works with the make-to-order system for truck production, and the company has worked to increase customer proximity to better understand its increasingly complex and varied demands. Thus, the company has had to use modular systems for product customization, given its need to deal with so many different part numbers in the same place. To meet such a level of customization, Company 4 has designed a whole new factory focused on product traceability and pulled production tools in combination with information systems.

Proposition 4.1: *The use of product development technologies such as 3D printing for prototyping, PLM, and simulation tools for planning contributes to operation flexibility as they expedite any necessary adjustments between product design and manufacturing and the choice of plant for production.*

Our exploratory approach allowed us to identify not only characteristics of the Industry 4.0 technologies but also complementary product design elements that are contingency factors to the implementation of such technologies, as described above and summarized in the following proposition:

Proposition 4.2: *Flexible design approaches such as modularization and design for manufacturing play a contingency role in implementing operation flexibility. The use of Industry 4.0 technologies should be combined with such product design approaches to improve flexibility.*

Routing flexibility

Regarding *routing flexibility*, the interviewee from Company 2 explained that all machines are connected to an Andon system, which automatically notifies which machine is the source of the problem in case of failure through. If a robot stops in the body shop and paint shop stations, the line stops, but the plant manages to continue production due to intermediate buffers defined in the process design steps. This is an example of a vertical integration system in which different layers of information are interconnected to execute the operations. Moreover, for Company 10, the visibility of production offered by *vertical integration* affords flexibility to make changes in the line*: "in low demand, we change the products in the line to achieve better resource utilization. This is possible because we have visibility from the factory to tell if production is going as planned"*. However, the interviewee from Company 7 remarks that differences in technological levels between manufacturing lines make such changes difficult. Also, vertical integration plays an important role in both *routing and operation* flexibility, since managing a flexible sequence of operations and routes requires an integrated system, and *vertical integration* allows to send information about the next production mix to all workstations automatically when a quick change in production is necessary.

Furthermore, the interviewees highlighted that this type of flexibility is also closely associated with process design. According to interviewees 1, 4, and 9, the process of designing new sequencing plans and new line layouts needs the support of *simulation tools* that will allow visualizing the line design and virtually simulating all line parameters, equipment, and buffer sizes. This tool brings flexibility gains because it improves layout changes, as noted by the interviewee from Company 4: *"We can implement product changes more quickly through simulation, so we do not need to stop production for testing, and consequently, the implementation of changes is more accurate"*.

Proposition 5.1: *Vertical integration provides greater visibility of the company's production lines, which supports the reconfiguration of system routes.*

Proposition 5.2: *The impact of Industry 4.0 technologies on Routing Flexibility is limited by how processes were designed.*

3.4.3 Summary of the findings

The findings and propositions are summarized in Table III. This table shows the main technology dimensions and specific technologies related to each type of flexibility. The table explains how these technologies contribute to them. The table also summarizes the contingency factors identified for each specific type of flexibility, as described above in the results.

Table 9. Summary of the findings

Dimension	Technology	Machine	Labor	Material	Operation	Routing
Base Technologies	Cloud Computing	Availability and remote access of management information and control systems				
	Data Analytic, Big Data, AI	Analysis and data collection allowing to monitor the behavior of the equipment and maintain the availability of the machine, reduce downtime, optimize setup times				
	Traceability System (IoT, RFID, GPS)	Automated identification and tracking of production items (raw material, components, products, etc.)				
Vertical Integration	Sensor, MES, SCADA, ERP	Production control, machine connection and reprogramming, according to changes in product mix and volume		Control of availability and supply of materials and reconfiguration of the material handling system Integration with suppliers to improve the flexibility of material supply	Control and configuration of re-sequencing	Visibility of production and readjustment of sequencing and routes
Multi-purpose Machine and Robots	Collaborative robots, Smart and Self-programmable machines, CNC	Equipment intelligence allows greater adaptability. Automatic reprogramming of machines according to product mix				
	3D Printing	Production of a wide variety of three-dimensional objects. It is used in the manufacture of spare parts for faster maintenance and to avoid line stoppages				
	AGVs e AIV for moving inventory or work in progress			Transport and allocation of raw materials according to scheduled operations and routes		
Modelling or simulation for production and operations	Simulation, Digital Twin				Simulation in designing processes, sequencing, routes, buffers, etc	Simulation in designing processes, sequencing, routes, buffers, etc.
Worker enhancement tools	Augmented reality, Virtual reality, Digital Guide Systems, Mobile Applications.		Augmented and virtual reality technologies are used as training support tools, for more efficient training, multitasking preparation, and improving safety and quality indicators. Support for workers' tasks: Mobile applications and inspection systems guide worker in daily tasks			
Product Development Tools	Simulation modelling for product design (Virtual Reallity e Augmented Reallity, simulation)				Technologies support design for manufacturing, which influence the design of more flexible sequences	
	PLM system					
	Digital prototype (3D)				Prototype validation associated with design tools for 3D visualization that can allow for faster product development and simulate various manufacturing sequences	
Contingency factors identified		Product variety, product variability, production volume	Friendly and ergonomic technologies	Product's physical restrictions (e.g., weight, rigidity, volume).	Flexible design approaches such as modularization and design for manufacturing	Process characteristics
		Flexibility from workers to acquire new digital skills.	Low-volume production systems			

3.5 DISCUSSIONS

Complementarily to the findings summarized in Table III, the framework represented in Figure 1 proposes a conceptual understanding of Industry 4.0 technologies, their interconnections, and contributions to the different types of manufacturing flexibility. This framework explains how companies pursue internal flexibility by adopting Industry 4.0 technologies. As depicted in the framework, companies perceive Industry 4.0 technologies as enablers of different internal manufacturing flexibility strategies. In this sense, findings show that Cloud Computing, Big Data, IoT, and Data Analytics (including AI techniques) impact all dimensions of flexibility. Therefore, they can be treated as general-purpose or base technologies to support manufacturing flexibility capabilities (FRANK *et al.*, 2019). These technologies alone do not ensure flexibility, but they allow for the identification and traceability of products, machines, and materials and provide real-time data on the operation, enabling faster decision-making.

The findings also showed that specific technologies are necessary to ensure flexibility requirements for the individual-resource and shop floor levels, as illustrated in the framework (Figure 1). Figure 1 also shows that as the results and other studies indicate, achieving different dimensions of flexibility highly depends on contextual factors such as the company's production volume, type of process, product variety, life cycle, and complexity (ANDERSEN *et al*., 2018).

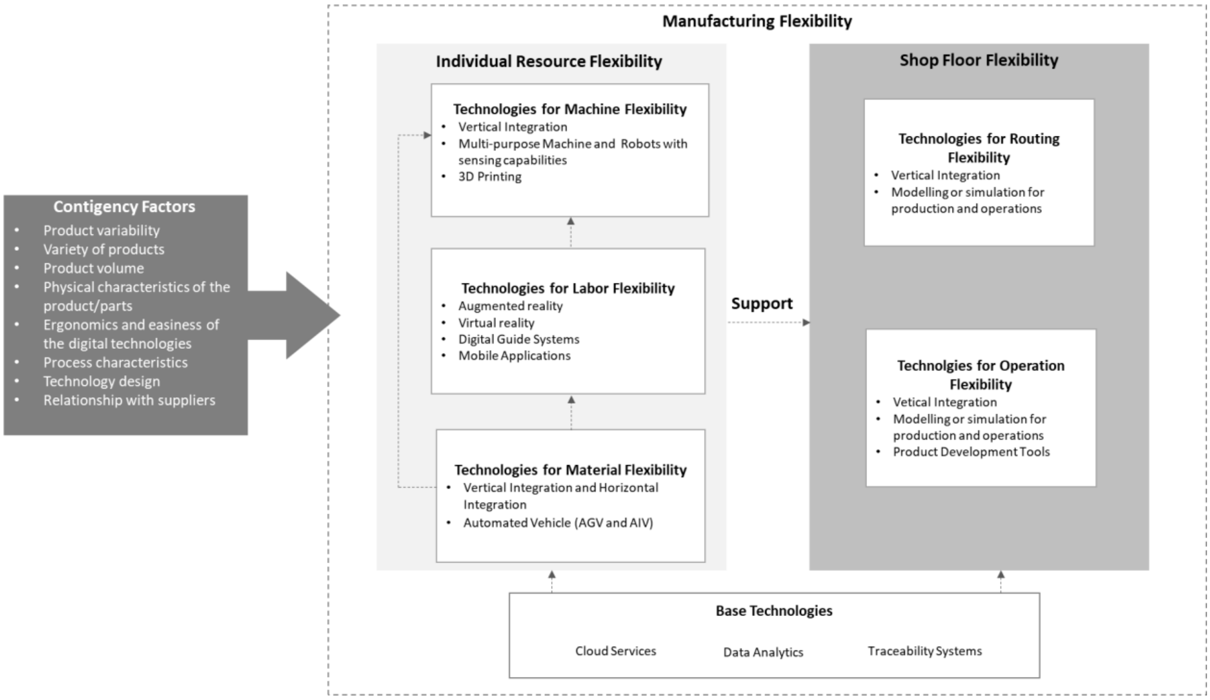

Figure 4. Conceptual framework summarizing the empirical finding

The results showed that companies seek flexibility mainly through investments in equipment (i.e., based on individual resources for manufacturing). Meanwhile, they pay little attention to broader flexibility approaches, such as developing new routines and processes. Such a lack of attention to flexibility has been highlighted by Dalenogare *et al.* (2018) when they explained some of the reasons why industries do not achieve operational flexibility as one of their main benefits from Industry 4.0. As they explain, factory preconditions bias Industry 4.0 investments, limiting what companies can implement for flexible production lines (DALENOGARE *et al.*, 2018). Thus, the need for investments to improve company infrastructure is one of the biggest challenges for the achievement of flexibility (CONTADOR *et al.*, 2020). The literature corroborates this view, showing that flexible production lines are one of the least implemented paths due to previous factory arrangement limitations (FRANK *et al.*, 2019). Therefore, the proposed framework highlights the importance of broader conditions and factors that managers should consider. In this sense, as depicted in the framework, the multiple sources of flexibility (people, technology, processes, etc.), their interrelationships, and the existence of contingency factors should be analyzed (YU *et al.*, 2015).

The results showed that companies give greater attention to machine flexibility. To this end, cobots, additive manufacturing, modular machines, and machines with AI are the most commonly employed technologies. They provide machines with connectivity and intelligence capabilities, allowing easier reconfigurability, faster setup, and better system and machine interconnectivity. Moreover, the results analyzed show that vertical integration technologies (i.e., integration of ERP, MES, and PLM) are necessary preconditions for flexibility, enabling greater information exchange to support the operation of flexible lines (FRANK *et al.*, 2019; TABIM *et al.*, 2021). This is in line with previous literature that found that through Industry 4.0 technologies, companies expect to improve production planning and control, increase the company's global competitiveness, and the quality of production lines (CONTADOR *et al.*, 2020).

The results showed that in companies with high product variety and short life cycles, the implementation of advanced technologies such as robots is difficult because they must be reprogrammed frequently, increasing production times and costs. In such cases, technologies enhancing labor productivity and flexibility are much more useful since workers are still the most flexible part of the manufacturing system (DORNELLES *et al.*, 2021). On the other hand, companies with high-volume, low-variety production environments seem to require highly automatized special-purpose machines to achieve market competitiveness. This productivity/flexibility trade-off is in line with mass manufacturing premises, as illustrated by the problems with collaborative robots, which are highly flexible but constantly stop operating. Similarly, multipurpose machines can manufacture several products, but setup times usually reduce their productivity. Thus, even though Industry 4.0 focuses precisely on overcoming this problem, developing highly automated machines that are easy to reprogram, flexible, and highly productive still seems to be a challenge.

Worker adaptation to Industry 4.0 technologies was the most frequently mentioned challenge for flexibility since workers currently lack the necessary knowledge and training to operate the technologies (DORNELLES *et al.*, 2021). Industry 4.0 requires a different type of worker, capable of performing cognitive work, including data processing, interpreting information, and decision making (ORTT *et al.*, 2020). This is also true for flexibility purposes. Besides, operators can participate in design and decision-making, providing operational information for greater work flexibility. Although these technologies are important, their design is still a limitation for wider use. A more ergonomic and flexible design allows for better configuration processes and helps operators with more complex tasks (LONGO *et al.*, 2017). Despite the potential of these technologies to assist workers, their use is still limited, and only a few companies employ them in dedicated production applications, such as maintenance and quality inspection (HOLM, 2018).

Material flexibility offers opportunities to manufacture products by different routes, increasing machine utilization and reducing flow time. Traditionally, automated material handling systems are not designed to be reconfigurable, and changes in layouts and material flow directions often require significant downtime for physical modifications and rescheduling. As the framework shows, with Industry 4.0 technologies, new opportunities arise to create flexible material handling systems, production management systems (ERP, MES), and material traceability systems, which are recognized as basic and essential technologies to enable the management of many materials within the factory. Moreover, autonomous vehicles such as AGVS enhance flexibility in terms of ease of programming and automatic reconfiguration of transport routes. However, their use is still limited by physical aspects of the product, such as the size and volume of transported materials.

The results also pointed to the importance of integrating suppliers through systems to better manage the materials that enter the line, as also stated. Supply chain flexibility is normally considered a key solution to reduce risks related to market uncertainties. Therefore, the literature points out that manufacturing flexibility requires hierarchical analysis within the company and horizontal integration with the supply chain (YU *et al.*, 2015).

Companies face serious difficulties in obtaining shop floor (i.e., Operation and Routing) flexibility. This is mainly because these two types of flexibility largely depend on the efforts necessary for flexible planning and process and product design, such as design for manufacturing techniques. In this sense, companies define their sequencing of operations and routes to optimize production times and process quality, which restricts the flexibility of the lines. In the case of routing flexibility, this may be because it requires high availability of alternative resources (EYERS *et al.*, 2018), which does not seem to be part of the flexibility strategy of the companies studied, probably because their targets were restricted to resource efficiency. This is in line with the flexibility and capital efficiency trade-off reported by Chan (2006).

Additionally, the companies studied primarily focus on increasing quality and productivity; thus, they invest in dedicated resources and equipment for each type of product, limiting routing flexibility (EYERS *et al.*, 2018). On the other hand, the digital transformation of the factory floor could allow for greater line visibility, which can be helpful if companies need to manufacture a certain product in another line. To this end, simulation technologies can be an important tool for managers to define new route plans (CHAN, 2006).

In Operation Flexibility, companies indicated that changes in operation sequencing are still a major barrier. Companies tend to define the production sequence according to the product's technical requirements or to optimize the line, making sequencing changes difficult to affect. As Figure 1 depicts, simulation tools can support *Operation Flexibility* as they enable process modeling and analysis to seek alternative operations sequencing. According to the results, a solution to this may be an approximation between product design and manufacturing to design products focusing on manufacturing and thus achieving operation flexibility. Thus, PLM and CAD systems are useful tools to translate knowledge between the areas.

The results also evidenced the importance of other concepts which are contingency factors to the Industry 4.0 technologies analyzed, such as modularity (mentioned by Company 7). These systems can be integrated with the CPS to manage complex, customized manufacturing processes and quickly adjust production capacity and functionality over time (MORGAN *et al.,* 2021). Also, lean tools, ERP, and MES are expected to help flexibility when combined with Industry 4.0 technologies (MARCON *et al.,* 2021). Andon systems combined with IoT allow equipment to react to error alerts, stop work, or change product routes (ROSIN *et al.,* 2019). Electronic Kanbans can automatically detect their inventory levels and order parts, enabling a more diverse configuration for different product designs (MARCON *et al.,* 2021). Furthermore, IoT can ensure that the right products go to the right workstations and automatically redirect products in case of errors, which is part of the *Jidoka* principle. The complementarity of these concepts to the firm's contingency factors is crucial for flexibility and productivity.

3.6 CONCLUSIONS

This article addresses a research gap by analyzing empirical data on the relationship between Industry 4.0 technologies and different types of internal flexibility. Although flexibility has been widely researched, Industry 4.0 brings a new perspective to this concept with technologies that enable connecting machines, visualizing production, and diminishing setup times to augment flexibility on the shop floor. This study contributes to the flexibility literature by discussing the necessity of Industry 4.0 base technologies to achieve more flexibility since they enable vertical integration, equipment connectivity, and information on the shop floor to allow product identification, increasing workers' skills. Moreover, systems such as MES, SCADA, and ERP enable flexibility given their capability to provide real-time information directly to the shop floor. Based on these empirical findings, a framework is proposed describing the link between the different types of flexibility and the Industry 4.0 technologies associated with them, and the contingency factors that influence Industry 4.0 technologies for flexibility.

Managerial Implications

The findings show that managers must consider flexibility systemically rather than take an isolated perspective. The concept demands design efforts, changes in the production line layout, workers' adaptation, and technologies to enable it. Besides, contingency and environmental factors that enable flexibility should be analyzed. In this sense, this article provides insights to managers on how internal contingency factors (those related to market and manufacturing contexts) and external contingency factors (investments, educational level, and product/technological innovation) impact technology implementation. While a comprehensive analysis of these factors should be considered, practitioners are recommended to focus on product design aspects, market variety demand, and the necessary investments initially.

Also, information systems allow technologies to work in an integrated way, while specific technologies provide and receive directions from them. This is not the usual perspective adopted by companies, as they tend to firstly adopt a flexibility-enabling technology, isolated from the rest of the system, while the bigger picture is considered only as an afterthought. The results show that this is a problematic approach since it tends to create isolated flexibility spots whereas the shop floor remains optimized for mass manufacturing. To avoid this problem, managers must develop the foundations of a flexible system by adopting base technologies, integrating the data generated by them with information systems, and rethinking product design and manufacturing processes jointly.

Limitations and Future Research

This study has some limitations that bring opportunities for future research. The study focused on companies in the Brazilian context; however, it is important to analyze companies in the context of other countries. Also, internal and external contingency factors that influence the adoption of technologies for flexibility should be studied in more detail, especially in smaller companies and companies with specific manufacturing contexts, such as lean companies or companies with a highly integrated supply chain. Another limitation is that this study does not intend to be prescriptive on how to implement manufacturing flexibility. As shown in the findings, several contingency factors can limit and shape the way technologies are implemented for flexibility. Therefore, this paper introduced the main variables that practitioners need to consider, which were introduced as main propositions. Future research can develop quantitative studies with large samples to further expand the insights generated in this article and find potential implementation patterns to establish prescriptive models. Still regarding future research, studies analyzing how Industry 4.0 technologies influence supply chain flexibility could bring important insights, as this article's results demonstrate that the integration of suppliers is an important aspect of flexibility, and these technologies are important drivers of integration. Moreover, quantitative studies evaluating the impact and problems of organizational, social, and product-related contingency factors on Industry 4.0-enabled flexibility are expected to complement this article's results.

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APPENDIX A. GUIDE TO THE INTERVIEW EXAMPLE

a. Please provide a brief explanation of your company, its market, main products, operations, production system, etc.
b. What criteria does your company focus on when investing in technologies? (Productivity, Costs, Flexibility). Is flexibility an important criterion for your company?
c. Explain what types of flexibility your company is looking for and why.
d. Describe which processes allow your company to be more flexible and its manufacturing strategies.
e. What types of Industry 4.0 technologies are important in your company to achieve such flexibility? What factors are considered before investing in these technologies for flexibility?
f. What were the most successful actions taken by your company during the adoption of these technologies for flexibility? And what were the most difficult problems?
g. What is your company's expected future investment to achieve the desired flexibility?

4. BEING DIGITAL AND FLEXIBLE TO NAVIGATE THE STORM: HOW DIGITAL TRANSFORMATION ENHANCES SUPPLY CHAIN FLEXIBILITY IN TURBULENT ENVIRONMENTS

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The growing environmental business uncertainties have forced companies to focus on developing more flexible supply chains. Digital transformation has been considered a key mean to achieve such flexibility, but the literature lacks empirical evidence about how digital technologies effectively contributes to it. Thus, this study aims to analyze how Smart Supply Chain (i.e., a supply chain enabled by digital transformation) contributes to supply chain flexibility and operational performance in environments surrounded by customer and supplier uncertainty. We adopt the organizational information-processing theory to explain the fit between information needs to reduce these uncertainties through more supply chain flexibility (sourcing, delivery, and manufacturing) and information capabilities provided by three main dimensions of the Smart Supply Chain (digital transformation strategy, digital base technologies, and digital front-end technologies). We relate these information-processing fit between Smart Supply Chain and flexibility with the boundary conditions of environmental uncertainty and operational performance improvements. Such relationships are analyzed through moderation and mediation regression tests based on 379 manufacturing companies surveyed. Our findings show that Smart Supply Chain has significant effect on operational performance through the sequential mediating role of the three supply chain flexibility dimensions. We also found that environments with high customer uncertainty increase the use of base technologies (IoT, cloud, big data, AI, and blockchain) to reach delivery flexibility and support manufacturing flexibility. When companies face a high supplier uncertainty, they use front-end technologies (i.e., robotics, 3D printing, simulation, and augmented reality) to increase sourcing flexibility. We show new advances in the field of supply chain flexibility through digital transformation.

Key Words: Digital Transformation, Industry 4.0; Business Uncertainties, Smart Supply Chain, Supply Chain Flexibility.

4.1 INTRODUCTION

For several decades, global value chains focused on building stable operations alongside the supply chains based on long-term inter-organizational relationships and cost efficiency through countries' specialization (BERGER *et al.*, 2005). However, this scenario has dramatically changed recently due to several market uncertainties provoked by situations like international commercial trade conflicts, the COVID-19 pandemic, or regional wars (EL BAS; RUEL, 2020). Additionally, the growing proliferation of emerging technologies has also created technological uncertainties (FRANK *et al.*, 2022). Therefore, increasing operational flexibility has become a key priority for companies to deal with uncertain conditions in this new global scenario (SREEDEVI; SARANGA, 2017; ENRIQUE *et al.,* 2022). This flexibility is recognized as the ability of companies to react to changing environments by adapting necessary processes quickly and with minimum use of resources (SCHNEEWEISS; SCHNEIDER, 1999; PÉREZ *et al.,* 2016). Flexibility is not only limited to the company boundaries; rather, it is a multidimensional concept that comprises the whole operations from the internal production to the external supply chain activities (SETHI; SETHI, 1990; KUMAR *et al.,* 2006). However, achieving such flexibility is extremely difficult because the supply chain is a complex system configurated by intra-organizational and inter-organizational relationships that take time to react and adapt to changing situations (SEEBACHER; WINKLER, 2015).

With the advent of the 4th Industrial Revolution, new opportunities have been envisioned to increase supply chain flexibility (DOLGUI *et al.,* 2020). Some scholars have proposed that companies can develop Supply Chain 4.0 or Smart Supply Chains, i.e., a supply chain enabled by digital transformation to improve information flows and operations activities (MEINDL *et al.,* 2021; FRANK *et al.,* 2019). The literature has highlighted digital tools like the Internet of Things (IoT), Artificial Intelligence (AI) that can help to integrate different tiers of the supply chain through real-time data flow (BÜYÜKÖZKAN; GÖÇER, 2018; LIU *et al.,* 2022). Such tools can also help to automate and anticipate decision-making (SHARMA *et al.,* 2022), and they enable hardware applications like 3D printing for quick provision of spare parts (CHAN *et al.,* 2018; DELIC; EYERS, 2020) and advanced robotics for transportation and distribution (MEINDL *et al.,* 2021). These are only some of the examples provided by the literature about how a Smart Supply Chain can use emerging technologies to be more flexible. However, most of the studies that focus on the Smart Supply Chain and operational flexibility do not consider the several different dimensions that represent a Smart Supply Chain (MEINDL *et al.,* 2021). Since Smart Supply Chain comprises both strategic and technological aspects of the digital transformation (NASIRI *et al.,* 2020), more evidence is still necessary about an integrative and holistic perspective of its contribution to increasing the required flexibility.

Furthermore, although the literature has defended the relevance of digital technologies implementation and more flexibility in the supply chain activities (e.g., HARTLEY; SAWAYA, 2019), there is a lack of empirical evidence of what happens with the firm's operational performance when these two perspectives are combined. Prior studies have considered how information technologies contribute to supply chain integration and flexibility (e.g., SWAFFORD *et al.*, 2008; JIN *et al.*, 2014; HUG *et al.*, 2017). However, when digital tools such as IoT, big data, AI, or blockchain are considered, the literature is still incipient about their contribution to supply chain flexibility and their combination to increase operational performance. This is important because prior results have also shown that, in some cases, when information systems in the Industry 4.0 are integrated, they can become less flexible to adapt to different situations (TABIM *et al.*, 2021). Although the literature has demonstrated that Smart Supply Chain can positively affect performance (LIU *et al.*, 2022), supply chain flexibility can also help performance under uncertainties (MERSCHMANN; THONEMANN, 2011), little is known about their combination to increase performance. Thus, *what happens when these different elements are combined, especially in turbulent contexts of high uncertainty? Can Smart Supply Chain support supply chain flexibility and, therefore, increase operational performance when companies face uncertain environments?*

We aim to explore the role of Digital Transformation in supply chain operations – what we call Smart Supply Chain – to support supply chain flexibility when facing uncertainty in upstream and downstream relationships. We also aim to analyze how a combination of Smart Supply Chain and flexibility contributes to operational performance. We explore the organizational information process theory (OIPT) to address the proposed questions. This theory affirms that firms facing uncertain environments will require to process more information which can be supported by the development of information processing capacity (FAN *et al.*, 2016; SRINIVASAN; SWINK, 2018; WONG *et al.*, 2020). We argue that Smart Supply Chain is a form of information-processing capacity that can help overcome such uncertainties and increase supply chain flexibility and operational performance. We test these relationships through a quantitative survey with 379 companies which was analyzed through regression and bootstrapping techniques. Our results show how the three dimensions of Smart Supply Chain, namely digital transformation strategy, base, and front-end digital technologies, are associated with three types of supply chain flexibility, i.e., sourcing, manufacturing, and delivery flexibility. We show complete and partial mediating effects of these three supply chain dimensions between Smart Supply Chain and operational performance, which enlightens the mechanisms through which companies increase performance when dealing with market and technological uncertainties as boundary conditions. Our results contribute to the debate on digital transformation in supply chains, showing how Smart Supply Chain can be effective for the uncertain contexts in which more flexibility is required.

4.2 THEORETICAL BACKGROUND

4.2.1 Supply Chain Flexibility and new opportunities in the Digital Transformation era

Supply chain flexibility is considered as the ability of companies to react to changing environments by adapting necessary supply chain processes quickly and with minimum use of resources (SCHNEEWEISS; SCHNEIDER, 1999; PÉREZ *et al.,* 2016). Flexibility has been one of the main concerns of the operations management literature for several decades (SANCHEZ; PÉREZ, 2005; STEVENSON; SPRING, 2007). Seminal papers proposed the main dimensions of flexibility (DUCLOS *et al.,* 2003; KUMAR *et al.,* 2006) and forms of configurations of the flexible supply chain (GARAVELLI, 2003; KUMAR *et al.,* 2008). Although the concept remains the same over the time, how to achieve and the results produced change because new technologies, practices, and contextual factors emerge, creating new conditions to study it (YU *et al.,* 2015).

Completing 250 volumes, the International Journal of Production Economics (IJPE) has made important contributions to this field, one of the main operations management journals studying supply chain flexibility. Different studies from this journal have contributed to understand several antecedents of internal and external flexibility sources (e.g., TANG; TOMLIN, 2008; BLOME *et al.,* 2014; SEEBACHER; WINKLER, 2015). Other ones have been focused on the conditions and risks for such implementation flexibility (e.g., KESSEN *et al.,* 2010; SEEBACHER; WINKER, 2015; SREEDEVI; SARANGA, 2017) and contributions when supply chain flexibility is achieved (e.g., TANG; TOMLIN, 2008; FRANCAS *et al.,*2009; GOSLIN *et al.,*2010; WAGNER *et al.,*2018; SHEKARIAN et al., 2020). Also, the IJPE literature has presented important literature reviews on this topic, such as Yu et al. (2015) and Kamalahmadi and Melat (2016), that showed how vast this topic has been for researchers in the whole operations management community, including also other top-tier journals of the field, and also special issues like the one from Chang and Lin (2010) that covered new opportunities in the field.

Regarding our proposed research problem, two streams deserve more careful attention. The first one is that previous studies have already acknowledged the role of supply chain flexibility under uncertainty, demonstrating the importance of it as a boundary condition (DAS; ABDEL-MALEK, 2003; MERSCHMANN; THONEMANN, 2011; JAFARI *et al.,* 2020). This has been addressed not only by the IJPE community but also in studies published in other field journals (e.g., MANDERS *et al.*,2017; ROJO *et al.*,2017). Such studies recognized that supply chain flexibility is highly required when the business environment becomes more turbulent and companies face uncertain conditions. On the other hand, prior literature has addressed the role of information technologies integration in the supply chain to support more flexible supply chains (e.g., SWAFFORD *et al.*, 2008; JIN *et al.*,2014; HUG *et al.*,2017). In general, such studies argue that integrating information technologies from the supply chain partners will be important for the supply chain to anticipate disruptions and become more agile in adapting the supply chain to changing scenarios.

Thus, why should we consider the contribution of digital transformation (Smart Supply Chain) to supply chain flexibility when information technologies have already been addressed in this field? The first answer is that digital technologies should not be treated simply as information technologies. While information technologies consider the background for digital transformation, as they enable computerization of the information processing, providing software and hardware, and information exchange between sources and recipients, digital transformation goes a step forward (SCHUH *et al.*, 2020). Digital transformation comprises at least four base technologies: IoT, Big Data, Cloud Computing, and AI (FRANK *et al.*, 2019; MEINDL *et al.*, 2021). In the case of supply chains (Smart Supply Chain), it is also extended to the adoption of blockchain technologies (ESMAEILIAN *et al.*, 2020; AGI; JHA, 2022). Such technologies bring a different perspective into the supply chain field because they enable a real-time information flow and the massive amount of data that can be processed to increase prediction capacity (BÜYÜKÖZKAN; GÖÇER, 2018). For instance, Agrawal et al. (2018) provide an example of Amazon, which improves prediction capacity based on Big Data and AI in the supply chain to change in the future from a business model based on buying-then-shipping to shipping-then-buying. As argued by the authors, this was not possible with information technologies integration, but now it becomes more feasible with Big Data and AI mechanisms. Such situations are examples in which digital transformation can become a new factor to enhance supply chain flexibility.

Furthermore, digital transformation in the supply chain (Smart Supply Chain) is also represented by new front-end technologies like collaborative robots, 3D printing, or augmented and virtual reality, which can also be useful in the supply chains (MEINDL *et al.,* 2021). Such technologies are enhanced by base technologies like IoT, cloud, or AI and can become a competitive factor in achieving flexibility. Therefore, this new context creates new conditions for the study of supply chain flexibility, as previously demonstrated by Enrique et al. (2022) in the manufacturing context, where flexibility has also been investigated for a long time. Still, now Industry 4.0 has created new conditions.

4.2.2 Organizational Information-Processing Theory (OIPT)

Smart Supply Chain is enabled by the base technologies that promote digital transformation (IoT, Cloud Computing, Big Data, AI, and Blockchain) (MEINDL *et al.*, 2021). Even when such technologies can be present in front-end applications (FRANK *et al.*, 2019), the main background of them is that they enhance the information processing capacity of firms through new forms and velocity of analysis that for innovation of the supply chain activities (YU *et al.*, 2021). Therefore, we propose to analyze this digital transformation process from the Organizational Information-Processing Theory (OIPT) perspective (GALBRAITH, 1974). This theory considers that companies have *information-processing needs* to perform their activities. Such needs should be attended to through the *information-processing capability*. The *organizational information-processing fit* that a company should meet when *information needs* and *capability* are matched will help increase organizational performance (PREMKUMAR *et al.*, 2005).

According to Premkumar et al. (2005), information processing is needed to reduce contextual *uncertainties* that companies face, and technologies can provide the information-processing capability to support such needs. Therefore, we follow this theory as it represents well our aim to investigate Smart Supply Chain and supply chain flexibility under uncertainty. First, Smart Supply Chain should provide the *information-processing capability*, as it comprises digital strategies and technologies that create the firm's conditions to process a high amount of information and data through decision-making processes (e.g., the anticipation of demands, pricing definition, etc.) and operational activities (e.g., a cobot can process data from the environment to react and response as required) (FRANK *et al.*, 2019; MEINDL *et al.*, 2021). Second, the achievement of operational flexibility under turbulent conditions will depend on how the company processes the *information needed* to make the right decisions (SWAFFORD *et* *al.*, 2008; BLOME *et al.*, 2014). In recent studies, this view about the *organizational information-processing fit* between digital technologies and flexibility through the OIPT has also been considered. For instance, Yu et al. (2021) analyzed the role of big data analytics to create information-processing capability and attend operational flexibility in hospitals, while Srinivasan and Swink (2015, 2018) associated supply chain integration and visibility with planning comprehensiveness and analytic capabilities under organizational flexibility. Such studies provide a robust background to support the adoption of this view in our empirical investigation.

4.2.3 Hypotheses development

We use the OIPT theory to propose the conceptual research model represented in Figure 1. We investigate the effects of Smart Supply Chain on supply chain flexibility as a form of *organizational information-processing fit* between the *information-processing capacity* and the *information-processing need* to achieve supply chain flexibility. We also argue that supply chain flexibility enhances operational performance (H2), mediating between Smart Supply Chain and operational performance (H2). This hypothesis is divided into two sub-hypotheses H2a and H2b, since we argue that source and delivery flexibility are antecedents of manufacturing flexibility. Finally, we propose that supply chain uncertainties act as a moderator in both relationships, between Smart Supply Chain and flexibility (H3) and between flexibility and operational performance (H4).

To consider our hypotheses, we follow the holistic view of supply chain flexibility proposed by Koste and Malhotra (1999) and Kumar et al. (2006). According to this view, supply chain flexibility covers both internal and external dimensions. The internal dimension is related to the manufacturing flexibility, i.e., the company's ability to respond to environmental uncertainty by adjusting the operational process to deliver the requested volume and mix of products and introduce and modify products (KUMAR *et al.*, 2006). On the other hand, external flexibility is related to network-oriented flexibility. It refers to a company's ability to respond to environmental uncertainty by configuring the supply chain and adjusting the flow of materials and information through sourcing flexibility and delivery flexibility (STEVENSON; SPRING, 2007; FANTAZY *et al.*, 2009). Sourcing flexibility refers to maintaining a flexible supply base through efficient supplier relationship management by developing collaborative approaches with key suppliers and making joint decisions (SREEDEVI; SARANGA, 2018). Delivery Flexibility, in turn, is related to the development of a flexible delivery strategy, adopting different kinds of transportation modes, and the capacity to change the warehouse layout and material and product handling (MAQUEIRA *et al.*, 2020). Next, we detail the proposed hypotheses represented in Figure 5 that connect Smart Supply Chain, uncertainties, and operational performance with these three forms of supply chain flexibility.

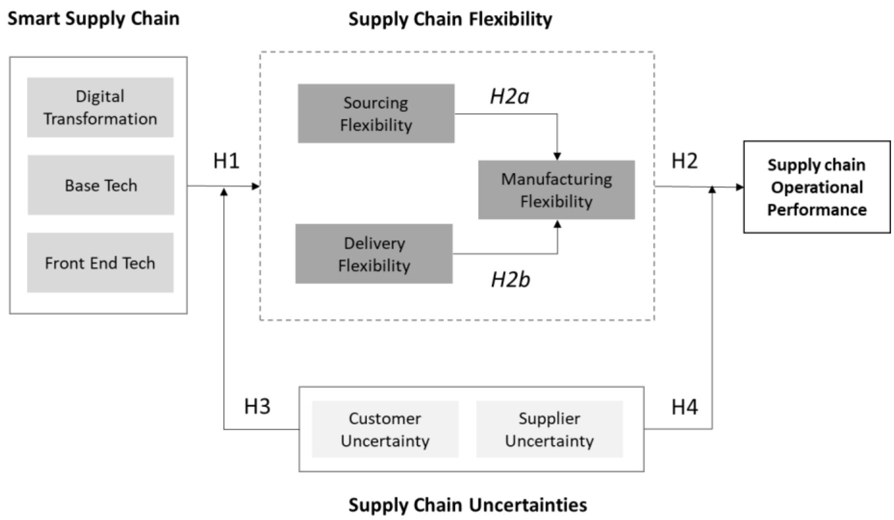

Figure 5. Conceptual research model

4.2.4 Smart Supply Chain enabling Flexible Supply Chain in the context of environmental uncertainty

Smart Supply Chain can be defined through two main dimensions, the strategic perspective of the supply chain digital integration and the technology perspective of digital solutions for supply chain operations (MEINDL *et al.*, 2021). Moreover, the technology perspective can be divided into base and front-end technologies, Frank et al. (2019) proposed for Industry 4.0 technologies. Base technologies are cross-cutting digital technologies focused on real-time data integration across the supply chain, and digital solutions run by IoT, big data, cloud computing, and AI (MANAVALAN; JAYAKRISHNA, 2018; Shao et al., 2021). Besides, blockchain technologies are also a key base technology in supply chain operations (ESMAEILIAN *et al.*, 2020; AGI; JHA, 2022). On the other hand, front-end technologies comprise hardware technologies runed by digital base technologies that aims to provide solutions to the supply chain operations, like 3D printing (DELIC; EYERS, 2020), robotics (REALYVÁSQUEZ- VARGAS *et al.*, 2019), simulation tools and augmented and virtual reality tools (REJEB *et al.*, 2021; DORNELLES *et al.*, 2022). We argue that these three dimensions (digital transformation strategy, base technologies, and front-end technologies) contribute increasing supply chain flexibility.

Regarding the digital transformation strategy, this dimension considers all the organizational efforts that the company makes to facilitate the implementation of digital technologies (NASIRI *et al.*,2020). This dimension also considers the openness that companies have to integrate data with external partners of the supply chain and how companies integrate supply partners to become more digitalized (BENITEZ *et al.*,2022). Consequently, this dimension is a keystone to becoming more flexible in the supply chain operations since the digital transformation strategy will define the way companies aim to develop their flexibility through digital solutions (HOLMSTRÖM *et al.*, 2019; ENRIQUE *et al.*, 2022). For instance, the supply chain will need to have more integrated data in centralized cloud solutions to become more flexible. This will be only feasible if companies are more open to sharing and integrating strategic information of their operations instead of behaving opportunistically with access to information from other partners (SON *et al.*, 2021). Without a strategic orientation toward digital transformation, companies tend to be technology 'fashionistas' but not leaders that provide an agile organization to the changing environment (WESTERMAN *et al.*, 2014)

From the technology perspective, base technologies allow the capture, analysis, and dissemination of large amounts of data to develop a smart supply chain (MANAVALAN; JAYAKRISHNA, 2018; SHAO *et al.*, 2021). When supported by AI tools, such technologies can make better predictions and anticipate supply chain demands (OH; JEONG, 2019; TOORAJIPOUR *et al.*, 2021). They also facilitate the synchronization of internal operations based on more proactive production planning and control processes (BUENO *et al.*,2020) and better visualization of the different layers of the supply chain (WANG *et al.*,2016). Moreover, real-time visibility of the supply chain is one of the starting points of a flexible supply chain that can adapt quickly to different changes. It is only possible when the various supply chain partners are integrated through IoT solutions run on cloud systems (DALENOGARE *et al.*,2018; DOS SANTOS *et al.*, 2020). Thus, base technologies should also be an antecedent of supply chain flexibility.

Finally, the front-end technologies are responsible for executing operational activities of the supply chain management based on the use of collected and analyzed data by base technologies. For instance, computer simulation can improve supply chain flexibility by simulating if forecasting could improve product routes and change production volume

(TERZI; CAVALIERI, 2004). Furthermore, some employees' use of augmented reality could also change warehouse space by guiding employees in more efficient ways to organize and structure the storage (REJEB *et al.,*2021; DORNELLES *et al.,*2022). The collaborative robots also improve flexibility given by the direct participation of employees in the most complex work and control phases and by eliminating the structural and technological limitations of automatic and fixed systems (REALYVÁSQUEZ-VARGAS *et al.,*2019). As shown qualitatively by Enrique et al. (2022), these are essential tools to increase the internal operational flexibility of Industry 4.0-oriented companies. As argued by these authors, these tools tend to be more flexible when the systems need to reconfigure routes and types of products to be produced. Some preliminary studies have also shown the usefulness of these tools alongside the supply chain. For instance, Delic and Eyer (2020) showed the benefit of 3D printing of flexible spare parts repositioned alongside the supply chain. Meindl et al. (2021) have also argued that simulation and virtual tools could also be useful for supply workers to reschedule and readapt quicker for their distribution or internal logistics activities. These are some examples that indicate that front-end digital technologies should support the supply chain flexibility of companies.

Based on our arguments regarding the above three dimensions of Smart Supply Chain, we argue that they should support the whole supply chain flexibility, as stated in the following hypotheses.

H1: Smart Supply Chain (i.e., digital transformation, base digital technologies, and front-end digital technologies) is positively associated with higher levels of supply chain flexibility (source, manufacturing, and delivery flexibility).

4.2.5 Smart and Flexible Supply Chain to increase operational performance in the context of environmental uncertainty

Several authors have widely recognized the impact of Smart Supply Chain on operational performance in the digital transformation field (e.g., BUCHI *et al.,* 2020; CHAUHAN *et al.,* 2020). For example, IoT and Big Data analytic tools allow the collection and analysis of data about supply chain operations and product performance, which can improve logistics operations and manufacturing practices (PORTER; HEPPELMANN, 2014; BUCHI *et al.,* 2020). Also, new digital technologies enable a closer approach to the customer and, consequently, the development of more customized solutions (BENITEZ *et al.*, 2022). Thus, the adoption of Smart Supply Chain tools should help companies improve their response to market demands, elevating the supply chain operational performance.

However, as Enrique et al. (2022) argued, digital technologies may have little contribution when they are not oriented before to support the structure of the company. These authors show that Industry 4.0 technologies can increase organizational flexibility, which will result in higher firm performance. Such results were evidenced by Enrique et al. (2022) in internal manufacturing activities, which we extend to the external supply chain operations. A company will be able to meet customer demands for product delivery better if the products can be flexibly manufactured or assembled and also if the incoming materials are also flexibly supplied (ZHANG *et al.*, 2005; MAQUEIRA *et al.*, 2020). Thus, the smart supply chain could potentialize the supply chain flexibility to improve operational performance. For example, companies can use machine learning to deepen the understanding about their operations and predict future customer behavior, so they can improve delivery time and reduce logistics costs (TOORAJIPOUR *et al.*, 2021). At the same time, they also need to create good coordination between suppliers and distributors to ensure material and product flow according to the machine learning predictions. In this sense, front-end technologies such as robots are recognized for guaranteeing great machine flexibility that allows to produce a large variety of products in the same production line to respond the customer demand (ZHONG *et al.*, 2017; ALCÁCER; CRUZ-MACHADO, 2019). However, the impact of robots is limited because the process and product need to be designed in a flexible way to facilitate the manufacturing of several products (DALENOGARE *et al.*, 2018; ENRIQUE *et al.*, 2022). In that way, companies will improve their operational performance efficiently because the adoption of digital technologies will impact on supply chain flexibility and operational performance. Therefore, manufacturing companies will be taking better advantage of the use of technologies, enhancing its use through flexibility, and achieving their desired operational performance goals.

H2: Supply Chain Flexibility mediates the relationship between Smart Supply Chain and operational performance.

However, the literature also argues that sourcing and delivery flexibility are necessary for manufacturing flexibility (DUCLOS *et al.*, 2003; MALHOTRA; MACKELPRANG, 2012, LIAO, 2020). For instance, in lean production, flexible management of the relationship with suppliers and quick adaptation to the customer demands are essential elements to increase the agility and response of the internal production system (MARODIN *et al.*, 2017). This means that upstream and downstream supply chain behaviors are antecedents of how manufacturing will be configured. This is especially important in the Industry 4.0 context, where data collected from products and from the suppliers' activities will help to organize the manufacturing production and planning based on integrated data from these external sources (FRANK *et al.*, 2019b; BUENO *et al.*, 2020). Therefore, we subdivide hypothesis H2 on the mediating role of supply chain flexibility between Smart Supply Chain and operational performance as follows:

H2a: Sourcing flexibility is an antecedent of manufacturing flexibility in the mediating role of supply chain flexibility between Smart Supply Chain and operational performance.

H2b: Delivery flexibility is an antecedent of manufacturing flexibility in the mediating role of supply chain flexibility between Smart Supply Chain and operational performance.

4.2.6 Supply chain uncertainties as boundary conditions between Smart Supply Chain and flexibility

Turbulent business environments create uncertainties in the companies' structure that require a response, reinforcing companies' decisions on technology investment or triggering some new implementations (FRANK *et al.*, 2022). The literature has shown that turbulent environments interact with digital transformation by reinforcing digital technologies' relevance to achieve organizational goals (CHEN; TIAN, 2022; LI, 2022). We use the OIPT to argue that this is because under uncertain conditions, in which companies have more information-processing needs to be able to make the right decisions. They will focus on increasing information-processing capability to fit such needs, which can be achieved through digital technologies like Smart Supply Chain (SRINIVASAN; SWINK, 2018; YU *et al.*, 2021). Such supply chain uncertainties can be rooted in two different sources: upstream uncertainties provoked by supplier's disruptions and changes, and downstream uncertainties caused by the customers' rapid demand changes (MERSCHMANN; THONEMANN, 2011). Thus, we propose the following hypotheses H3:

H3: Supply Chain uncertainties positively moderate the relationship between Smart Supply Chain and supply chain flexibility.

At the same time, the literature has also demonstrated that environmental uncertainty acts as a moderator between supply chain flexibility and firm performance (MERSCHMANN; THONENMANN, 2011). Supply chain flexibility is more pursued when companies face turbulent environments and need to adapt quickly to changing organizational contexts in order to keep competitiveness (CANDANCE *et al.*, 2011; SHEKARIAN *et al.*, 2019). A good practical example of this was during the pandemic of COVID19, when global manufacturers started to change their focus toward more flexible factories that can quickly change their production features in order to reset any disruption in the supply chain (EL BAZ; RUEL, 2020; BELHADI *et al.*, 2021). Following the OIPT view, achieving higher flexibility because of the increase of information-processing capability through its antecedent (i.e., Smart Supply Chain, as hypothesized in H1) will help to fit to the information-processing need to be able to reconfigure the organizational processes quickly in uncertain environments (i.e., flexibility required, as hypothesized in H2 and H3), which should help to obtain better organizational performance (PREMKUMAR *et al.*, 2005). Therefore, flexibility will increase when supply chain uncertainties are present, and Smart Supply Chain supports such flexibility. Thus, we propose the following hypothesis:

H4: Supply Chain uncertainties positively moderate the relationship between supply chain flexibility and operational performance.

4.3 RESEARCH METHOD

4.3.1 Sampling

Our research was carried out through a cross-industry survey with experts in the supply chain and operations management fields. The target respondents were top executives, directors, and managers, especially from large manufacturing firms operating in Brazil (location of the survey) with mass production models on their shop floors. This was necessary since firms that develop or aim to develop flexible systems usually are large firms with a vast product portfolio and a volatile market demand (market-push trajectory) (CASTELLACI *et al.*, 2008). To validate our questionnaire, we sent a preliminary version to executives from the supply chain and operations management field and obtained 27 feedbacks regarding our survey. Then, our questionnaire was sent three times to our target population via email through SurveyMonkey platform from the beginning of October till the end of November 2021. We obtained a total of 399 answers with a total of 379 useful answers to our analysis. Because our survey was designed for supply chain and operations management field, we asked about the enterprise's supply tier, which was represented by 67.81% in tier 1, 23.75% in tier 2, and 8.44% in tier 3. As expected, most of the respondents were from large companies representing a total of 83.91% of our sample population. To measure this, we followed the IBGE's (2015) classification which defines 500 or more employees as large companies. The overall respondent profile was essentially composed by directors (42.48%), managers (34.04%), and coordinators or supervisors (15.56%). Table 10 shows our population composition and further details described in this section.

Table 10. Population description and composition

Description	(%)	Category	Description	(%)
Automotive	19.79%	Company size	Small and medium companies	16.09%
Non-durable consumer goods	19.79%		Large companies	83.91%
Durable consumer goods	10.29%	Supply chain's tier	Tier 1	67.81%
Electronics	6.33%		Tier 2	23.75%
Construction	6.33%		Tier 3	8.44%
Chemicals and Petrochemicals	6.33%	Respondent's profile	Director	42.48%
Agribusiness	6.07%		Manager	34.04%
Energy	4.49%		Coordinator or Supervisor	15.56%
Mining	3.43%		President/Vice/CEO	5.28%
Steel Industry	3.43%		Owner/Partner owner	2.64%
Capital goods	3.17%			
Pharmaceutical	2.37%			
Paper And Cellulose	1.58%			
Digital industry	1.06%			
Agriculture production	1.06%			
Transport	0.53%			
Others	3.96%			

4.3.2 Survey instrumentation

The survey instrumentation was based on pre-formatted constructs retrieved from the literature on flexibility, digital transformation, supply chain, and operations management. To this study we utilised five blocks of questions: (i) sample composition; (ii) digital transformation; (iii) flexibility; (iv) supply chain uncertainty; and (v) supply chain performance. Our utilised items are presented in Appendix A, which highlights our main statistical results regarding item grouping. For Smart Supply Chain, we utilised three constructs namely [FRONT-END], [DT_STRATEGY], and [BASE]. These constructs were retrieved from previous studies of Frank et al. (2019), Nasiri et al. (2020), and Meindl et al. (2021) about digital transformation in manufacturing. The first, known as [DT_STRATEGY], we retrieved from Nasiris et al. (2020) study and formed a four-item scale construct that comprises the strategical aspects and goals regarding digital transformation implementation in supply chains. This construct considers aspects like digitize all supply chain, data collection from different sources, the creation of a stronger communication network between different sectors, and improvement of the interface with customers through digitization (NASIRI *et al.,* 2020). For the constructs related to Industry 4.0 technologies, we adopted a composite measure for them. In other words, because the different nature and purpose of Industry 4.0 technologies (e.g., IoT connect systems, while AI give decentralized decision to flexible systems), our approach was a formative construct (i.e., the sum of indexes) rather than a reflexive construct normally deployed by techniques like Confirmatory Factor Analysis (CFA).

For front-end technologies [FRONT-END] we considered a four-scale formative scale including simulation, augmented reality, 3D printing, and robotics. According to Frank et al. (2019) these technologies are considered front-end technologies in Industry 4.0 because they enable the four 'smart' dimensions (MEINDL *et al.,*2021) which are concerned with operational and market needs. Therefore, they have an end-application purpose for the companies to enable Smart Supply Chain. For base technologies [BASE], a five-item formative scale composed by Internet of Things, Cloud Computing, Big Data, Artificial Intelligence, and Blockchain was formed. Four of these technologies (IoT, cloud, big data, and AI) are considered base in Industry 4.0 because they are necessary to allow companies digital transformation process (Frank et al., 2019). Moreover, blockchain is also considered a base technology in supply chain management literature (FREDERICO *et al.*, 2019; QUEIROZ; WAMBA, 2019; MEINDL *et al.*, 2021) since it is a paramount for secure transactions and relationships alongside supply chain's ties.

For supply chain flexibility, we considered three major types of flexibility used in literature: sourcing flexibility [SOUR_FLEX], delivery flexibility [DEL_FLEX], and manufacturing flexibility [MAN_FLEX]. According to Kumar et al. (2006) and Sreedevi and Saranga (2017) sourcing flexibility is defined as the extent of responsive ability through the use of supplier-specific capabilities and the use of interorganizational collaborative capabilities in upstream relationships. Thus, SOUR_FLEX is a four-item scale composed by features as quick new supplier identification, easiness to add or remove suppliers, openness and easiness to make contractual adjustments with suppliers, and mutual decision with main suppliers about product/project/process design modifications. On the other hand, delivery flexibility is the ability of a firm to quickly and effectively adjust the inventory, packaging, warehousing, and transportation of physical products to meet customer needs (JIN *et al.*, 2014; SREEDEVI; SARANGA, 2017). DEL_FLEX is a four-item scale construct which considers the easiness to add or remove carriers or distributors, easiness to change warehouse space and load capacity, easiness to change merchandise delivery schedule, and the existence of a defined and flexible delivery strategy. Finally, manufacturing flexibility refers to the ability of the organization to manage production resources and uncertainty to meet various customer requests (ROJO *et al.*, 2017; SREEDEVI; SARANGA, 2017; MAQUEIRA *et al.*,2020). MAN_FLEX has five-item scales which correspond to the ability to operate with various production volumes and different service levels, the efficiency to change production volumes and/or services, the ability to produce various combinations of products, the capability to develop new products and/or services every year, and the ability to change the mix of products and/or services efficiently.

In the case of supply chain uncertainty, we used two constructs: supplier uncertainty [SUPPLIER_UN] and customer uncertainty [CUSTOM_UN] mostly used in supply chain literature to measure supply chain relationships uncertainty (JAWORSKI; KOHLI, 1993; MERSCHMANN; THONEMANN, 2011; QI *et al.*, 2011; SREEDEVI; SARANGA, 2017; ZHOU *et al.*, 2019). For SUPPLY_UN we measured this construct by including a three-item scale of uncertainties related to materials and components prices bought by the company, dependence on suppliers' materials for production, and frequent supplier material delays handling. For CUSTOM_UN we also measured this construct with a three-item scale by considering uncertainties related to customers preference frequent change, frequent product and service demands from new customers, and new customers with different needs than the current customers. Finally, for performance we measured two constructs, one for our original model (Operational Performance) and another one for our robustness check (Financial Performance). OPER_PERF was measured with a three-item scale including improvement in the last two years in delivery reliability over customer orders, lead time, and order time reduction (MERSCHMANN; THONEMANN, 2011; YU *et al.*, 2018; MAQUEIRA *et al.*, 2020). While FINAN_PERF (FLYNN *et al.*, 2010; JAYARAMAN *et al.*, 2013; ASARE *et al.*, 2013; YU, 2015;

SAEED *et al.*, 2019; AMOAKO-GYAMPAH *et al.*, 2020) was measured with a three-item scale construct: sales grown, profit on sales increasement, and market share grown in the last two years.

Finally, regarding our control variables, we controlled the firm size and supply chain tiers, since it can affect how firms make their processes more flexible and digital (THOMÉ *et al.*, 2014; GLIGOR, 2018, DELIC; EYERS, 2020). We used one dummy for size [large = 1; 0 = small or medium], and two dummies for three level of supply chain tiers (tier 1 – B2C; tier 2 – B2B of finalized goods and solutions; tier 3 – B2B of raw-material and basic components).

4.3.3 Construct definition and variable handling

To build our constructs, we used confirmatory factor analysis (CFA) approach to ascertain unidimensionality of our metrics**.** Overall, our constructs showed goodness of fit, since our reference values for the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha fell in the acceptable values (HAIR *et al.*, 2018), as shown in our Appendix A. In respect to our factor loadings reference values, all items showed a good or high factor value, which explain their aggregation in the referred construct. Moreover, as previously explained, for technology constructs (BASE and FRONT-END) we adopted a formative approach by summing the scales from the respondents. This was necessary since the technologies are in essence different, however, we reported some indexes like Alpha's Cronbach and factor loadings to evidence their consistency. Lastly, we measured the final and complete model including all constructs and our model showed a goodness of fit (RMSEA = 0.060; CFI = 0.884; $\Delta\chi 2$: 1231.27).

As recommended by Hair et al. (2018), we also checked discriminant validity by using a series of two-factor model estimations among the constructs. Since our model has 7 independent constructs, we performed a factorial (k-1) approach, totalizing 21 tests for discriminant validity. As recommended by Cable and DeRue (2002), we performed pairwise comparisons between CFA models for each construct, looking for their respective goodness of fit. In the first step the correlation between the two constructs was restricted to a unit. In the second step the model restriction was freed, and we calculated the goodness of fit for the original constructs. In this test, all the results showed discriminant validity ($\Delta\chi 2 > 3.84$, p-value $p < 0.01$), evidencing our constructs are measured with theoretically different concepts (BAGOZZI *et al.*, 1991). As a final test, we assessed the normality of our data by examining the skewness and kurtosis values. The results suggest that our variables for the general model are normally distributed since all values fall between the thresholds of ±2.58 ($\alpha = 0.01$) (HAIR *et al.*, 2018). We also analyzed the means, standard deviations and the correlations for our constructs and control variables incorporated in the model. Appendix B summarizes all descriptive statistics, as well as normality and correlations.

4.3.2 Response bias and common method variance

Because bias can be a potential issue in survey design, we employed a series of procedures and statistical medicines to attenuate it as recommended by Podsakoff et al. (2012). Firstly, because our survey is composed by single respondents, common method variance (CMV) can be a potential concern. As initial procedure, we pre-validated the questionnaire with 27 executives from supply chain and operations management field to better clarity our utilised instruments. We randomized the order of the questionnaire blocks to prevent potential associations between the variables to avoid social desirability bias. For the magnitude of CMW, we employed the Harman's single factor test in which a single factor loads on all measured items from our model. This test suggests if the total variance extracted by one factor exceeds 50%, common method bias is present in your study (PODSAKOFF *et al.*, 2012). The single factor explained 25.51% of the total variance indicating CMV is not a concern in our study. However, since other authors (WILLIAMS *et al.*, 2010; SIMMERING *et al.*, 2015) recommend other approaches to measure CMV, especially for single respondents, we also performed the marker variable technique.

The marker variable technique considers adding a variable to the survey, which is expected to be theoretically unrelated to the substantive variables measured in the model (LINDELL; WHITNEY, 2001). We used "use of human resources from external partners to develop digital transformation in the supply chain" as a marker, since our model was oriented to internally development of digital transformation and not outsourcing. When added to our models the marker variable did not perform a significant change in the models (i.e., most of sigma from F-change were above the threshold of 0.1 or the model did not suffer a significant influence from the addition of this variable). This item was added in all estimations necessary for hypothesis testing and the results were compared with the outputs without markers. The results remained stable with the adding of a marker variable, which means that there were no significant changes in the models. Hence, we concluded that response bias should not be a concern in this dataset.

4.3.3 Data analysis

For data analysis, we performed a set of hierarchical OLS regression models to test our hypotheses. To this end, we first standardised all independent variables using a mean-centring Z-score. Overall, we tested four OLS models, where the first stage of each hierarchical regression was a model only with the control variables. Depending on the model, the hierarchical set from the following stages was different. For instance, for DEL_FLEX and SOUR_FLEX the second stage was the inclusion of digital transformation constructs (DT_STRATEGY, FRONT-END, BASE), while the third stage was uncertainty constructs and the fourth stage the moderation effects from uncertainty. For MAN_FLEX, the second stage was the inclusion of digital transformation constructs and the third stage the inclusion of DEL_FLEX and SOUR_FLEX constructs. Finally, for OPER_PERF, the second stage was the inclusion of flexibility constructs, the third stage was the inclusion of uncertainty constructs, and the fourth stage the moderation effect of uncertainty constructs. For mediation effect, we performed the PROCESS macro from Hayes (2017). To assess mediation effects, we calculated the indirect effects of the relationships as suggested by Preacher and Hayes (2008). PROCESS analysis allows for a bootstrapping procedure to examine the conditional indirect effects, a more powerful procedure than Sobel's z test to test for mediation effects (Zhao et al., 2010). We set up 5,000 bootstrap samples as suggested by Preacher and Hayes (2008). Our final model contains three control variables (size, tier1, and tier2), eight independent variables (FRONT-END, DT_STRATEGY, BASE, DEL_FLEX, SOUR_FLEX, MAN_FLEX, CUSTOM_UN, and SUPPLIER_UN) which some (flexibility) are considered dependent in some models, and one dependent variable (OPER_PERF).

Furthermore, to start our regression models some assumptions like linearity, homoscedasticity, normality, multicollinearity, and power design must be checked (COHEN, 1992; HAIR *et al.*,2018). We analyzed collinearity by plotting the partial regressions for the independent variables, while homoscedasticity was visually examined in plots of standardized residuals against a predicted value. All these requirements were met in our dataset for regression analysis. Normality we also checked as previously explained by assessing the skewness and kurtosis parameters. For multicollinearity we checked the variance inflation factor (VIF) to ascertain our regression estimates are not unstable and have high standard errors. Our results indicate a low VIF (< 3.5) for all variables, far below the threshold of 10 (HAIR *et al.*, 2018). Finally, for power design, we used g-power analysis with a reference value of 0.80 and effect size of 0.15 as suggested by Cohen (1992), to verify the feasibility of using an OLS approach with the proposed sample size (n = 379). We tested all models (DEL_FLEX, SOUR_FLEX, MAN_FLEX, and OPER_PERF) using the main variables as predictors to check for the minimum sample size to perform the regression. The minimum necessary to achieve a statistical power significance level was the threshold of 109 observations. Since our sample is far away the minimum necessary, this analysis suggests we have a sample size large enough to proceed with the OLS statistical analyses.

4.4 RESULTS

Our results report four independent models in a hierarchical structure for each model. We also present a different structure for our mediation analysis, following Hayes (2017) approach, who suggests the calculation of the indirect effects as a post-hoc analysis. For the OLS procedure, we present Table 11 which highlights our main results from regression analysis. As shown in Table 11, all final stage models (i.e., Models 3 or 4) were significant at $p < 0.001$. As a result, for the final step of each model we had: SOUR_FLEX ($F = 4.815$, $p = .000$), DEL_FLEX ($F = 5.584$, $p = .000$), MAN_FLEX ($F = 24.510$, $p = .000$), and OPER_PERF ($F = 4.886$, $p = .000$). Unstandardized coefficients are reported in Table 11 since all scales were standardized with Z-scores because they represent a standardized effect (Goldsby et al., 2013).

Regarding our H1 (Smart Supply Chain on Supply Chain Flexibility) we have statistical support from DT_STRATEGY for all flexibility constructs. However, we did not have statistical support for BASE. FRONT-END was only statistically associated to DEL_FLEX ($B = .181$, $p = .006$). For hypotheses H3 (Environmental Uncertainty moderating the relationship between Smart Supply Chain and Supply Chain Flexibility), we only found statistical evidence for CUSTOM_UN x DT_STRATEGY on SOUR_FLEX ($B = .162$, $p = .009$) and SUPPLIER_UN x BASE on DEL_FLEX ($B = .133$, $p = .058$). For hypotheses H4 (Environmental Uncertainty moderating the relationship between Supply Chain Flexibility and Operational Performance), we found support for CUSTOM_UN x MAN_FLEX on OPER_PERF ($B = .103$, $p = .079$).

Regarding the mediation analysis proposed in hypothesis H2, we used Hayes' (2017) bootstrapping approach (Table 12). The iterative process allowed us to assess the direct effect of Smart Supply Chain constructs on OPER_PERF. In this case, DT_STRATEGY and BASE have a significant and direct association with OPER_PERF. Moreover, we also tested these effects individually, and FRONT-END also showed a positive association with OPER_PERF (B = .154, p = .045), supporting the full direct effects of Smart Supply Chain on operational performance. We also tested the hypothesis on the mediation role of supply chain flexibility (H2, H2a, H2b) in a sequential procedure in which Smart Supply Chain constructs were considered the direct effects, while DEL_FLEX and SOUR_FLEX were set as mediators, between Smart Supply Chain and MAN_FLEX (H2a, H2b), and, finally, all the supply chain flexibility constructs mediating between Smart Supply Chain and OPER_PERF (H2). These results are summarized in Table 3. The results support a complete mediation effect of DEL_FLEX and SOUR_FLEX between FRONT-END and MAN_FLEX and then with OPER_FLEX, and partial mediation when we tested the similar paths for DT_STRATEGY and BASE. Therefore, our findings support hypothesis H2 regarding the mediating role of supply chain flexibility (Figure 5) and the intermediate role of sourcing and delivery flexibility as antecedents of manufacturing flexibility (H2a, H2b).

After our results, we also assessed the statistical power of our models by analysing our regression models through Cohen's f2 estimation (COHEN *et al.*, 2003, p.95). By calculating the population effect size from all the four final models in the last stage of our OLS hierarchical procedure, we obtained a statistical power of ≈ 0.95 at $\alpha = 0.01$ for all models. Therefore, this suggests our results are in accordance with the minimum statistical power necessary for regression models (COHEN *et al.*, 2003).

4.4.1 Robustness checks

We performed a series of robustness checks to ensure our results previously presented are stable and consistent. We explored how the results of our regressions analyses might vary using three distinct approaches: (i) inclusion of a new construct; (ii) individual analysis from predictors; and (iii) inclusion of a competing model. For the first (i) approach, we included a new construct, namely "own digital resources" [OWN_DIG_RES]. We assume that when a company focuses on resources to enable digital transformation, these resources do not directly impact flexibility. Basically, we argue this construct is an antecedent to enable digital transformation, which can support a supply chain's flexibility. Therefore, there is no direct association to these types of resources on flexibility constructs. To this end, we measured [OWN_DIG_RES] with CFA approach (RMSEA = 0.051; CFI = 0.994; AVE = 0.55; Cronbach = 0.85; CR = 0.98) in a five-item scale construct composed by: necessary information to develop digital transformation in the supply chain (0.79); sufficient human resources to develop the digital transformation in the supply chain (0.63); the necessary technological resources to develop the digital transformation in the supply chain (0.89); the necessary financial resources to develop the digital transformation in the supply chain (0.72); and the organizational culture necessary to develop digital transformation in the supply chain (0.65). Our assumption was confirmed when we added this construct in models where [DEL_FLEX; SOUR_FLEX; and MAN_FLEX] were the dependent variables, showing that [OWN_DIG_RES] was not statistically significant in all models. For the second approach (ii), we analyzed the individual effect of each construct in our models, and overall, we found consistency with our main findings presented in Table 11. In addition, we also confirmed [FRONT-END] has a significant and positive effect on [OPER_PERF], which validate our H3, as previously discussed when we presented mediation results. Finally, for approach (iii), we utilized a financial performance construct (see Appendix A) as a competing model. Our assumption is that this performance metric will not suffer a direct and positive effect from these relationships were since all constructs in our model have the primary goal to improve operational aspects of the supply chain and not corporate performance aspects. As expected, this competing model was not supported, while our main model showed robust results reported above. In addition, the R^2 from the competing model showed a low value (i.e., below 0.100), and we did not find similar results to our main model [OPER_PERF]. Therefore, these procedures suggest our models are not overfitted, and we have consistency in our analysis.

Table 11. Results of the regression analysis[(a)]

	SOUR_FLEX				DEL_FLEX				MAN_FLEX			OPER_PERF			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Firm size	.082	.014	.000	-.025	-.119	-.172	-.156	-.198* (p=.098)	.055	-.005	.069	-.329** (p=.013)	-.333*** (p=.007)	-.316** (p=.011)	-.340*** (p=.007)
Tier1	-.175	-.341** (p=.024)	-.327** (p=.031)	-.291* (p=.056)	-.151	-.368** (p=.019)	-.382** (p=.015)	-.362** (p=.023)	.085	-.115	.069	-.177	-.168	-.209	-.197
Tier2	.299* (p=.084)	-.324** (p=.050)	-.284* (p=.089)	-.235	-.339* (p=.064)	-.423** (p=.014)	-.465*** (p=.008)	-.437** (p=.013)	.001	-.058	.149	-.374* (p=.051)	-.315* (p=.085)	-.394** (p=.033)	-.384** (p=.039)
DT_STRATEGY		.204*** (p=.000)	.211*** (p=.000)	.194*** (p=.001)		.277*** (p=.000)	.270*** (p=.000)	.264*** (p=.000)		.256*** (p=.000)	.120** (p=.014)				
BASE		.055	.059	.088		-.114	-.120* (p=.098)	-.086		.162*** (p=.007)	.060				
FRONT-END		.075	.083	.032		.223*** (p=.000)	.216*** (p=.001)	.181*** (p=.006)		-.046	.000				
CUSTOM_UN			-.066	-.068			.071	.056						.127** (p=.010)	.118** (p=.019)
SUPPLIER_UN			.017	.016			-.024	-.020						-.032	-.046
SOUR_FLEX											.059		.054	.068	.052
DEL_FLEX											.388*** (p=.000)		.104* (p=.081)	.094	.101* (p=.093)
MAN_FLEX													.199*** (p=.000)	.170*** (p=.003)	.197*** (p=.001)
CUSTOM_UN x DT_STRATEGY				-.055				.010							
CUSTOM_UN x BASE				-.055				-.057							
CUSTOM_UN x FRONT-END				.162*** (p=.009)				.062							
SUPPLIER_UN x DT_STRATEGY				-.025				-.035							
SUPPLIER_UN x BASE				.109				.133* (p=.058)							
SUPPLIER_UN x FRONT-END				-.044				-.029							
CUSTOM_UN x SOUR_FLEX															.004
CUSTOM_UN x DEL_FLEX															.001
CUSTOM_UN x MAN_FLEX															.103* (p=.079)
SUPPLIER_UN x SOUR_FLEX															-.014
SUPPLIER_UN x DEL_FLEX															-.019
SUPPLIER_UN x MAN_FLEX															.027
F-Value	1.275	8.782***	6.868***	4.815***	1.762	11.631***	9.035***	5.584***	0.340	10.346***	24.510***	3.615**	9.225***	7.832***	4.886***
R^2	.010	.124	.129	.156	.014	.158	.163	.177	.003	.143	.346	.028	.13	.145	.158
Adj.R^2	.002	.110	.11	.124	.006	.144	.145	.145	-.005	.129	.332	.020	.115	.126	.126
R Square Change	.010	.114***	.005	.026*	.014	.144***	.005	.013	.003	.124***	.203***	.028**	.101***	.015**	.013

[(a)] Unstandardized beta coefficients are reported since the main variables were standardized before regression. n = 379. *** < 0.01, ** < 0.05, * < 0.10.

Table 12. Indirect effects (bootstrapping outcome)

Interactions	**Direct effect**				**Indirect effect**			**Total Effect**				**Conclusion**
	Effect	95% confidence interval		Sig.	Effect	95% confidence interval		Effect	95% confidence interval		Sig.	
		LLCI	ULCI			LLCI	ULCI		LLCI	ULCI		
DT_STRATEGY-SOUR_FLEX-MAN_FLEX-OPER_PERF	.1946	.0977	.2914	.0001	.0162	.0056	.0313	.2761	.1855	.3666	.000	**Partial**
DT_STRATEGY-DEL_FLEX -MAN_FLEX -OPER_FLEX	.1877	.0920	.2835	.0001	.0243	.0041	.0488	.2761	.1855	.3666	.000	**Partial**
FRONT-END-SOUR_FLEX-MAN_FLEX- OPER_PERF	.0753	-.0198	.1705	.1204	.0160	.0064	.0291	.1586	.0652	.2520	.000	**Complete**
FRONT-END-DEL_FLEX-MANF_FLEX -OPER_PERF	.0685	-.0264	.1634	.1565	.0261	.0079	.0483	.1586	.0652	.2520	.000	**Complete**
BASE-SOUR_FLEX-MAN_FLEX_OPER_PERF	.1634	.0689	.258	.0007	.0176	.0067	.0332	.2367	.145	.3284	.000	**Partial**
BASE-DEL_FLEX-MAN_FLEX -OPER_PERF	.1625	.0698	.2552	.0006	.0199	.0045	.0407	.2367	.145	.3284	.000	**Partial**

4.5 DISCUSSIONS

We summarized our results and their connections with the OIPT in the framework of Figure 6. This framework shows that the digital transformation strategy is on the top of the structure because it directly affects all supply chain flexibility dimensions. When associated with operational performance, it is also partially mediated by supply chain flexibility dimensions. Therefore, the results indicate that the digital transformation strategy provides the complete organizational view to implement digital transformation and support the increase of flexibility. From the OIPT perspective, this represents the requirement of creating a strategic alignment for *organizational information-processing fit* (GALBRIATH, 1974), as represented in Figure 6. In other words, companies need to develop a digital transformation strategy that supports all the dimensions of the supply chain flexibility structure in order to create information-processing capability that fits the information processing needs (PREMKUMAR *et al.*, 2005). Our results showed that this is the basic requirement for Smart Supply Chain in turbulent environments to achieve higher flexibility and operational performance.

Considering sourcing flexibility, one could be surprised with a first look at the results, where base digital technologies did not show significant associations with it, while front-end technologies did when moderated by customer uncertainty. We expected that technologies like IoT, Big Data or Cloud Computing should provide more flexibility (FRANK *et al.*, 2019). However, by investigating the elements of sourcing flexibility, it is important to notice that they consider the ability of the company to easily switch the source of supply (JIN *et al.*, 2014; ROJO *et al.*, 2017; SREEDEVI; SARANGA, 2017). Since IoT-based solutions as those presented in the base digital technologies, require an end-to-end horizontal integration between the focal company and the suppliers (WANG *et al.*, 2016). The results could suggest that such solutions will not enhance flexibility (or maybe be even negative, as suggested by the negative sign in the interaction with customer uncertainty reported in Table 10, although without statistical significance). On the other hand, front-end digital technologies consider tools that can be helpful to select easily new sources of supply, especially when the company cannot stabilize the sources of supply due to the high dynamism of the market (moderating effect of customer uncertainty). For instance, simulation tools can help analyze which new source of supply can respond faster to each demand (TERZI; CAVALIERI, 2004, VIEIRA *et al.*,2019). Augmented reality and robotics can help automate the reception and quality control of the new type of raw material supplied (DORNELLES *et al.*, 2022), and 3D printing can reduce the dependence of the supply of some very specific components required by the company (DELIC; EYER, 2020; HOHN; DURACH, 2021).

From the OIPT point of view of sourcing flexibility, such front-end technologies are supported by *information-processing capability* because they need a large amount of data and interconnectivity to operate these solutions (e.g., pieces are manufactured in 3D printers based on AI models of generative design that analyze and create the best solution for broken components). However, they go beyond by providing not only information but also a real solution, either by a digital image like in augmented reality and simulation or printed components. We call this expanded *information-processing capability*, which is intended to create cyber-physical solutions (i.e., solutions like virtual models or physical elements) that fit what we call as an *information-dependent objective need* (in this case, the need of switching quickly from one source of supply to another). The expanded *information-processing capability* occurs under customer uncertainty, which is an *information boundary condition* about the market behavior due to rapid changes in product and customer demands. We represent these concepts from OIPT in our framework of Figure 6.

Second, we found that delivery is more flexible when companies collect and analyze more data in the context of suppliers' uncertainty (i.e., moderating the role of supplier uncertainty between base technologies and delivery flexibility). Supplier uncertainty represents the risk of increasing input prices, suffering supply delays or even supply disruption (SREEDEVI; SARANGA, 2017). From the OIPT perspective, supplier uncertainty also represents an *information boundary condition* because the lack of information about supplier behavior creates an uncertain condition that moderates this relationship (ZHU *et al.*, 2018). This affects the capacity of planning the delivery and ensures that customers will receive their products as agreed with the company, independently of the problems the company can suffer in the supply chain. Therefore, the results suggest that companies enhance their *information-processing capability* by adopting digital technologies like IoT, Cloud, Big Data, Blockchain, and AI, which are oriented to increase the real-time data collection and processing in order to improve the decision-making process based on useful and updated information (ZHU *et al.*, 2018). Such technologies can help to predict risks and problems with the supply and, based on this, anticipate deliveries, or reschedule such deliveries before disruptions may happen

(SRINIVASAN; SWINK, 2015). Therefore, this allows to create of an *organizational information-processing fit* between the *information needs* represented by the information required to adapt the delivery system quickly and the *information-processing capability* represented by the base technologies operating as monitoring and prediction systems of the supply behavior under an information boundary condition.

At the same time, front-end digital technologies are directly associated with delivery flexibility but did not show statistical significance in the moderation with uncertainties. In this sense, our results evidence the usefulness of such tools to support delivery flexibility, as hypothesized, but independently on facing or not uncertainties. Front-end technologies like augmented reality, collaborative robots, simulation, and 3D printing applications are increasing in the downstream of supply chain management (DELIC; EYERS, 2020; MEINDL *et al.*, 2021). They are a form of increasing flexibility, like in the case of train spare parts, printed in 3D printers to quickly respond to maintenance demands near the customer (DELIC; EYERS, 2020; CHAN *et al.*, 2018). This significantly increases the service level offered to the customer in the delivery system and represents an expanded information-processing capability to fit information-dependent objective needs, as explained above.

Finally, our results showed that the information-processing fit between Smart Supply Chain and supply chain flexibility can, in general, act as a reaction to uncertain conditions and help to improve supply chain operational performance. This is achieved when manufacturing flexibility is in the structure's core, as shown in Figure 6. This is in line with previous findings from Enrique et al. (2022). The authors showed that Industry 4.0 technologies can be organized to support manufacturing flexibility as the central dimension of the industrial digital transformation. They showed that digital technologies and manufacturing flexibility depend on several companies' internal and external factors. Thus, in this present study, we show that such external and internal conditions are essentially those related to the information-processing requirements achieved through Smart Supply Chain and supply chain flexibility. Therefore, this present study provides a zoom-out of the external structure that connects digital transformation with manufacturing flexibility to increase operational performance. Complementarily, Enrique et al. (2022) made a zoom in into the manufacturing flexibility conditions. Thus, both studies provide complementary findings that expand the view of Industry 4.0 and flexibility in operations management.

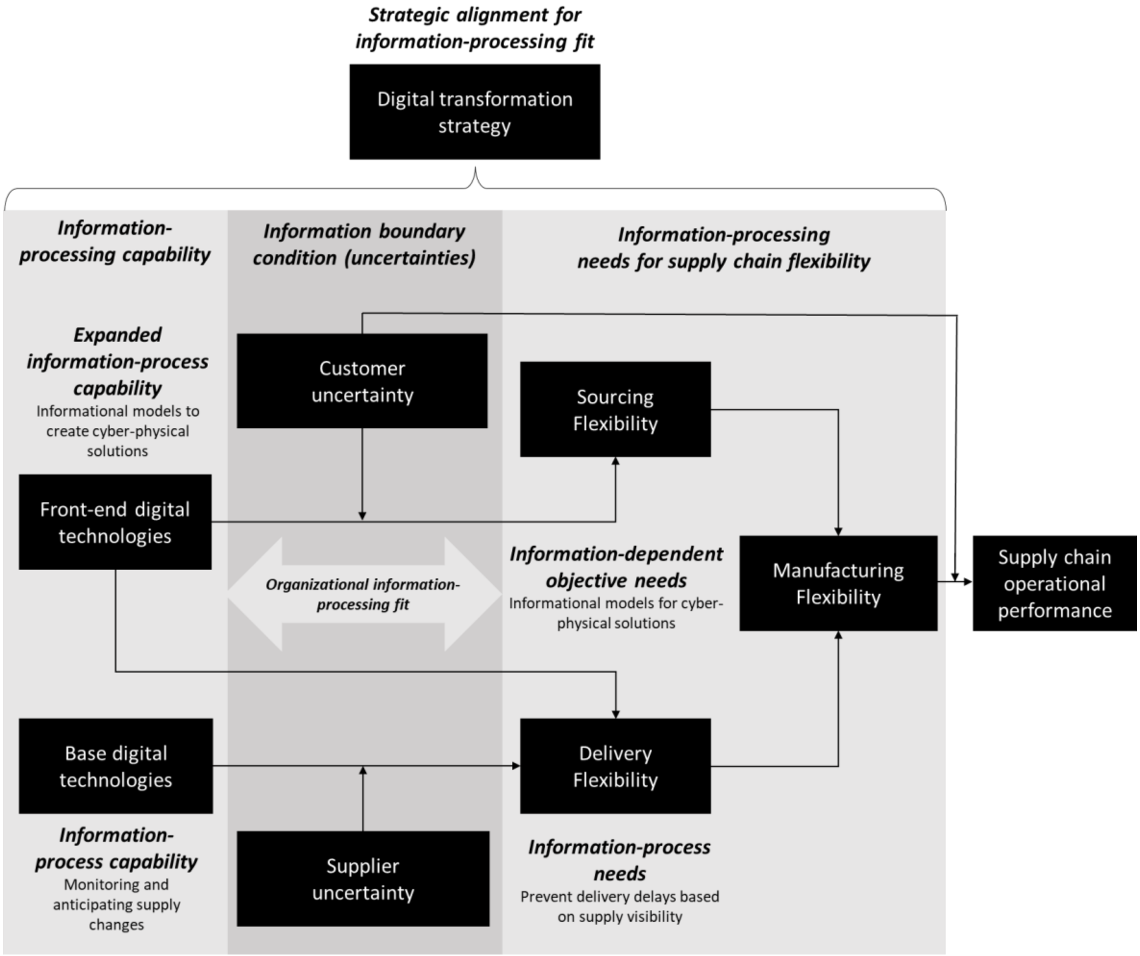

Figure 6. Framework representing the findings and their relationship with OIPT

4.6 CONCLUSIONS

Our results contribute to the theory by showing the connections between Smart Supply Chain and Supply Chain Flexibility and how they are important to better deal with uncertainty based on the OIPT. We also contribute to advancing OIPT from the supply chain perspective since we showed that there is a general mediation effect of supply chain flexibility between Smart Supply Chain and operational performance. This could lead companies to rethink how they would organize the adoption of digital base and front-end technologies based on their digital strategy and how they would change their supply chain operations to become more flexible, mainly focusing on supply flexibility, distribution flexibility, and sourcing flexibility. For this transition from a supply chain flexibility using digital technologies, the company needs to analyze the uncertainties of both consumers and suppliers. Therefore, the OIPT argues that information processing can reduce uncertainty, and our study demonstrates that smart supply chain and supply chain flexibility can support companies to fit such information-processing needs with new information-processing capability.

Against a current and growing context of high uncertainties, our results and discussions provide a foundation for the future implementation of digital transformation by proposing the consolidation of Smart and Flexible Supply Chains. As a key contribution, we show how combining these two concepts can provide more capability for companies to deal with rapidly changing environments. Also, by applying this OIPT to Smart Supply Chain, we provide a new view of the supply chain flexibility literature, especially in the context of the volume 250 of IJPE. Our study presented a historical perspective on the studies developed over the last decades and the new frontier in this subject when considering new turbulent conditions and digital transformation opportunities.

Practical implications

We provide the following recommendations to supply chain practitioners based on our findings. First, managers need to set a digital transformation strategy that will drive the implementation of Smart Supply Chain technologies to achieve supply chain flexibility. Such strategy should be focused on the required fit between these technologies and specific types of supply chain flexibility (i.e., sourcing, delivery, or manufacturing). Front-end technologies can be used in both sourcing and delivery, while base digital technologies are proven to be useful for delivery flexibility when supplier uncertainty is a threat. Second, managers should structure sourcing and deliver flexibility to support manufacturing flexibility and not the contrary. Our study showed that these two external dimensions are antecedent of the manufacturing flexibility and mediate the contribution of digital technologies. Third, practitioners should take care of manufacturing flexibility as the heard of the supply chain flexibility that will help increase operational performance. As argued in the Industry 4.0 literature (DALENOGARE *et al.*, 2018; FRANK *et al.*, 2019), manufacturing should be the core of an Industry 4.0 oriented structure, while the external support of digital technologies will help manufacturing to achieve its goal of producing according to the market requirements and demands. Finally, practitioners can find a set of technologies from Industry 4.0 that they can use in practice to support supply chain activities.

Limitations and future research

Recent studies have shown that manufacturing flexibility in the Industry 4.0 context can be deployed in several dimensions and can be supported by different manufacturing digital technologies (ENRIQUE *et al.*,2022). We did not include such a level of detail. Rather, we remained in the macro-structure of the supply chain. Therefore, future studies should advance in the connection between these micro-elements that were assumed as a black box in our study. Moreover, the recent literature has argued that Industry 4.0 and digital transformation should be considered as a socio-technical system for its implementation (MARCON *et al.,* 2022). This is an important limitation of our study because we only focused on a technological and organizational perspective, while the social elements that involve supply chain workers has not been considered in this study. Therefore, future studies need to advance our research to the field of the social elements by analyzing how smart workers can support flexibility as they do in manufacturing (DORNELLES *et al.*, 2022). As demonstrated by Meindl et al. (2021) in an analysis of more than 5,000 studies from the ten years of Industry 4.0, the integration of studies between social and workers elements with Smart Supply Chain is one of the greatest gaps in the nowadays literature on digital transformation and Industry 4.0 in the operations management field. Thus, future opportunities can arise from the integration of our findings with this social perspective of supply chains (CHEN *et al.*, 2017). Finally, the role of sustainability in supply chain management should also be considered because the current turbulent environments and uncertain scenarios have raised more concern about how digital transformation and supply chains can also contribute to sustainable operations (LIU *et al.*,2019). Our study did not include such an element, but future studies can integrate our findings with this subject and provide advances in this direction.

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APPENDIX A: QUESTIONNAIRE

Questionnaire items to assess Digital Transformation Strategy (DT_STRATEGY) (Adapted from Nasiri et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.049; CFI = 0.998; AVE = 0.63; Cronbach = 0.87; CR = 0.87. Factor loadings are shown in parentheses.*
a. We aim to digitalize everything possible in the supply chain (0.84).
b. We aim to collect large amounts of data from different sources in the supply chain (0.83).
c. We aim to create a stronger communication network between different sectors of the supply chain with digital technologies (0.85).
d. We aim to improve the interface with customers with digitization efficiently (0.63).

Questionnaire items to assess Front-End Technologies (FRONT-END) (Adapted from Frank et al., 2019). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. We only reported Cronbach of this construct because we performed a formative approach. Cronbach = 0.80. Factor loadings are shown in parentheses.*
a. We use robotics in our company processes and in the supply chain (0.69).
b. We use computer simulation in supply chain processes (0.66).
c. We use augmented reality in supply chain processes (0.73).
d. We use 3D printing in supply chain processes (0.76).

Questionnaire items to assess Base Technologies (BASE) (Adapted from Frank et al., 2019; Narayanamurthy and Tortorella, 2021). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. We only reported Cronbach of this construct because we performed a formative approach. Cronbach = 0.90. Factor loadings are shown in parentheses.*
a. We use Internet of Things in our supply chain processes (0.81).
b. We use Cloud Computing in our supply chain processes (0.75).
c. We use Big Data Analytics in our company processes and in the supply chain (0.84).
d. We use Artificial Intelligence in supply chain processes (0.81).
e. We use Blockchain in the supply chain processes (0.78).

Questionnaire items to assess Sourcing flexibility (SOUR_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.085; CFI = 0.977; AVE = 0.36; Cronbach = 0.69; CR = 0.69. Factor loadings are shown in parentheses.*
a. Our company can quickly identify a new supplier when needed (0.60).
b. Our company can easily add and remove suppliers when needed (0.70).

c. Our company is able to make contractual adjustments in the relationship with suppliers with ease (0.63).
d. Our company makes decisions together with the main suppliers (in relation to design/product modifications, project/process modifications, etc (0.46).

Questionnaire items to assess Delivery Flexibility (DEL_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.050; CFI = 0.994; AVE = 0.42; Cronbach = 0.74; CR = 0.74. Factor loadings are shown in parentheses.*
a. Our company can easily add or remove carriers or distributors (0.57).
b. Our company can easily change warehouse space and/or load capacity (0.68).
c. Our company is able to change merchandise delivery schedules with ease (0.67).
d. Our company has a defined and flexible delivery strategy (0.67).

Questionnaire items to assess Manufacturing Flexibility (MAN_FLEX) (Adapted from Jin et al., 2014; Rojo et al., 2017; Sreedevi and Saranga, 2017; Maqueira et al., 2020). *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.073; CFI = 0.989; AVE = 0.52; Cronbach = 0.83; CR = 0.84. Factor loadings are shown in parentheses.*
a. Our company is able to operate with various production volumes and/or with different service levels (0.75).
b. Our company can change production volumes and/or services efficiently (0.79).
c. Our company is able to produce various combinations of products (0.60).
d. Our company manages to develop new products and/or services every year (0.66).
e. Our company has the ability to change the mix of products and/or services efficiently (0.79).

Questionnaire items to assess Supply Chain Uncertainty (including customer uncertainty and supplier uncertainty) *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.084; CFI = 0.970; AVE = 0.59; Cronbach = 0.80; CR = 0.85. Factor loadings are shown in parentheses.*
Customer Uncertainty [CUSTOM_UN] (Adapted from Zhou et al., 2019; Jaworski and Kohli, 1993; Merschmann and Thonemann, 2011; Sreedevi and Saranga, 2017; Qi et al., 2011).
a. Our customers' preferences change frequently (0.87).
b. Our company frequently receives demand for products and services from new customers (0.54).
c. Our company's new customers have different needs than current customers (0.62).
Supplier Uncertainty [SUPPLIER_UN] (Adapted from Zhou et al., 2019; Jaworski and Kohli, 1993; Merschmann and Thonemann, 2011; Sreedevi and Saranga, 2017; Qi et al., 2011).
a. The price of raw materials and components that our company buys changes frequently (0.65).
b. Our company is highly dependent on suppliers to acquire the materials needed for production (0.62).
c. Our company must deal with supplier delays in material deliveries frequently (0.52).

Questionnaire items to assess Performance (including operational performance and financial performance) *Concordance Likert scale: 1 - strongly disagree to 5 - strongly agree. RMSEA = 0.047; CFI = 0.991; AVE = 0.54; Cronbach = 0.65; CR = 0.87. Factor loadings are shown in parentheses.*
Operational Performance [OPER_PERF] (adapted from Merschmann & Thonemann, 2011 ; Yu et al., 2018; Maqueira et al., 2020).
a. Our company has improved the delivery reliability of customer orders over the past two years (0.81).
b. Our company has improved the lead time for delivering customer orders over the past two years (0.87).
c. Our company has reduced customer order time over the past two years (0.83).

Financial Performance [FINAN_PERF] (adapted from Amoako-gyampah et al., 2020; Asare et al., 2013; Flynn et al., 2010; Jayaraman et al., 2013; Saeed et al., 2019; Yu, 2015).
a. Our company's sales have grown in the last two years (0.70).
b. Profit on sales has increased in the last two years (0.51).

c. Market share has grown over the past two years (0.65).

Questionnaire items for control variables

a. Please inform the size of your company in the number of employees (based in IBGE - Instituto Brasileiro de Geografia e Estatística, 2015)
b. Please inform the position of your company in the supply chain (two dummies):
    Tier 1 - Supplier of products/services to the final consumer;
    Tier 2 - Provider of products or solutions to other companies;
    Tier 3 - Suppliers of Raw Materials and Basic Inputs to other companies.

Appendix B: Bivariate correlation matrix

	SOUR_FLEX	DEL_FLEX	MAN_FLEX	DT_STRATEGY	BASE	FRONT-END	CUSTOM_UN	SUPPLIER_UN	OPER_PERF	Size	Tier1	Tier2
SOUR_FLEX	1											
DEL_FLEX	.496**	1										
MAN_FLEX	.354**	.553**	1									
DT_STRATEGY	.316**	.336**	.347**	1								
BASE	.279**	.242**	.272**	.648**	1							
FRONT-END	.236**	.285**	.286**	.469**	.724**	1						
CUSTOM_UN	-.012	.133**	.256**	.155**	.171**	.222**	1					
SUPPLIER_UN	-.017	-.004	.116*	-.056	-.046	.073	.273**	1				
OPER_PERF	.192**	.273**	.293**	.295**	.253**	.169**	.172**	.018	1			
Firm size	.040	-.046	.024	.062	.128*	.073	-.054	.022	-.125*	1		
Tier1	.025	.052	.046	.225**	.208**	.153**	-.043	.039	.048	.006	1	
Tier2	-.073	-.097	-.038	-.183**	-.177**	-.075	.134**	-.015	-.095	-.026	-.810**	1
Mean	3.501	3.321	3.830	3.697	13.192	8.926	3.554	3.901	.161	.839	.678	.237
S.D.	.84	.89	.848	.924	5.953	4.363	.917	.762	.368	.368	.468	.426
Skewness	-.448	-.333	-.86	-.612	.231	.808	-.415	-1.018	1.853	-1.853	-.765	1239
Kurtosis	-.28	-.585	.4	-.18	-1204	-.252	-.487	1.441	1.440	1.440	-1.422	-.468

**. Correlation is significant at the 0.01 level (2-tailed).

5. CONCLUSIONS

This work presented three articles, each corresponding to a specific objective of this dissertation. Figure 7 presents the relationship between the three articles of the dissertation. While Article 1 addresses which technologies companies tend to implement when they seek to achieve flexibility as an operational objective, Articles 2 and 3 seek to show how different levels of flexibility can be achieved with I4.0 technologies at both the shop floor and the supply chain levels.

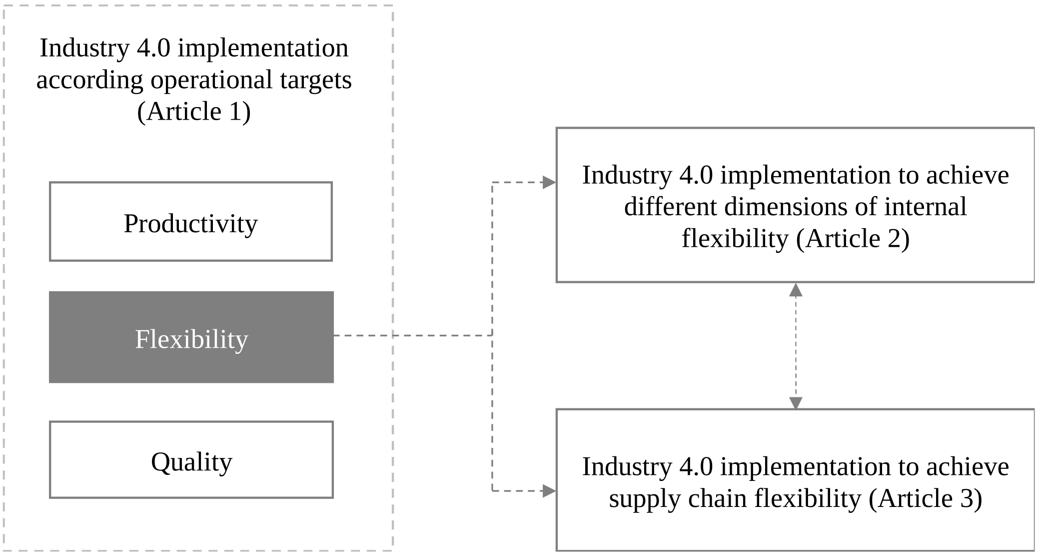

Figure 7. Articles relationship

Article 1 presented a quantitative analysis of a survey conducted in 92 companies to determine which Industry 4.0 technologies companies adopt when pursuing three different goals: productivity, manufacturing flexibility, and process quality. It was found that manufacturing companies tend to adopt 18 technologies grouped in four different arrangements represented by technology clusters: Vertical integration, digital manufacturing, advanced manufacturing, and online traceability. From the flexibility point of view, the results showed that companies that aim to achieve manufacturing flexibility implement technologies related to vertical integration, digital manufacturing, and advanced manufacturing.

Article 2 presented a qualitative analysis of 11 case studies to demonstrate how Industry 4.0 technologies allow for internal flexibility in companies. Flexibility was analyzed specifically regarding individual and shop floor resources. Moreover, the technologies implemented for the different types of flexibility desired were identified. The results demonstrate that technologies can improve flexibility at both levels. However, companies focus primarily on machine flexibility, and broader aspects of this concept are also needed.

Finally, Article 3, based on organizational information processing theory (OIPT), analyzed the impact of digital transformation on the supply chain to achieve supply chain flexibility and increase operational performance in the context of uncertainties. The results showed that flexibility mediates the relationship between the smart supply chain dimensions and operational benefits. Furthermore, according to the results of the moderation tests, companies adopt certain technologies depending on the type of uncertainty they face.

The three articles that make up this dissertation intend to form a theoretical framework that makes it possible to understand the implementation strategy of Industry 4.0 technologies to achieve flexibility, as seen in Figure 8.

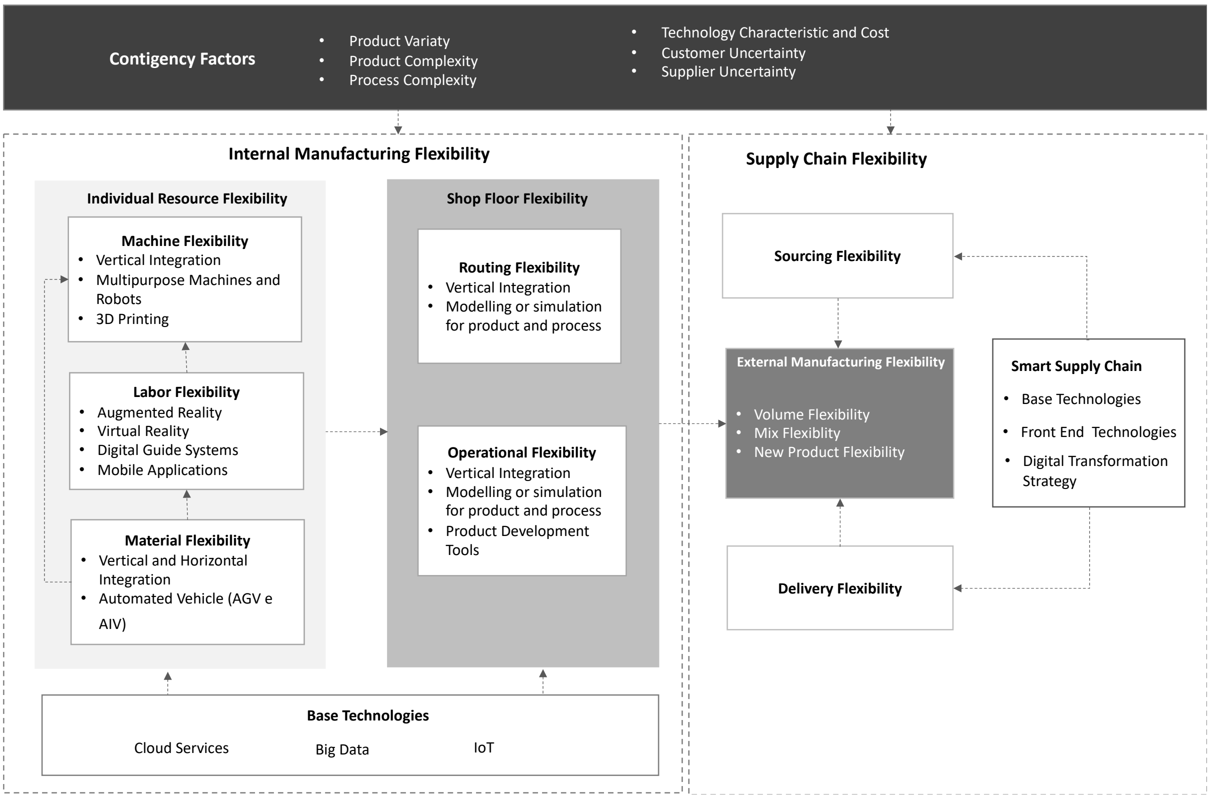

Figure 8. Conceptual framework to implement Industry 4. technologies to achieve operational flexibility

5.1 CONTRIBUTIONS

This study adds to the literature on operational flexibility and provides a new perspective for Industry 4.0 theory, showing the interconnection between different aspects of flexibility and technologies, as shown in Figure 8. The results showed that I4.0 technologies must be adjusted to meet companies' production goals. Moreover, this study demonstrated that production goals should not be seen individually but as complementary and/or competing. Therefore, Industry 4.0 arrangements can also be combined and adapted for different multi-target approaches. These results can be a starting point for investigating the detailed implementation of such technologies to reach the desired production goals.

Regarding flexibility, results show the need to implement the base technologies of Industry 4.0 to reach internal flexibility in manufacturing, as they would allow for vertical integration and equipment and information connectivity at the shop floor, thus, enabling product identification and increasing workers' qualification. In addition, there are also specific technologies for each type of internal flexibility, such as robots that facilitate machine flexibility or augmented reality that affects operators' flexibility. As a result, internal manufacturing flexibility, to respond to variations in demand and supply of materials, has an impact on the flexibility of volume and on the flexibility of the introduction of new products and product mix flexibility.

Nevertheless, investing in technologies for internal flexibility is not enough to achieve high flexibility at the plant level. Mainly in the context of uncertainties, it is necessary to invest in the digital transformation of the supply chain, aiming to provide flexibility to the supply of raw materials and distribution to meet the changes in the volume and mix of products. In this respect, the results added to the theory by illustrating the connections between smart supply chain and supply chain flexibility and how they are important to better deal with uncertainty. They also contributed to the advancement of the OIPT from a supply chain perspective, as there is a positive sequential effect in which supply chain flexibility mediates the relationship between smart supply chain and operational performance.

Furthermore, the results found may also help managers in their digital transformation strategies, especially in the current context of high uncertainties. Strategically, to be able to support the various dimensions of flexibility, companies should start creating an investment plan for technologies and operational management. In this regard, manufacturing companies should start developing an internal transformation strategy by investing in digital technologies that have an impact on the flexibility of resources, routes, and operations, as well as on the design of more flexible processes and products. Subsequently, they should encourage the adoption of digital-based and front-end technologies. Thus, according to their digital strategy together with suppliers, they should be able to change supply chain operations, making these more flexible, especially concerning the flexibility of supply and distribution.

In addition, companies should consider the context in which they are inserted and adjust their strategies according to the contingency factors shown in the results. The context should not be seen as static, because these factors change over time. Therefore, longitudinal studies should be carried out to understand the ongoing digital transformation process and how it affects flexibility and operations in supply chains. Moreover, these studies should also focus on understanding the mechanism used by manufacturing companies to drive digital transformation toward internal and supply chain flexibility.

5.2 LIMITATIONS AND FUTURE RESEARCH

The study also has has several limitations. First, our study focuses on Brazilian companies, which have particular characteristics of culture, laws, among others. For this reason, studies with companies from other countries and sectors are necessary. In addition, we adopt a primarily a technological approach. In this sense, a socio-technical approach could better explain the relationship between the concepts studied. Furthermore, given that response time and sustainability are among the main indicators that companies look nowadays, future studies could focus on how companies could adopt flexible technologies and processes to achieve greater results in relation to these two indicators.