Fourth industrial (r)evolution? Investigating the use of technology bundles and performance implications

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Abstract

Purpose – The purpose of this paper is to investigate how different manufacturing technologies are bundled together and how these bundles influence operations performance and, indirectly, business performance. With the emergence of Industry 4.0 (I4.0) technologies, manufacturing companies can use a wide variety of advanced manufacturing technologies (AMT) to build an efficient and effective production system. Nevertheless, the literature offers little guidance on how these technologies, including novel I4.0 technologies, should be combined in practice and how these combinations might have a different impact on performance.

Design/methodology/approach – Using a survey study of 165 manufacturing plants from 11 different countries, we use factor analysis to empirically derive three distinct manufacturing technology bundles and structural equation modeling to quantify their relationship with operations and business performance.

Findings – Our findings support an evolutionary rather than a revolutionary perspective. I4.0 technologies build on traditional manufacturing technologies and do not constitute a separate direction that would point towards a fundamental digital transformation of companies within our sample. Performance effects are rather weak: out of the three technology bundles identified, only "automation and robotization" have a positive influence on cost efficiency, while "base technologies" and "data-enabled technologies" do not offer a

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competitive advantage, neither in terms of cost nor in terms of differentiation. Furthermore, while the business performance impact is positive, it is quite weak, suggesting that financial returns on technology investments might require longer time periods.
Originality/value – Relying on a complementarity approach, our research offers a novel perspective on technology implementation in the I4.0 era by investigating novel and traditional manufacturing technologies together.

Keywords Manufacturing technology, Industry 4.0, Smart manufacturing, Technology bundles, Performance
Paper type Research paper

Quick value overview

Interesting because: The relationship between traditional and I4.0 production technologies has so far not been analyzed in the literature. Furthermore, complementarity theory indicates that bundles of technology provide a greater improvement than individual technologies. This study investigates bundles of I4.0 technologies in combination with traditional advanced manufacturing technologies (AMT). This introduces an evolutionary perspective where, instead of a revolutionary transformation, I4.0 technologies are implemented as stepwise use cases combined with the existing technology base of companies. The study also investigates how bundles of "new" and "old" technologies influence performance.

Theoretical value: It was found that there are three technology bundles: basic physical manufacturing technologies, data generation or data processing technologies and automation and robotization technologies. Technologies connected to automation and robotization offer a competitive cost advantage, while the remaining two bundles do not offer operations performance benefits. Furthermore, there was no evidence for an immediate financial benefit of implementing novel I4.0 and traditional manufacturing technologies.

Practical value: Companies should not expect quick business returns from their investments in basic physical manufacturing technologies, or data generation or data processing technologies. However, they need to make these investments to remain in business because these become qualifying technologies. Investment in automation and robotization is particularly worthwhile for larger enterprises.

Introduction

In the context of the fourth industrial revolution [including Industry 4.0 (I4.0) in a manufacturing] manufacturing companies implement new digital technologies that enable intelligent products and production processes. The purpose of using these advanced technologies is to increase the operational and business performance of companies (Cheng *et al.*, 2018; Szász *et al.*, 2020). Therefore, understanding the impact of I4.0 technologies on the existing technology base and on performance is vital for companies to make plans and decisions about their future technology investments.

Though definitions are diverse, I4.0 is generally used as an umbrella term to denote the appearance and use of a critical mass of novel technologies that create a new manufacturing context characterized by smart products and processes where all actors are digitally interconnected and share real time information (e.g. Frank *et al.*, 2019; Szász *et al.*, 2020; Meindl *et al.*, 2021). While I4.0 is expected to fundamentally revolutionize manufacturing (Schwab, 2016), current studies and practical reality indicate that this is not entirely the case (Buer *et al.*, 2021): digital technologies are usually implemented in isolation (Maghazei *et al.*, 2022), manufacturers face several challenges during the implementation (Raj *et al.*, 2020; Enrique *et al.*, 2022), and in many cases, the expected performance benefits are also missing (Dalenogare *et al.*, 2018; Losonci *et al.*, 2022). According to the Oxford Language Dictionary, a revolution should bring a "*dramatic and wide-reaching change in conditions*", but whether such change is happening, or we are merely at the beginning of it, is still debated. Completely digitally transformed and intelligent factories are still very scarce, which indicates that traditional and new technologies are combined with each other, pointing towards a gradual ("evolution"), rather than a radical, "digital-only" transformation of the manufacturing technology base ("revolution").

Although numerous studies have been conducted on the implementation and performance impact of I4.0 technologies (e.g. Dalenogare *et al.*, 2018; Szász *et al.*, 2020), the relationship between traditional and I4.0 production technologies has not been analyzed so far. A widely accepted approach in the technology and management literature, however, is that the production system of companies is built of so-called technology configurations which in a "package" can induce a greater improvement in performance than what individual technologies are expected to achieve separately. This is the exact argument raised by the so-called complementarity theory (Furlan *et al.*, 2011). The definition of I4.0 itself also highlights the importance of interconnectedness and integration of different technologies. In this light, it is surprising that the joint investigation of traditional and I4.0 technologies is still scarce. This is an important gap in the literature and filling this gap by the bundling approach might also explain the contradictory findings in terms of the performance benefits of I4.0.

Thus, we formulate the following two research questions:

RQ1. How are I4.0 and traditional manufacturing technologies bundled together in practice?

RQ2. How do different technology combinations influence the operations and business performance of manufacturing firms?

Our preliminary hypothesis is that instead of a revolutionary, complete digital transformation, novel I4.0 technologies gradually replace some and complement the remaining, already existing, traditional technologies of companies, thus describing a slow, stepwise development path instead of a revolutionary industrial transformation. It also means that production technologies can be connected to each other in many ways and these systems formed by technological combinations can affect company performance in different ways.

Our approach is also in line with the recently introduced "use case" concept in technology management literature: to find useful practical applications of an emerging technology managers generally experiment in an iterative manner, connecting the technology with various existing areas of the factory (Maghazei *et al.*, 2022).

To answer the two research questions, in the following section we introduce the literature on manufacturing technology bundles and performance implications to point out the gaps intended to be filled by answering RQ1 and RQ2. Then, our data and the measurement model are described. After analysis the results are discussed and implications are formulated.

Literature review

Technology bundles

AMT represent an umbrella term that describes "*a variety of technologies which primarily utilize computers to control, track or monitor manufacturing activities*" (Boyer *et al.*, 1997, p. 332). These technologies include pioneering solutions of the third industrial revolution, such as computer-aided design (CAD), numerical control machinery (CNC), computer-aided manufacturing (CAM), real-time process control system, automated material handling, bar coding, flexible manufacturing systems (FMS), robotics, decision support systems, manufacturing resource planning (MRP II), or electronic data interchange (EDI) (Beaumont *et al.*, 2002; Dangayach and Desmukh, 2005). The list of AMTs contains both hardware-based and software-based technologies that are integrated through computing technology (Udo and Ehie, 1996). I4.0 can be conceptualized as a newer wave of AMT, which includes more advanced, smarter and more automated technologies than classic AMTs (cf. Maghazei *et al.*, 2022).

A key issue of our paper is, in what combination companies use these technologies and how traditional and I4.0 technologies relate to each other if they are combined (c.f., Tortorella and Fettermann, 2018; Frank *et al.*, 2019). According to Voss (2005) "*there is a growing view that we are looking at bundles of practices not just single practices. There is frequently strong complementarity between practices leading to joint use; an example is lean manufacturing*" (Voss, 2005:1,225). Indeed, in lean manufacturing usually four bundles are considered: just-in-time (JIT), total quality management (TQM), total productive maintenance (TPM) and human resource management (HRM) (Shah and Ward, 2003; Tortorella *et al.*, 2021). We can also find this approach in the supply chain integration literature, where supply and demand side (Frohlich and Westbrook, 2001) or external and internal practices (Das *et al.*, 2006) are grouped. While these practice bundles in lean and supply chain management are supported by empirical studies (and therefore represent taxonomies), we could not find a similar empirical bundling approach for manufacturing technologies. A partial exception is Benitez *et al.* (2023). Their study provides some case-based background to how various I4.0 technologies, such as 3D printing or IoT can become a platform, which serves as a basis for the implementation of other new technologies. These technology combinations can also be considered as bundles, where the individual elements strengthen each other. Nevertheless, while the study provides interesting examples, the cases are very different from each other and low in number, thus limiting the generalizability of the results.

Early studies on AMT use a typology of design technologies for designing products and processes (e.g. Computer-aided engineering (CAD), CAE and Computer-aided production planning (CAPP)), manufacturing technologies for manufacturing and physical transformation (e.g. Computer-aided manufacturing (CAM), Automated storage and retrieval system (AS/RS)) and administrative technologies for tracking (e.g. Manufacturing resources planning (MRP), shop floor control) (Boyer *et al.*, 1996; Jonsson, 2000; Cheng *et al.*, 2018). Using these typologies, the studies deal with clustering companies based on the level of adoption of various technologies. This means, however, that technology bundles are conceptually defined, but are not empirically derived or verified.

With the increasing interest towards the I4.0 technologies, some researchers provide similar theoretical groupings of new technologies. For example, Dalenogare *et al.* (2018) define two sets of I4.0 technologies, one related to product development (e.g. 3D printing, integrated engineering systems) and one related to manufacturing (e.g. sensors, big data analytics), to investigate their expected benefits related to product and operations performance. Demeter *et al.* (2021) group technologies based on the dominance of virtual vs. physical attributes, putting IoT, cloud, big data analysis, simulation and virtual/augmented reality into the former group, while 3D printing or autonomous robots into the latter one, with sensors and actuators connecting the two groups. The authors suggest that the physical technology group is generally more mature than the virtual one (Gartner, 2018), which resonates with our "revolution versus evolution" reasoning, meaning that fully digitally transformed smart factories are still farther away and newly emerged manufacturing technologies complement the traditional ones. In a literature review, Culot *et al.* (2020) also acknowledge the physical-digital dichotomy and conceptually group I4.0 technologies into four main categories: (1) Physical/digital interface technologies (IoT, cyber-physical systems, visualization), (2) Digital/physical process technologies (3D printing, advanced robotics, new materials, energy management), (3) Network technologies (cloud, interoperability and cybersecurity, blockchain), (4) Data processing technologies (simulation and modeling, machine learning and artificial intelligence (AI), big data analytics). The four bundles are differentiated along two factors: whether it is hardware or software dominated and whether it is single-unit or network focused. Frank *et al.* (2019) and Meindl *et al.* (2021) differentiate between two layers of I4.0 technologies: front-end technologies (smart manufacturing, smart product, smart working and smart products) and base technologies (IoT, cloud, big data, analytics), the latter providing a platform for connection and intelligence to the former. Cimini *et al.* (2020) focus on the principal features of I4.0 technologies and group them into three categories: (1) Automation technologies (e.g. advanced manufacturing solutions, advanced robotics), (2) information exchange (e.g. cybersecurity, IoT and big data) and (3) decision support systems (e.g. simulation, augmented reality). Patrucco *et al.* (2022) focus on an even narrower set of I4.0 technologies in a buyer-supplier relationship context to empirically derive three technology groups: (1) Big Data and Cloud Computing, (2) Tracking and Tracing (e.g. radio frequency identification (RFID), quick response (QR) code, Bluetooth technologies) and (3) Simulation and Modeling (e.g. 3D printing, advanced simulation software, 3D modeling). Nevertheless, neither other types of I4.0 technologies, nor traditional manufacturing technologies are considered in their research. Chiarini and Kumar (2021) review the literature on the variety of I4.0 technologies and conceptually bundle some of these (e.g. the "AR and smart human interfaces" bundle includes several technologies, such as smart screens, 3D glasses, exoskeletons). However, their main focus is not on technology bundles, but rather on the complementarity of I4.0 and Lean Six Sigma solutions. Enrique *et al.* (2022), on the other hand, explicitly focus on discovering I4.0 technology bundles by factor analysis. With traditional manufacturing technologies being excluded from their research, four different bundles are defined: digital manufacturing, vertical integration, advanced manufacturing (i.e. robots and 3D printing) and online traceability. Benitez *et al.* (2023) rely on the findings of previous literature to group technologies on a logical basis, creating groups of vertical integration (Enterprise resource planning (ERP), Manufacturing execution system (MES) and Supervisory control and data acquisition (SCADA)), base technologies (IoT, cloud, big data, AI), virtualization (virtual commissioning, digital manufacturing, machine vision, augmented/virtual reality, edge computing, smart grids) and physical processes (3D printing, collaborative robots, industrial robots, flexible lines). Furthermore, they examine case studies about how various technologies (such as IoT, 3D printing, ERP) can become platforms providing a connection point for other technologies and becoming integrated systems, thus supporting the bundling hypothesis. The different approaches to technology bundling in the I4.0 context, as well as the gaps in this literature are highlighted in Table 1.

Thus, while there is a clear research intention to better understand technology bundles, literature offers little empirical guidance on how manufacturing technologies are combined and how they build on each other to create efficient and effective production systems in the I4.0 era. We intend to fill this gap by answering RQ1.

Performance effects of technology bundles

In early AMT literature there has been a vivid interest in exploring the relationship between AMT and performance. These studies, however, similarly to papers presented in Table 1, use conceptually predefined technology bundles. Based on these bundles, companies are clustered to find typical configurations (Boyer *et al.*, 1996; Jonsson, 2000). Usually, clusters represent companies using each bundle at low, medium, or high level and have different performance implications, if they have an effect at all. Boyer *et al.* (1996), for example, did not find impact on profitability along the different company groups, while Jonsson (2000) found differences in both operational (measured by flexibility) and business performance (market and financial measures).

Nevertheless, these kinds of analyses do not offer a response to how different technology bundles can contribute to performance. Furthermore, being relatively old, these studies do not consider I4.0 technologies.

Considering the performance impacts of I4.0 technologies, in particular, López-Gómez *et al.* (2018) identified that the highest benefits can be achieved by the reduction of labor costs, defects and errors and material costs; by increased outputs; and by improved delivery and service performance. However, they did consider various technologies separately. In a

Table 1.
Summary of the literature on technology bundles in an Industry 4.0 context

Source	Technology bundles	Empirical validation of the bundles	Traditional technologies included	Performance effect of bundles investigated
Dalenogare *et al.* (2018)	Product development technologies; manufacturing technologies	No (derived based on their expected benefits)	No	No (expected performance only)
Demeter *et al.* (2021)	Physical technologies; virtual technologies	No (conceptually derived)	No	No
Culot *et al.* (2020)	Physical/digital interface technologies; digital/physical process technologies; network technologies; data processing technologies	No (conceptually derived)	No	No
Frank *et al.* (2019), Meindl *et al.* (2021)	Front-end technologies; base technologies	No (conceptually derived)	No	No
Chiarini and Kumar (2021)	Big data collection and analysis; smart products and customer interaction; AR and smart human interfaces etc	No (conceptually derived)	No	No
Cimini *et al.* (2020)	Automation; information exchange; decision support system	No (conceptually derived)	No	No
Patrucco *et al.* (2022)	Big data and cloud; tracking and tracing; simulation and modeling	Yes (factor analysis)	No	Yes (supply chain performance)
Enrique *et al.* (2022)	Digital manufacturing; vertical integration; advanced manufacturing; online traceability	Yes (factor analysis)	No	No
Benitez *et al.* (2023)	Vertical integration; base technologies; virtualization; physical process	No (conceptually derived)	No	No
Summary	*Existing approaches are divergent in the literature in terms of technology bundling*	*Very little empirical support for the bundles*	*No investigation of how traditional and I4.0 technologies are combined*	*Little focus on the performance impact of technology bundles*

Source(s): Authors' work

literature review followed by large-scale empirical analysis Szász *et al.* (2020) find that early I4.0 technologies have a positive impact on the four basic operations performance indicators, namely cost, quality, delivery and flexibility. Older AMT technologies offer similar advantages (Jonsson, 2000; Cheng *et al.*, 2018). Although the positive performance impact of advanced technologies is clear, we do not know how various technologies are bundled together to achieve these results.

From a technological perspective, organizations can be viewed as entities using different technological configurations for achieving a higher competitive advantage and a better operational performance. From this perspective the theory that best describes organizations is the complementarity theory. The synergetic effects of bundling practices will eventually lead to an overall performance that is greater than the sum of the performance contributions of each of its parts (Furlan *et al.*, 2011). Further research of this concept showed how complementarity has an impact on performance and highlighted that complementarity among different activities could account for business growth without any of the usual assumptions in the literature of economics of scale. Over the last 3 decades complementarity has become a common concept within management theories (Furlan *et al.*, 2011; Choi *et al.*, 2008; Guidetti and Mazzanti, 2007). Moreover, many digital technologies should be implemented simultaneously to ensure their proper functioning (Benitez *et al.*, 2023). Consequently, the performance effects of using technology bundles could be explained with the complementarity theory, as companies that adopt one of the digital technologies, are more likely to make use of another technology to benefit from their combination (Enrique *et al.*, 2022).

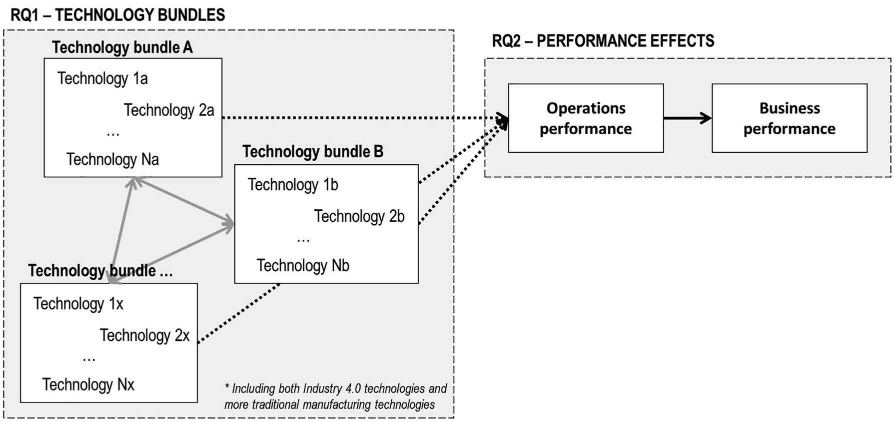
In this paper, we also propose that – especially with the emergence of I4.0 technologies – there is no one best way of using technology bundles at manufacturing companies and that these bundles can have a different impact on operations performance, such as the traditional performance dimensions of cost, quality, delivery and flexibility. Furthermore, enhanced operations performance should also translate to an improvement in the business performance of the firms, thus indirectly ensuring a high enough return on investment in manufacturing technologies.

Thus, the general research framework based on the two research questions investigated in this study is summarized in Figure 1.

Research methodology

Data

We use survey data on 165 manufacturing plants from 11 countries based on the latest edition of the Continuous Innovation Network (CINet) survey database. The CINet represents a global network of researchers and practitioners focusing on advancing the field of (continuous) innovation in industrial, service and public organizations (https://www.continuous-innovation.net/). The CINet survey is managed by a group of researchers representing a range of European universities and has already accumulated the experience of three global survey rounds. The survey focuses on manufacturing, product development and strategic activities, the unit of analysis being the single manufacturing plant within a company. Given our research objective, we focus exclusively on the manufacturing function of these units. The CINet survey is a multiple-respondent survey, where manufacturing-related questions are directed to the chief operations officer (COO) or a person in an equivalent



Source(s): Authors work

Figure 1. General research framework

position, while product development questions are answered by the chief technology officer (CTO) or a manager with a similar role. Some general questions, such as the business performance of the manufacturing unit compared to competitors, were answered by both respondents. Given that our study refers to technologies used in the production/operations function and their performance effect, COO items are used in this paper, except for the business performance construct where agreement between respondents was assessed before using the items in our study.

Survey data collection was carried out between November 2016 and June 2017, targeted at manufacturing plants belonging to manufacturing industries (ISIC Rev. 4 10–32). Respondents represent a wide range of countries and a diverse set of small, medium-sized and large firms. The final sample used in this paper contains 165 valid questionnaires that offer relevant data on our variables of interest. To ensure that this sample size is suitable for structural equation modeling, a post-hoc power analysis was carried out (Faul *et al.*, 2007), indicating that at a 5% significance level the statistical power (*1-β*) of our results is 98.03%, meaning that the probability of type II errors is less than 2% (*β*). The composition of the final sample by country and industry is presented in Table 2.

Potential response bias was handled by two procedures. First, the questionnaire was pre-tested with company managers and academics with relevant experience in the field. Questionnaire items were discussed with each participant and where doubts regarding the wording of the items were raised, the item was reformulated in cooperation with pre-test participants (Gastaldi *et al.*, 2022). Second, for the business performance items, where both COO and CTO respondents provided separate answers, we used the direct consensus model (Chan, 1998) based on the hypothesis that the true organizational-level business performance (relative to main competitors) can only be assessed if there is sufficient consensus among the individual respondents from the same organization. Agreement of COO and CTO respondents was evaluated by computing intraclass correlations (ICC(1) and ICC(2)) and the within-group reliability indicator ($r_{WG(j)}$). For the business performance items, all three indicators are well above the general threshold used in previous literature: ICC(1) = 0.73 (exceeding the 0.12 threshold), ICC(2) = 0.84 (exceeding the 0.7 threshold) and $r_{WG(j)}$ = 0.89 (exceeding the 0.7 threshold), strongly indicating that item responses are consistent and there is sufficient agreement between respondents from the same organization so that the aggregation of their responses can truly represent organizational-level business performance (Klein and Kozlowski, 2000; Dunlap *et al.*, 2003; Fischer *et al.*, 2014). Additionally, early and late-response bias, as well as non-response bias was checked in all original country samples with no significant effects being discovered (Gastaldi *et al.*, 2022).

Table 2.
Composition of the sample by country and size

Country	Frequency	Pct	Size	Frequency	Pct
Spain	34	20.6%	≤99	39	23.6%
Pakistan	30	18.2%	100–249	61	37.0%
Italy	25	15.2%	≥250	65	39.4%
Sweden	23	13.9%	*Total*	*165*	*100.0%*
Brazil	11	6.7%			
Denmark	10	6.1%			
Hungary	9	5.5%			
Switzerland	9	5.5%			
Canada	6	3.6%			
Austria	5	3.0%			
Netherlands	3	1.8%			
Total	*165*	*100.0%*			

Source(s): Authors' work

Given that our survey includes several single-respondent, self-reported questionnaire items, common method bias is a potential problem (Podsakoff *et al.*, 2003). To treat this issue, we applied several procedural and statistical methods to assess and reduce common method variance. First, the CINet questionnaire is designed to inherently reduce common method bias: technology and performance items used in this study are placed in different sections of the survey (technologies on p. 6, operations performance on p. 8, business performance on p. 4), reducing the potential bias of respondents to reflect on previous answers when filling in the questionnaire. Second, respondent anonymity was fully protected: their name and other personal data that could identify them, such as e-mail addresses or social media profiles, were not included in the survey. This procedure also makes respondents more inclined towards reflecting reality in their answers. Third, as a statistical procedure, we applied Harman's single factor test (Podsakoff *et al.*, 2003) by loading all items used in our study in an exploratory factor analysis (EFA). The unrotated factor solution shows that 5 factors exceed the 1.0 eigenvalue threshold with the first factor accounting for only 25.38% of total variance. Last, we also applied the collinearity approach with a random dependent variable added to our model (Kock and Lynn, 2012). Given that all variance inflation factor (VIF) values related to the random variable are way below the recommended 3.3 threshold, we conclude that the amount of common method variance is not large enough to distort our results.

Measures

Based on the two research questions formulated in this paper, our measurement model should cover three major thematic areas, i.e. manufacturing technologies, operations performance and business performance. While previous literature offers several established operationalizations for operations and business performance (*RQ2*), manufacturing technologies, especially the bundles of technologies that would include novel I4.0 items, have no established measurement method (*RQ1*). Therefore, following the approach of Enrique *et al.* (2022), we apply EFA to discover existing bundles of manufacturing technologies. To make these results more robust, we complement this approach with a confirmatory factor analysis (CFA) to validate a measurement model consisting of all three constructs of interest: technology bundles developed through EFA, as well as operations performance and business performance measures already established in the literature.

Given the role of I4.0 technologies in creating an interconnected manufacturing system, in this paper we solely focus on technologies used in manufacturing and the administrative tasks connected to manufacturing, filtering out new product/process development and design activities which are less connected to the production process *per se* (Table 3). Traditional technologies are based on previous AMT literature (Boyer *et al.*, 1996; Vázquez-Bustelo *et al.*, 2007), while I4.0 items are adopted from Szász *et al.* (2020), based on the notion of physical (*AMT*) and digital (*Smart*) technologies (Table 1, Demeter *et al.*, 2021).

While certainly the list of technologies can be further broken down into more dissected items, we also targeted a more parsimonious measurement model with broader technology categories that apply to a wider population of manufacturing firms.

Results of the EFA are shown in Table 4 with principal component analysis as the extraction method and varimax rotation. The Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test show that the correlation structure between technology items is adequate for factor analysis: KMO = 0.821, Bartlett's test of sphericity $\chi^2(36) = 427.239$, $p = 0.000$. Results also indicate that the 3-factor solution is the best fit for the underlying data, with the first three factors explaining 65.199% of total variance. Table 4 shows the results with factor loadings higher than 0.40 displayed in the table. The first factor clearly contains basic, overarching physical manufacturing technologies, therefore we label this factor as "Base technologies" (*BaseTech*). The second factor contains data generation or data processing

Table 3. Manufacturing technology measures

Item	Item wording In our company, the degree of use of the following tools, techniques and systems is . . . (1 = low, 5 = high)	Mean (st. dev.)	Source
Robot	Industrial robots for machining and/or handling operations	2.54 (1.30)	Boyer *et al.* (1996), Vázquez-Bustelo *et al.* (2007)
AS_RS	Automated materials storage and retrieval systems (AS/RS)	2.13 (1.20)	
JIT_Kanban	Just-in-time/Kanban controlled production	2.96 (1.32)	
RFID	Automatic identification/bar code systems/RFID	2.91 (1.50)	
MRP_ERP	Manufacturing resource planning (MRP II)/enterprise resource planning (ERP)	3.56 (1.21)	
CNC	Computer numerically controlled machines tools (CNC)	2.88 (1.56)	
FMS	Flexible manufacturing and/or assembly systems (FMS/FAS)	2.74 (1.32)	
AMT	Advanced manufacturing technologies (e.g. water and photonics-based/laser cutting, additive manufacturing/3D printing, high precision technologies, micro/nano-processing)	2.42 (1.28)	Industry 4.0 Szász *et al.* (2020)
Smart	"Smart" ICT applications supporting supplier/customer collaboration, connectivity (plants, equipment, robots, lines, workers), data processing (big data)/information mining, modeling/simulation	2.65 (1.22)	Industry 4.0 Szász *et al.* (2020)

Source(s): Authors' work

Table 4. Results of the EFA

Item	Factor 1 (*BaseTech*)	Factor 2 (*DataTech*)	Factor 3 (*RobotTech*)
CNC	*0.846*		
FMS	*0.807*		
AMT	*0.744*		
MRP_ERP		*0.820*	
Smart		*0.677*	*0.400*
RFID		*0.550*	*0.515*
JIT_Kanban		*0.518*	
AS_RS			*0.862*
Robot			*0.633*
Eigenvalue	*3.780*	*1.091*	*0.997*
% of variance (cumulative)	*42.001*	*54.126*	*65.199*
Cronbach alpha	*0.831*	*0.746*	*0.633*

Source(s): Authors' work

technologies, thus being labeled as "Data-driven technologies" (*DataTech*). One item (*RFID*) has a significant cross-loading as it is both based on data, but at the same time it helps the automation of processes. To a lesser extent a similar issue can be identified in the case of the *Smart* variable which is in concordance with the practical reality of using these technologies. Nevertheless, loading values indicate that both items might be more related to the data-driven factor than to the automation and robotization factor (later confirmed by CFA as well). Thus, the last factor contains only two items denoting "Automation and robotization technologies"

(*RobotTech*). Furthermore, it is important to highlight that I4.0 technologies (labeled here as *AMT* and *Smart*) do not form a separate factor, but they are loaded separately on already existing factors. Thus, EFA results suggest that these technologies are mainly built on existing, older manufacturing technologies and are bundled together by manufacturing plants rather than the new technologies replacing the old ones to create a purely I4.0 based, smart production environment.

Next, CFA is applied to validate manufacturing technology measurement as well as operations and business performance constructs. Operations performance is measured as two distinct constructs related to cost (*CostPerf*) and differentiation performance (*DiffPerf*), while business performance (*BusPerf*) includes market and financial indicators, all being measured relative to main competitors (1 = much lower, 3 = equal, 5 = much higher). The exact wording of the items is presented in Table 5.

To assess our final measurement model (Table 6), best practice procedures recommended by Hair *et al.* (2021) are followed. First, indicator reliability, internal consistency reliability and convergent reliability are investigated. Indicator reliability is assessed by calculating the path loadings between the constructs and their indicators. All loadings exceed or are very close to the commonly used 0.70 threshold, all of them being highly significant. Only one problematic item is identified, namely *IntQual* with a 0.515 loading. Here we followed the recommendations of Hair *et al.* (2021): given that this loading is still higher than the absolute lower threshold of 0.40, while other reliability measures [composite reliability (CR), ρA and average variance extracted (AVE)] are met on the construct-level, the item is kept in our measurement model to remain as consistent as possible with similar measurement models previously applied in the literature.

Next, internal consistency is evaluated using three indicators, namely, Cronbach's alpha, composite reliability (CR) and Dijkstra–Henesler's ρA. Values exceed or are very close to the commonly accepted threshold of 0.70, none of them falling below 0.60 (Henseler *et al.*, 2016), showing an appropriate reliability of the constructs. Furthermore, AVE scores are computed

Construct	Item	Item wording Over the past three years, our performance relative to our main competitors was, on average. . . (1 = much lower, 3 = equal, 5 = much higher)	Mean (st. dev.)	Source
CostPerf	*Cost*	Cost effectiveness (including ordering cost, manufacturing cost, quality cost, inventory cost; man, machine, material efficiency)	3.76 (0.86)	Demeter *et al.* (2016), Gastaldi *et al.* (2022)
	Invt	Finished product inventory level	3.43 (0.94)	
DiffPerf	*IntQual*	Internal quality (e.g. conformance to product specifications, percentage of scrap and rework)	3.97 (0.80)	
	ExtQual	External quality (e.g. product quality and reliability; ease of product maintenance, repair, disassembly and recycling; defect products returned by customers)	4.03 (0.77)	
	DelivTime	Customer order delivery time	3.95 (0.88)	
	DelivRel	On-time delivery	3.97 (0.87)	
	SizeFlex	Order size flexibility	3.95 (0.85)	
BusPerf	*Sales*	Sales	2.71 (1.14)	
	NetProfit	Net profit	2.58 (1.16)	
	dProfit	Profit growth	2.80 (1.08)	

Source(s): Authors' work

Table 5.
Performance measures

Construct	Item	Loading	AVE	Cronbach alpha	CR	ρA
BaseTech	CNC	0.855	0.747	0.831	0.899	0.842
	FMS	0.893				
	AMT	0.845				
DataTech	MRP_ERP	0.658	0.568	0.746	0.839	0.764
	JIT_Kanban	0.788				
	RFID	0.812				
	Smart	0.746				
RobotTech	AS_RS	0.871	0.731	0.633	0.845	0.638
	Robot	0.839				
Cost_Perf	Cost	0.892	0.722	0.621	0.838	0.651
	Invt	0.805				
Diff_Perf	DelivRel	0.823	0.520	0.762	0.841	0.784
	DelivTime	0.798				
	ExtQual	0.755				
	IntQual	0.514				
	SizeFlex	0.671				
BusPerf	Sales	0.852	0.691	0.776	0.869	0.808
	NetProfit	0.895				
	dProfit	0.737				

Source(s): Authors' work

Table 6.
Assessing measurement model reliability and validity

to measure the convergent reliability of each latent construct. All AVE values exceed the 0.50 threshold required for convergent validity (Hair *et al.*, 2021).

As a final step, the discriminant validity between constructs is assessed by using the Fornell–Larcker criterion and, as more recently suggested, by the heterotrait-monotrait ratio (HTMT). Both methods show clearly sufficient discriminant validity. HTMT ratios presented in Table 7 are all significantly below one.

Analysis

Structural model assessment and findings

Having a valid and reliable measurement model, partial least squares structural equation modeling (PLS-SEM) is implemented in SmartPLS 4.0 to estimate the strength of relationships between the main constructs (Ringle *et al.*, 2022). The following relationships were included in our model: in terms of the manufacturing technology bundles, we hypothesize that first each manufacturing plant develops its base technology (*BaseTech*) which then enables the collection of data related to those technologies and requires administrative processes to manage the operation of these technologies (*DataTech*). Moreover, base manufacturing technologies can further be automated and robotized

	BaseTech	BusPerf	CostPerf	DataTech	DiffPerf
BaseTech					
BusPerf	0.184				
CostPerf	0.193	0.430			
DataTech	0.686	0.237	0.127		
DiffPerf	0.179	0.334	0.775	0.313	
RobotTech	0.647	0.200	0.425	0.664	0.262

Source(s): Authors' work

Table 7.
Discriminant validity assessment using HTMT ratios

(*Robot_Tech*). This process is also enabled by the data-based technologies that collect data on manufacturing processes and support automation. Thus, we hypothesize that *BaseTech* drives the implementation of *DataTech* and *RobotTech*, while *DataTech* has a further positive impact on the implementation of *RobotTech*. Beside the interconnectedness of different technology bundles, the structural model also assesses their individual impact on the two operations performance indicators (*CostPerf* and *DiffPerf*). Furthermore, based on the sandcone model (Ferdows and De Meyer, 1990) we also include a positive link between differentiation performance and cost efficiency, arguing that better performance in terms of quality, delivery and flexibility enables a manufacturing plant to become more cost efficient. Finally, we propose that higher operations performance in terms of both indicators should lead to a better business performance (*BusPerf*).

To further strengthen the validity of our research model, control variables are included. The first control variable is related to the size of the manufacturing unit expressed as the number of employees in 2016. To be able to perform further subgroup analyses, a binary variable is created to differentiate between large manufacturing units and SMEs, the cutoff value being at 250 employees. Size has been generally used as a contingency variable in technology-related studies and can have a significant influence on technology investments and performance (Szász *et al.*, 2023). The second control variable is related to the economic development of the country the respondent unit is located in. We use the latest classification of countries released by the IMF (2022) to differentiate between developed and developing economies. Previous research has demonstrated that the country context might matter when investigating technology use and their performance implications (Szász *et al.*, 2020). We account for the impact of the two control variables on both operations performance indicators (*CostPerf* and *DiffPerf*) and on the business performance indicator (*BusPerf*).

Finally, to estimate the relationships between the constructs, we run the PLS algorithm with standardized data, stop criterion set to 1e−7, the maximum number of iterations to 3,000, the algorithm creating a total of 5,000 bootstrap samples. Path coefficients and significance levels are summarized on Figure 2. For sake of simplicity, the effect of control variables is not shown.

In terms of technology bundles, results of the structural model indicate that *BaseTech* has a strong positive impact on *DataTech* (+0.502, $p = 0.000$), which supports our presumption that base technologies are a precondition to be able to generate and harness data related to manufacturing. Furthermore, *BaseTech* also enables a higher level of implementation of robotized and automated solutions (*RobotTech*), the two technology constructs being also positively related to each other (+0.285, $p = 0.002$). The effective implementation of robotized and automated solutions (*RobotTech*) requires additional manufacturing data and the capability to process these data (*DataTech*), which is also supported by the strong relationship between the two latter constructs (+0.348, $p = 0.000$). Thus, while we created separate manufacturing technology bundles, SEM results suggest that these technology bundles reinforce each other, building up together the production system of manufacturing firms.

Nevertheless, the separation of the three technology bundles is supported, beside EFA and CFA results, by their differences in operational performance impacts. Base technologies alone have no impact on operational performance, the path coefficient between *BaseTech* and the two operational performance indicators (*CostPerf*, *DiffPerf*) not being significantly different from zero (*BaseTech*→*CostPerf*: −0.037, $p = 0.688$; *BaseTech*→*DiffPerf*: −0.067, $p = 0.508$). Data-based administrative technologies (*DataTech*) have a significantly negative impact on cost performance (−0.239, $p = 0.003$) and no significant impact on differentiation (+0.145, $p = 0.139$). This means that data-based technologies do not (yet) offer a competitive edge in terms of differentiation and can actually harm the cost competitiveness of manufacturing firms. On the other hand, robotization and automation (*RobotTech*) has a positive impact on

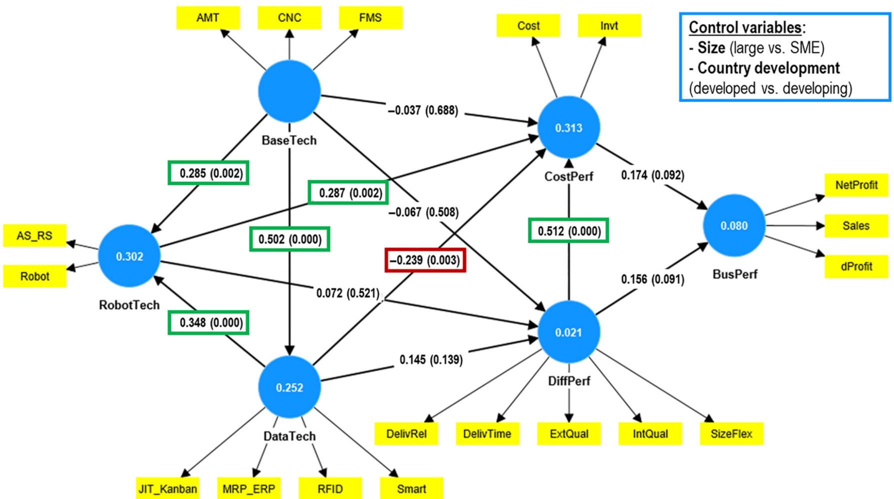


Figure 2.
Results of the structural model

Note(s): Path coefficients with *p*-values on the arrows, the significant path coefficients being marked; r-squared values in constructs
Source(s): Authors work

cost performance (+0.287, $p = 0.002$), meaning that these solutions can readily confer a cost advantage for manufacturing companies, making their production operations more cost efficient. At the same time, our results show no immediate positive impact at all on differentiation (+0.072, $p = 0.521$). Taken the opposite findings on the performance impact of *DataTech* and *RobotTech* together, it is worth noting that the indirect effect of *DataTech* on *Cost Perf* (i.e. *DataTech*→*RobotTech*→*CostPerf*) is significantly positive (+0.100, $p = 0.016$), meaning that while *DataTech* directly harms the cost efficiency of the firm, it is a necessary precondition for automation and robotization which in turn improves cost efficiency.

In terms of performance effects, there is a strong confirmation of interrelatedness between operational performance indicators, *DiffPerf* being positively and significantly associated with *CostPerf* (+0.512, $p = 0.000$), confirming the classic sandcone model (Ferdows and De Meyer, 1990). Surprisingly, however, the impact of the two operational performance indicators on business performance is positive, but not strong enough to become statistically significant on the $p = 0.05$ level (*CostPerf* →*BusPerf*: +0.174, $p = 0.092$; *DiffPerf* →*BusPerf*: +0.156, $p = 0.091$). This result suggests that a competitive performance in terms of differentiation or cost efficiency is not always directly and immediately translated to higher business performance (i.e. sales and profitability) relative to competitors.

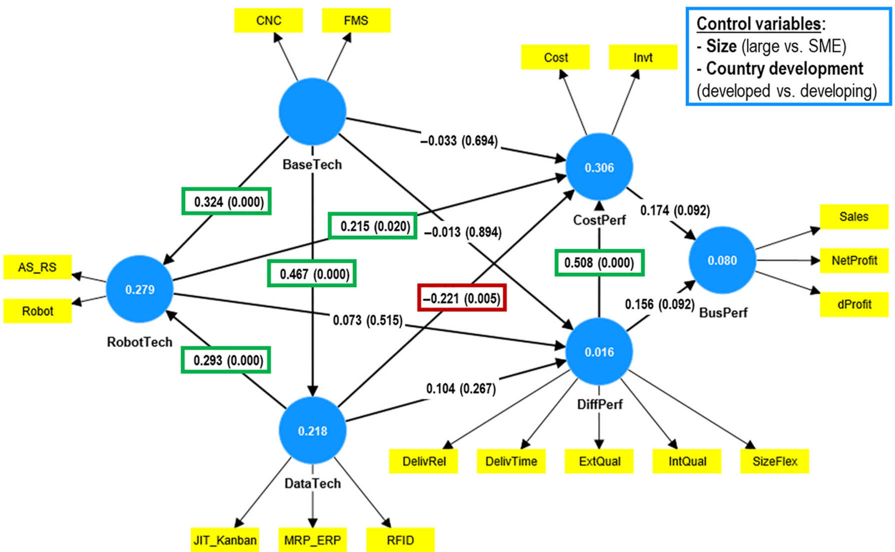
Robustness check

Given that technology bundles are not created along the division between traditional and I4.0 technologies (Table 4), we further assess whether I4.0 technologies do make a difference in terms of the performance effect of different technology bundles. While doing so, we also further test the robustness of our research model and the stability of the relationships when eliminating certain items from our constructs (Hair *et al.*, 2020). More specifically, we test the same measurement and structural model as before (Table 5, Figure 2), but this time without the two items that collectively describe I4.0 technologies (*AMT* and *Smart*). This way the *BaseTech* and *DataTech* construct composition changes. Using a similar CFA approach, analysis shows that the constructs are valid and reliable without the two I4.0 items as well. Thus, a research model containing purely traditional manufacturing technologies can be tested using SEM. The results are detailed in Figure 3.

Results of the robustness check show that our structural model and path coefficients remain stable even if some variables are removed from the model, further supporting the reliability of our results. From a conceptual perspective, however, this finding means that the addition of I4.0 technologies to the production system of manufacturing firms does not significantly improve the performance impact of technology bundles, path coefficients between the three technology bundles and the two operations performance indicators remaining fairly stable. This suggests that I4.0 technologies cannot currently confer a general competitive edge to manufacturing companies in terms of operations performance (note that operations performance is measured as *current* performance of the respondent firm *compared to* main competitors).

Multigroup analysis

Given the unexpected weak links between technology bundles and performance indicators, we further perform multigroup analyses (MGA) along the categories of the control variables involved in our study (Sarstedt *et al.*, 2011). Given that measurement invariance between the groups could only be established in case of the size variable, it is meaningful to compare the path coefficients of the model between large manufacturing firms and SMEs only, while the developed versus developing country approach has to be dropped (Henseler *et al.*, 2016). This difference might be accountable to the fact that only few developing countries were involved in the study, while in terms of size, the sample is more balanced (Small and medium-sized enterprise (SME), $n = 100$; large, $n = 65$). Based on this result, we apply the bootstrap-based MGA and test whether path coefficients have significant differences between the large and SME manufacturers. SmartPLS 4.0 offers multiple methods to test the significance of the



Source(s): Authors work

Figure 3. Robustness check – results of the structural model without I4.0 items

path coefficient differences between subgroups. Table 8 lists the results based on both bootstrap MGA, parametric test and the Welch-Satterthwaite test (Ringle *et al.*, 2022).

MGA results suggest that the model is fairly similar between large and SME firms, further supporting the robustness of our results. Only two path coefficients are worth investigating in terms of a significant difference between the two groups. The first one estimating the impact of *BaseTech* on *CostPerf* is around the significance limit, two of the three tests indicating that there might be a significant difference between the two groups. However, given that the difference is quite weak in terms of p-values and that the path coefficients are not significant in either of the two size categories (large: -0.173, $p = 0.100$, SME: $+0.163$, $p = 0.213$), this apparent difference has no meaningful conceptual relevance. On the other hand, however, the impact of *RobotTech* on *CostPerf* seems to significantly differ between large manufacturing firms and SMEs, all three tests indicating a statistically significant difference between the two groups in terms of the value of the path coefficient. This finding suggests that size acts as a moderator on the relationship between *RobotTech* and *CostPerf*: large manufacturing units experience a strong positive impact of using *RobotTech* on cost efficiency ($+0.527$, $p = 0.000$), while the same relationship in SMEs becomes non-significant (0.063, $p = 0.606$). Thus, robotization and automation technologies can contribute to better cost performance at large manufacturing units, while SMEs do not benefit of such cost performance impact.

Discussion

Results of our analysis suggest that there are 3 main bundles of manufacturing technologies (*RQ1*): (a) *base technologies*, that are fundamental manufacturing technologies that have an overarching effect on the way products are produced (CNC technology, additive manufacturing, flexible manufacturing systems, high precision technologies, etc.), that can be complemented/enhanced by (b) *automation and robotization* (e.g. industrial robots, automated materials handling and storage) and by (c) *data-enabled technologies* (e.g. MRP II/ERP, kanban controlled JIT production, automatic product identification, connectivity solutions, big data analytics, modeling and simulation). This result is partially in concordance with previous AMT literature, which differentiates between manufacturing and administrative technologies (note: AMT literature considers a third group too, referring to design technologies, which were not examined in this paper) (Boyer *et al.*, 1996; Jonsson, 2000; Cheng *et al.*, 2018). Our taxonomy confirms this separation, even when I4.0 technologies are added to the equation. However, we found two subgroups within the manufacturing technologies group (base technologies and automation/robotization). We assume that the key difference between the two groups is the volume of products they handle. This assumption is supported by the MGA, which shows a difference between the impacts of these technologies on cost performance: large companies can benefit significantly more from implementing automation/robotization.

An entirely novel and unexpected finding, however, is that our factor analysis indicates that newly emerging I4.0 technologies are used complementary to already existing technologies and do not form an independent bundle, as presumed by previous research. New AMT complement other base technologies, while smart technologies complement existing data-based technologies. While this result is quite logical, it questions the direction of the literature, which deals exclusively with new I4.0 technologies (Benitez *et al.*, 2023; Demeter *et al.*, 2021; Frank *et al.*, 2019; Meindl *et al.*, 2021), without taking into consideration how these new technologies are combined with more established ones. Thus, as recently suggested, “use cases” of emerging technologies in connection with the existing technological base of companies might provide a more practical way to extract value from I4.0 technologies (Maghazei *et al.*, 2022).

Table 8. Multigroup analysis results (large firms versus SMEs)

	Large		SME		Difference in coeff	*p*-value (large vs SME)		
	Coeff	*p*-value	Coeff	*p*-value	(SME-large)	Bootstrap MGA	Parametric test	Welch-Satterhwaite
BaseTech → CostPerf	−0.173	0.100	0.163	0.213	0.336	*0.047*	0.066	*0.047*
BaseTech → DataTech	*0.487*	*0.000*	*0.500*	*0.000*	0.013	0.949	0.922	0.923
BaseTech → DiffPerf	0.063	0.670	−0.070	0.588	−0.134	0.502	0.504	0.498
BaseTech → RobotTech	0.215	0.156	*0.323*	*0.007*	0.108	0.570	0.573	0.575
CostPerf → BusPerf	0.155	0.339	0.188	0.223	0.033	0.841	0.887	0.883
DataTech → CostPerf	*−0.330*	*0.011*	−0.201	0.062	0.129	0.440	0.446	0.444
DataTech → DiffPerf	−0.081	0.690	*0.296*	*0.012*	0.376	0.101	0.086	0.110
DataTech → RobotTech	*0.484*	*0.000*	*0.268*	*0.022*	−0.216	0.210	0.229	0.222
DiffPerf → BusPerf	0.285	0.069	0.092	0.479	−0.193	0.337	0.343	0.342
DiffPerf → CostPerf	*0.622*	*0.000*	*0.503*	*0.000*	−0.119	0.328	0.359	0.338
RobotTech → CostPerf	*0.527*	*0.000*	0.063	0.606	−0.465	*0.033*	*0.016*	*0.016*
RobotTech → DiffPerf	−0.089	0.716	0.096	0.487	0.185	0.511	0.477	0.510

Note(s): Coeff. = path coefficient; values in italic are significant at the $p = 0.05$ level
Source(s): Authors' work

Results of the PLS-SEM show that the three technology bundles have different impacts on operations performance (*RQ2*).

First, *base technologies* have no significant effect. This result is surprising as AMTs (both older and newer ones) are claimed to have a positive effect on costs as well as on quality, delivery or flexibility (Cheng *et al.*, 2018; Jonsson, 2000; López-Gomez *et al.*, 2018; Szász *et al.*, 2023). A possible explanation for this result can be that operations performance was measured relative to competitors. Thus, the correct interpretation of our results is that if companies apply the same technologies, they do not necessarily achieve higher performance than the competitors (even if a performance improvement is attained). These results might suggest that, as such base technologies spread in the economy, they become qualifying factors – they are necessary to stay in competition, but do not readily offer a competitive advantage. Adding the I4.0-related AMT to this bundle did not change the impact of base technologies on operations performance, although probably some companies could gain advantage by being first adopters. The question is, however, the ratio of the newest technologies within the bundle. If it is low because of the slow and gradual adoption, then its impact will be negligible.

Second, *automation and robotization* has a positive impact on cost efficiency, but no effect on differentiation factors (quality, delivery, flexibility). Since technologies serving automatic material handling and robotic technology are usually developed for mass production purposes, having positive effect on costs while no differentiation effect makes sense. Thus, it is not surprising either that additional subgroup analysis indicated that larger companies could benefit significantly more than smaller ones, in line with previous findings (Szász *et al.*, 2023). Given that these technologies can partially or fully replace humans (Acemoglu, 2017), their economic return is direct and therefore easily measured and realized.

Third, results are different for *data-enabled technologies*. Data-based administrative technologies have only a negative impact on costs (and no significant impact on differentiation), suggesting that manufacturing companies that employ these technologies incur higher operating costs relative to their competitors. Implementing these technologies usually results in more complex systems, relying on additional ICT experts and data scientists (Demeter *et al.*, 2021). Therefore, especially at the beginning of these investments, but due to fast developments of the field later on as well, these technology implementation projects are more costly (Buer *et al.*, 2021). Furthermore, they themselves do not add direct value to operations as manufacturing automation and robotization technologies do. Nevertheless, they still have positive indirect impact on performance, as they are important enablers of better automation and robotization and in general can contribute to faster and more evidence-based decision making or better capacity utilization (López-Gomez *et al.*, 2018; Patrucco *et al.*, 2022). Although not significant at 5% level, but at 10% both cost and differentiation have a positive impact on business performance. Therefore, we can state that technology investments might pay off for companies. The few existing findings in the literature are also ambiguous in this aspect (Cheng *et al.*, 2018; Jonsson, 2000). One potential explanation could be related to a temporal aspect: technology investments need longer time to pay off until their operational performance effects are translated to tangible, competitive business performance gains.

Relevance and contribution

Manufacturing systems are more and more complex, combining many different technologies. Understanding the relationship of these technologies is crucial, especially in a technology-driven era. So far, literature used technology typologies without testing how they are bundled in practice. Furthermore, newer I4.0 and older AMT technologies were not discussed together, neither in terms of bundling, nor related to their potential performance benefits.

Our paper aimed to partially fill this gap by relying on the arguments of the complementarity theory, showing that different technology bundles exist that combine I4.0 technologies with traditional ones. Thus, our findings suggest that I4.0 technologies are complementary to existing, traditional manufacturing technologies, instead of completely replacing them and forming a separate bundle. Furthermore, we cannot witness a breakthrough performance effect of I4.0 technologies. These findings support the evolutionary, rather than the revolutionary perspective.

The existing literature typically classified technologies into three groups: design, manufacturing and administrative technologies. Our findings indicate a notable distinction within the manufacturing technologies, separating them into two key bundles with different performance implications: base technologies (capable of flexible small-scale production) and automation/robotization technologies (more efficient in large-scale manufacturing). These technology bundles remain stable even when I4.0 technologies are added.

The practical relevance of our results is connected to the reality that manufacturing companies encounter many obstacles with the introduction of I4.0 technologies and expected performance impacts after the introduction are frequently lacking. Our study contributes to easing these challenges by focusing on manufacturing technology bundles in a novel approach and aiming to assess performance effects along these bundles.

Based on our research, on the one hand, companies should not expect quick business return from their investments in base and administrative technologies. Still, they need to make these investments: not to gain competitive advantage, but to remain in business.

On the other hand, leveraging automation/robotization can swiftly yield cost advantages. However, for reaping the benefits, a substantial scale is necessary. Hence, this investment is particularly worthwhile for larger enterprises. However, while automatization/robotization can certainly yields results, realizing its full potential may require a more extended timeframe.

Limitations and further research

A limitation of this study is that we only considered manufacturing and administrative technologies connected to the production function, while neglecting design technologies, so their relation to other technologies remains unclear. Furthermore, the technologies were measured on a high level, without offering the possibility for a fine-grained assessment of individual I4.0 technologies.

Another limitation is the timeframe of data collection (2016–2017). Whether I4.0 could gain more ground in the following period and bring a revolutionary shift in technology bundling and performance effects deserves further investigation.

As for additional further research, it would be worthwhile to investigate not only the performance compared to competitors, which is surely important in the market, but also how companies can improve operations performance in time due to investing into various technology bundles. Furthermore, although we found that company size affects the impact of automation, it is still worth investigating whether production volume is the real cause behind this result. Finally, it should be highlighted that during technology implementations the technology is just one element and not necessarily the most important one to achieve success. Therefore, it is a promising avenue for future research to consider all other elements of the socio-technical system surrounding I4.0 implementation when assessing the success of such projects.

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