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RESEARCH ARTICLE

Implementing industry 4.0 for flexibility, quality, and productivity improvement: technology arrangements for different purposes

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ABSTRACT
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.

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KEYWORDS
Industry 4.0; production targets; smart manufacturing; technology adoption; digital transformation

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 Pérez, Serrano Bedia, and López Fernández 2016; Eslami et al. 2021). 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; Grassi et al. 2021; Jiang et al. 2022). 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 and 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, and Kao 2015; Brettel, Klein, and Friederichsen 2016; Zhong et al. 2017; Nayernia, Bahemia, and Papagiannidis 2021), or with production targets and expected benefits that drive the decision-making for investing in Industry 4.0 technologies (Dalenogare et al. 2018; Frank, Dalenogare, and Ayala 2019). A detailed description of these studies is provided in Appendix A. Most of these studies

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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, Erol, and Sihn 2016; Vasiliev, Aleksandrova, and 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 and Saranga 2017; Kamalahmadi, Shekarian, and Mellat Parast 2021; Eslami 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 organised 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 categorised 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 organised 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.

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, Dalenogare, and Ayala 2019). Industry 4.0 comprises several technology applications, including Smart Manufacturing, Smart Products and Services, Smart Supply Chain, and Smart Working (Frank, Dalenogare, and Ayala 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, Wang, and Yang 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 realise 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, Soares, and Barros (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 and 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, and Milling 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 and Slack 2001; Größler, Grübner, and Milling 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, Cugno, and Castagnoli 2020; Cugno, Castagnoli, and Büchi 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 hypothesises 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 and Meyer 1990), this study acknowledges that some targets can be pursued simultaneously (or not) by adopting Industry 4.0 related technologies.

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' (2002) 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 summarise costs and delivery since it represents the rate between total output (product delivery) and total input (cost reduction) (Huang et al. 2003). Any other production target should derivate from these three essential priorities of manufacturing decision-making (Boyer and Lewis 2002). Next, the study provides evidence about the reasons for such connection and the hypotheses derived from such production targets.

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). Productivity gains can be associated with several resources, such as labour productivity, space utilisation, inventory turnover, energy costs, and equipment utilisation (Backhaus and Nadarajah 2019; de la Fuente-mella et al. 2019). Prior studies have shown that increased industrial computerisation and automation have generated stable productivity growth in companies using fewer workers (Autor, Mindell, and Reynolds 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 utilise materials, combined with optimisation 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 organise 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 and 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 optimise manufacturing processes, especially in terms of resources and energy consumption, representing the second-highest production cost in many sectors (Fatorachian and Kazemi 2018). Moreover, additive manufacturing maximises the use of materials and the manufacture of a wide variety of parts, also permitting scalability (Alcácer and 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 and Kumar 2020; Büchi, Cugno, and Castagnoli 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, Dalenogare, and Ayala 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.

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, and Sakakibara 1994; Goyal, Agrawal, and Saha 2019). Process quality considers implementing best practices and technologies to standardise processes, improve and maintain equipment operation, and check for potential failures and non-conformities in the production line (Flynn, Schroeder, and 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. 2016a; Aleksandrova, Vasiliev, and Alexandrov 2019). Sensing capabilities on the shop floor enable the tracking of materials, supporting product components' traceability to identify non-conformities (Ramadan, Al-maimani, and 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, and Rastogi 2019). Moreover, the intensive use of automated machines and robots helps implement standardised 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, and Lanzilotto 2016; Tzimas, Vosniakos, and Matsas 2019; Urbas and Vukašinović 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 (2020), 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.

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, organisational flexibility, and operational flexibility (Pérez-Pérez et al. 2018; Aldrighetti et al. 2022). 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 and 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; Pérez Pérez et al. 2016).

Operational flexibility has been identified as one of the main targets of Industry 4.0 (Long, Zeiler, and Bertsche 2017; Fatorachian and 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, and Tseng 2018; Haleem and Javaid 2019). Smart and reconfigurable machines facilitate new products, as they are much more flexible than fixed automatic systems (Wang et al. 2016b). Assembly lines can also be benefited by the combination of the labour 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 and 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, Zogopoulos, and Vlachou 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 and 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, and Vlachou 2017; Coronado et al. 2018; Schamp et al. 2019; Zhuang, Gong, and Liu 2020). However, although several Industry 4.0 technologies are proposed to increase flexibility in the production system, Frank, Dalenogare, and Ayala (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.

Summary of the conceptual research model

Figure 1 shows the conceptual research model that summarises 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.

Research method

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 representatives). The final sample was composed of 41% of small enterprises (<100 employees), 37% of medium enterprises (100–500 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 1 shows the characteristics of the sample.

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 and Weng 2018; Frank, Dalenogare, and Ayala 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, Giglio, and Van Dun 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

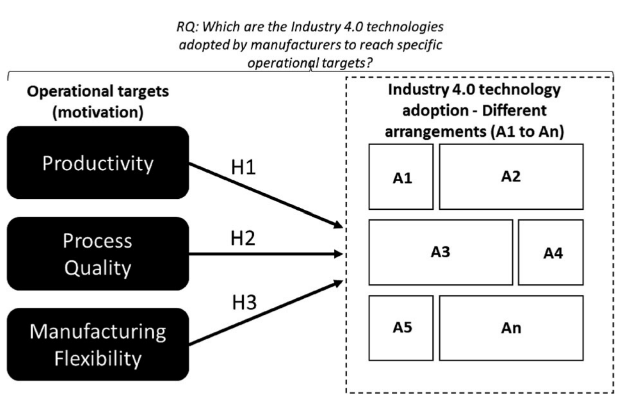

Figure 1. Conceptual research model.

Table 1. Demographic characteristics of the sample.

Category	Description	(%)	Category	Description	(%)
Main industries attended by the manufacturing companies of the sample (diversity of the products provided by the investigated sector)	Agriculture	48%	Company's size	Small (< 100 employees)	**41%**
	Biotechnology	1%			
	Chemicals	24%		Medium (100 - 500 empl.)	**37%**
	Construction	10%			
	Energy	15%		Large (> 500 empl.)	**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%			

Table 2. Rotated Factor-Loading Matrix from EFA.

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

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 list of technologies and production targets assessed in the questionnaire are provided together with the results, in Tables 1 and 2, while the full questionnaire is provided in Appendix B.

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 and Overton 1977).

Some strategies proposed by Podsakoff et al. (2003) were adopted to deal with potential common method variance. Firstly, the procedure was to randomised 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.

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 summarise 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 synthesise 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, 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, Dalenogare, and Ayala 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 prioritising 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 prioritise the same target. For the comparison of means, Levene's test was used to define whether the t-test should assume equal variance at $p < 0.05$.

Results

Industry 4.0 technology arrangements

The data analysis synthesised 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 4 also shows the reliability analysis for the three constructs using Cronbach's alpha, all above 0.75 (Hair et al. 2009).

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, and 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. 2018). 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, Ayala, and Frank 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. 2019).

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 (Büchi, Cugno, and Castagnoli 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 and 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

Table 3. Correlation matrix and descriptive analysis.

	Mean	S.D.	Skewness	Kurtosis	1	2	3	4	5	6
1- Vertical_integration	2.984	0.999	0.202	−0.897	–					
2-Digital_manufacturing	2.278	0.705	1.170	1.747	0.709***	–				
3- Online Traceability	3.076	1.183	0.114	−1.347	0.332***	0.336***	–			
4-Advanced manuf.	2.359	0.924	0.607	−0.160	0.486***	0.555***	0.294***	–		
5-Manuf. flexibility	2.315	1.157	0.789	−0.246	−0.053	−0.087	−0.090	−0.097	–	
6-Produtivity	4.217	0.767	−0.842	0.548	−0.189**	−0.169*	0.054	−0.003	0.206**	–
7-Product quality	4.250	0.909	−1.506	2.619	−0.165*	−0.083	−0.018	0.071	0.091	0.488***

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4. Independent Samples T-Test for comparison of means.

Industry 4.0 technology arrangements	Model 3: Technology adoption levels (Mean±S.D) for Productivity			Model 2: Technology adoption levels (Mean±S.D) for Process Quality			Model 1: 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 $p < 0.05$).

are becoming more usual and integrated with data and machine-to-machine communication, to operate in an integrated process in the factory (Frank, Dalenogare, and Ayala 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 and Cevikcan 2017; Schuitemaker and 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).

Production targets and industry 4.0 technologies

Table 3 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 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.

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 organised 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 summarised 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, Dalenogare, and Ayala 2019; Chae and Olson 2021). 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, Dalenogare, and Ayala 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.

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 and 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 and 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.

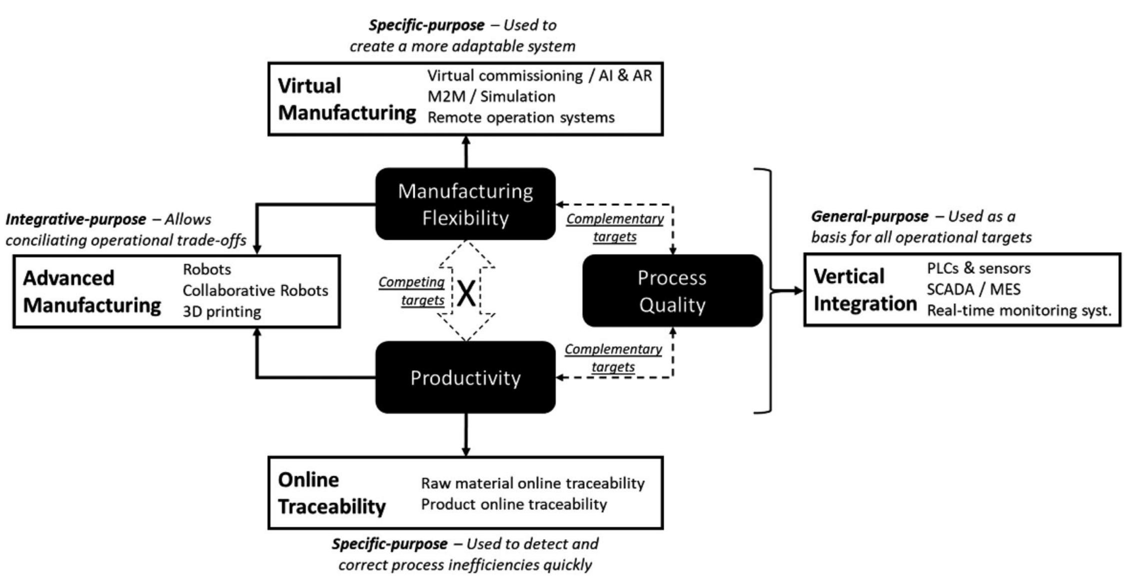

Figure 2. Conceptual framework of the empirical findings.

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, Ayala, and Frank 2021; Schuh et al. 2020). Visibility means that decision-makers will be able to 'realise' 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, Ayala, and Frank 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 visualise 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 (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 and 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 and Slack 2001; Größler, Grübner, and Milling 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, Al-maimani, and Noche 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. 2016a,b). 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, Bagheri, and Kao 2015; Rosin et al. 2020).

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 and 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, Mindell, and Reynolds 2020; Büchi, Cugno, and Castagnoli 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, Hao, and Zhang 2014; Niaki and Nonino 2017) and that robots may sometimes be too 'rigid' for flexible operations, but help for productivity (Autor, Mindell, and Reynolds 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).

Organising 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 organising 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.

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, Erol, and Sihn 2016; Mittal et al. 2018; Santos and Martinho 2019) since this is a general-purpose technology arrangement useful to any target. Considering previous studies on *Vertical Integration* (e.g. Tabim, Ayala, and Frank 2021; Dalenogare et al. 2018), 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 organising the activities based on the information flow from the manufacturing stations (Tabim, Ayala, and Frank 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. 2022). 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 emphasises 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, Dalenogare, and Ayala (2019). A similar sequence of steps is proposed when companies aim *for Flexibility* (Figure 3). In such a case, *Vertical Integration*

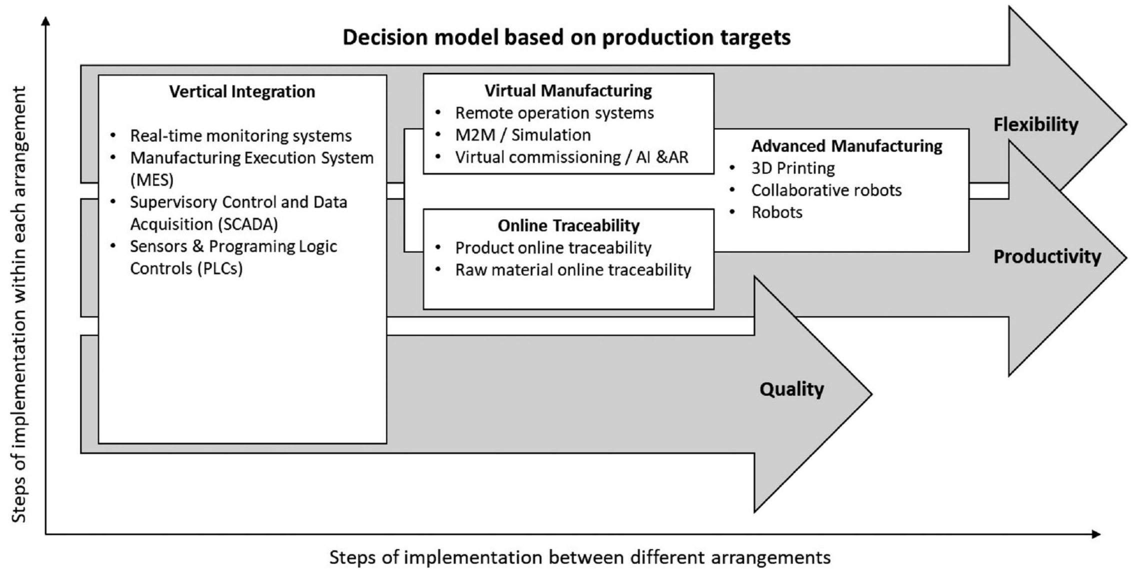

Figure 3. Decision model to implement Industry 4.0 technologies according to the expected production targets.

is followed by *Virtual Manufacturing* because the virtualisation 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 virtualisation of the factory that allows simulation and organisation 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, Dalenogare, and Ayala 2019; Dalenogare et al. 2018).

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, Yi, and Yin 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 summarises 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 emphasised 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, Ayala, and Frank (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; Dreyer et al. 2022; Almeida et al. 2022). Such studies could be adapted to investigate how companies prioritise 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 analysed in future studies.

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Note

1. Other variables from this survey were used in Frank, Dalenogare, and Ayala (2019). This other study focused on investigating the implementation patterns of Industry 4.0 technologies through cluster analysis. Frank, Dalenogare, and Ayala (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, Dalenogare, and Ayala (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.

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Data availability statement

Data available on request due to privacy restrictions

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Appendices

Appendix A. Literature review.

Authors	Aim	Method	Industry 4.0 implementation	Operational Target/ Performance
Fatorachian and Kazemi 2018	This study investigated the academic research and industrial reports in the industry 4.0 area and smart Manufacturing to provide insights on the execution of Industry 4,0	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 • Flexible and agile engineering and Manufacturing • Improved information sharing and decision-making • Improved integration and collaboration • Improved Resource Productivity • Mass customisation
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 customisation, Improvement of product quality, Reduction of product launch time. **Operational:** Reduction of operational costs, Increase productivity, Increase processes visualisation, and control. **Side-Effects:** Improving sustainability (externalities), Reduce of labour claims (worker satisfaction)
Tortorella, Giglio, and Van Dun 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).

(*continued*)

Appendix A. Continued.

Authors	Aim	Method	Industry 4.0 implementation	Operational Target/ Performance
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 implementation efforts.	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 programmes	Four constructs measured operational Performance. **Quality:** Conformance quality, Product quality and reliability **Flexibility:** Volume flexibility, Mix flexibility **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, Cugno, and Castagnoli (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, Singh, and Luthra (2021)	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 between digitalization and the firm's Performance regarding its supply chain competency and operational Performance.	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 • 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	**Operational Performance:** Decrease in operating costs,Decrease in time required for creating and delivery of new 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

(*continued*).

Appendix A. Continued.

Authors	Aim	Method	Industry 4.0 implementation	Operational Target/ Performance
Li, Dai, and Cui (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, organisational context, and environmental context of firms in the implementation of the digital manufacturing technologies (DMT)	Structural equation modelling Sample Sizes: 931	**DMT construct:** • Use of advanced processes, such as laser and water cutting, 3D printing, high precision technologies • Development towards 'the factory of the future' (e.g. smart/digital factory, adaptive manufacturing systems, scalable Manufacturing) • Engaging in process automation programmes (e.g. automated machine tools and handling/transportation equipment, robots) • Engaging in product/part tracking and tracing programs (bar codes, RFID)	**Operational Performance Construct:** **Flexibility:** Mix Flexibility, Volume Flexibility **Delivery:** Delivery Speed Delivery Reliability **Design:** New Product Introduction Ability Product Customization Ability **Quality:** Product Quality, Conformance Quality
Cugno, Castagnoli, and Büchi 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)