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How to improve firm performance? – The role of production capabilities and routines

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Abstract

Purpose – In the multilayered capability framework the authors integrate two layers, namely functional level production capabilities and shop floor-level production routines (PRs). The authors examine how these two layers are interlinked, and additionally, they explore how these layers contribute to firm performance.

Design/methodology/approach – The authors tested the hypotheses using structural equation modeling (SEM) on a sample of manufacturing firms.

Findings – Regarding the capability layers, the authors found that at the functional level, production dynamic capabilities (PDCs) drive the renewal of production ordinary capabilities (POCs), and that at the shop floor level, deployment of Industry 4.0 (I4.0) is influenced by lean production. Regarding the direct links between capability layers, the authors showed that PDCs and POCs have different roles in shaping shop floor PRs: PDCs is linked to I4.0, and lean methods is impacted by POCs. Concerning performance implications, only PDC and POC have significant impact on firm performance (the latter is negative), while PRs do not.

Research limitations/implications – Although, contextual factors (e.g. technology intensity, size) do not influence our findings, the potential country-effect and the dominance of medium-sized firms offer future research directions.

Practical implications – If production managers want to contribute to business performance, they should be more susceptible to resource renewal (PDCs) than to their general (POCs) or specific (PRs) exploitation efforts. As they exploit current resource stocks, they face a trade-off: they must consider that beyond their positive impacts on operational performance, their implications on business performance will be controversial.

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Originality/value – Scholars usually examine one layer of capabilities, either capabilities or routines, and associate that with one dimension of performance, either financial and market measures or operational indicators. The authors propose a multilayered capability framework with a complex view on performance implications.

Keywords Production dynamic capabilities, Lean, Industry 4.0, Firm performance

Paper type Research paper

1. Introduction

The way companies gain competitive advantage as they adapt themselves to environmental changes is explained by several strategic management (SM) concepts. Our research relies on the dynamic capabilities (DCs) view (Teece *et al.*, 1997). Specifically, DCs indicate a company's ability to renew its resources in the changing environment to gain competitive advantage (Winter, 2003; Helfat and Peteraf, 2009). In the most general approach of DCs, sensing, seizing and reconfiguring capacities are entangled at firm level (Teece, 2007). A more practical and high-resolution elaboration of DCs appears at a functional level related either to a specific function, for example, R&D and innovation (Ilmudeen *et al.*, 2020; McKelvie and Davidsson, 2009), information technology (Wamba *et al.*, 2017), marketing (Xu *et al.*, 2018) or covering several functions (Danneels, 2016; Wilden and Gudergan, 2015).

Beside DCs, scholars also define ordinary capabilities (OCs) at firm (Teece, 2014; Swink and Hegarty, 1998) and functional levels (Danneels, 2016). OCs represent the available resource stocks that "make the living" of the firms (Danneels, 2016). These general resource stocks are rooted in routines (Qaiyum and Wang, 2018). Unfortunately, the relations of OCs with routines (practices) that direct daily activities are not detailed.

Scholars in production and operations management (POM) have also defined exploration- and exploitation-type production capabilities (Peng *et al.*, 2008; Swink and Hegarty, 1998; Wu *et al.*, 2010). These concepts are identical to production dynamic capabilities (PDCs) and production ordinary capabilities (POCs). However, these capability-related works also overlook the role of specific production routines (PRs) that direct shop floor-level execution. The missing link between the production capabilities and PRs is a striking tension in the literature, with potentially significant practical implications.

To examine this link, our paper proposes a multilayered capability framework. It links functional-level production capabilities (PDCs, POCs) and shop floor-level PRs in a hierarchical structure. PRs are represented with actual challenges of manufacturing firms, like the deployment of lean and Industry 4.0 (I 4.0). Additionally, we link this capability structure to firm performance. The top-down approach of SM highlights competitive advantage (usually measured by business performance), and the bottom-up approach of POM emphasizes operational (and sometimes business) performance improvements (Sabella *et al.*, 2014; Galeazzo and Furlan, 2018; Koh *et al.*, 2019). So, we explore these two dimensions of firm performance.

Our study aims to answer the following research questions:

RQ1. How are the layers of production capabilities interlinked?

RQ2. How do they contribute to different dimensions of firm performance?

The paper is organized as follows. The literature review starts with the introduction of DCs. Then by reconciling the SM and POM literature, we describe PDCs, POCs and PRs. We also outline their performance effects. Then, related to our research questions, we elaborate hypotheses and propose a research model. The methodological part contains the presentation of the questionnaire survey, the characteristics of the sample and the measurement of the variables. In the results part, we test our hypotheses using a structural model. The discussion highlights the theoretical relevance and practical implications. The study ends with concluding remarks and future research directions.

2. Literature review and hypotheses development

2.1 Approaching capabilities and their performance effects

As depicted in Figure 1, SM and POM literature scrutinizes different layers of capabilities and highlights distinct dimensions of performance implications.

2.1.1 Strategic management literature. SM is interested in "higher-level" capabilities linked to firm and functional levels. At the firm level, DCs show how a firm can renew its resources to gain competitive advantage in a continuously changing environment (Winter, 2003; Helfat and Peteraf, 2009; Teece, 2014; Teece *et al.*, 1997; Eisenhardt and Martin, 2000; Danneels, 2016). DC theory also defines OCs (Teece, 2014) that are the essential resource stocks setting direction for the everyday operations. It is widely assumed that the renewal of this resource stock is driven by DCs.

This literature also offers an interpretation of strategic abilities at the functional level. Danneels (2016) has determined key components of DCs and OCs in different functional areas. His production-like (technological) capabilities represent the facility-technology-process-people('s skills) scheme. Firms acquire and build new resources (as indicated by PDCs) and exploit current resource stocks (as captured by POCs) related to his scheme's components. Although Teece *et al.* (1997) and Pisano (2017) refer to specific PRs (e.g. lean and quality management) as seminal concepts that influenced DCs, this level of the capability hierarchy is usually overlooked in SM.

Regarding the performance effects, authors are aiming to explore how DCs are related to sources of competitive advantage. Theoretically (Teece *et al.*, 1997; Pisano, 2017), DCs are intended to influence market performance and other financial measures (Laaksonen and Peltoniemi, 2018) that reflect competitive advantage. In the empirical research, findings on the relationship between DCs and competitive advantage show that the relationship is often indirect, temporary or nonexistent (Ambrosini and Bowmanx, 2009). The possible indirect relationship can be explained by a two-level competition model that differentiates product market competition and capability-level competition (Pisano, 2017). Pisano (2017) argues that capability-level competition is less visible externally, and it is about internal factors such as operations, organization and technology.

In summary, SM literature's (Figure 1, SM) main effort is to disentangle DCs and explore how DCs contribute to competitive advantage, sometimes also going down to functional (e.g. production) levels.

POM developed three sub-streams around interpreting the role of capabilities, or more specifically around the role of DCs in manufacturing firms (Figure 1, POM).

2.1.2 The production capability sub-stream. These works (Chikán *et al.*, 2022; Peng *et al.*, 2008; Swink and Hegarty, 1998; Wu *et al.*, 2010) can be directly linked to the SM literature. However, there are some content-wise differences. The main components of production (technological) capabilities around facilities, technologies, processes and skills (Danneels, 2016) are rarely adopted in POM (Chikán *et al.*, 2022). POM extends the boundaries of production capabilities as they additionally cover innovation and product design (Swink and Hegarty, 1998; Peng *et al.*, 2008; Wu *et al.*, 2010), continuous improvement (Swink and Hegarty, 1998; Peng *et al.*, 2008; Wu *et al.*, 2010) and leadership (Peng *et al.*, 2008). Furthermore, POM researchers usually separate resources (physical elements) from operational capabilities that they consider as "firm-specific sets of skills, processes, and routines, developed within the operations management system, that are regularly used in solving its problems through configuring its operational resources" (Wu *et al.*, 2010, p. 726), or simply "as bundles of routines" (Peng *et al.*, 2008, p. 732), referring to its more abstract level. We can also find distinctions between growth/innovation capabilities (identical to our PDCs) and steady-state/improvement capabilities (identical to our POCs) (Swink and Hegarty, 1998; Peng *et al.*, 2008). All the studies (Chikán *et al.*, 2022; Swink and Hegarty, 1998; Wu *et al.*, 2010) connect production capabilities to operational performance indicators like cost, quality, service, time and flexibility.

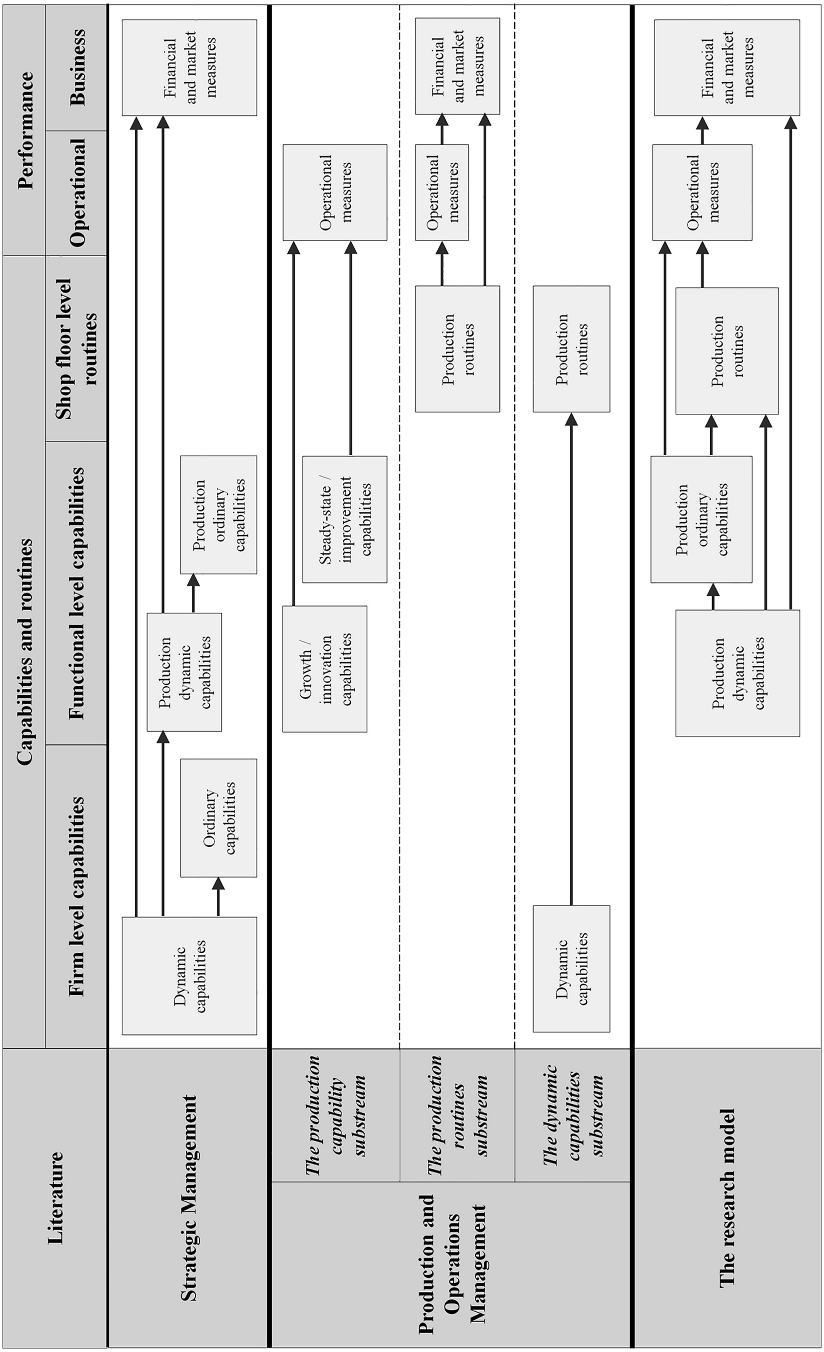

Figure 1.
The summary of the existing research streams in the strategic management and in the production and operations management

2.1.3 The production routine sub-stream. It explores the modus operandi of PRs, for example, total quality management (Hackman and Ruth, 1995; Sabella *et al.*, 2014), advanced manufacturing technology (Gupta and Yakimchuk, 1989; Voss, 1986), lean management (Shah and Ward, 2007; Galeazzo and Furlan, 2018) or I4.0 technologies (Koh *et al.*, 2019; Szász *et al.*, 2021). Although the routines seem to be independent from the capability literature, this sub-stream is implicitly built on the resource-based view, and it assumes the embeddedness of routines into the (renewal of) resource stock. In other words, this sub-stream does not separate PRs (practices) from operational capabilities. The main objective of this sub-stream is to present how these practices contribute to the operational and business performance of the firm (e.g. paper on lean: Chavez *et al.*, 2013; De Toni and Tonchia, 1996 or on I4.0: Felsberger *et al.*, 2020; Szász *et al.*, 2021).

2.1.4 The dynamic capability sub-stream of POM. Several papers link directly the firm-level DCs to PRs, like I4.0. They do not consider specificities of functional capability (Demeter *et al.*, 2021; Dubey *et al.*, 2019), and the performance impact are only implicitly handled.

Based on these sub-streams in literature, we can identify an interlinked web of capabilities and routines directing production. In the proposed multilayered capability framework, depicted at the bottom of Figure 1, we link functional level capabilities (PDCs and POCs) and shop floor-level routines (PRs) in manufacturing context. Only speculations are available about the links between these layers, and these links were not tested empirically. Furthermore, as discussed, two different sets, namely competitive advantage related and operational performance indicators, are also linked to this framework. Therefore, our study is unique in that it connects capability layers to performance dimensions as shown in Figure 1.

2.2 The multilayer capability framework and hypotheses development

In this section we introduce our proposed framework and elaborate our hypotheses simultaneously. First, the link between the components of the two different capability layers are discussed (H1 and H2), and then their relationship is elaborated (H3). Next, we grasp the link between the two different dimensions of performance (H4) and, finally, find the sources of operational (H5) and business (H6) performance.

2.2.1 Functional level – decomposing production capabilities. Production capabilities in the POM literature (Peng *et al.*, 2008; Swink and Hegarty, 1998; Wu *et al.*, 2010) resemble production-related DCs and OCs in the SM literature. Both studies emphasize adjustment to changes in the environment and differentiate exploration- (dynamic) and exploitation-type (ordinary) capabilities. However, while in DC theory DCs drive OCs at firm level as the renewal leads to a new level of resources to exploit (Danneels, 2016), we seldomly see this explicit “hierarchy” in POM. One seminal exception is Chikán *et al.*’s (2022) production-focused work. They adapt Teece’s approach to manufacturing context that claims that DCs “. . . can enable an enterprise to upgrade its ordinary capabilities and direct these” (Teece, 2018 p. 43). Based on the DCs theory, we formulate the first hypothesis about the link between production capabilities.

H1. Production dynamic capabilities directly and positively influence production ordinary capabilities.

2.2.2 Shop floor-level execution – the production routines. The shop floor level is a key area in manufacturing organizations (and so in POM literature), so scholars have devoted tremendous efforts to document specific PRs. We find lean management (Womack and Jones, 2003; Shah and Ward, 2007; Åhlström *et al.*, 2021) among the most influential PRs in POM of the last 20–30 years. Lean methods highlight process organization and people’s skills to exploit available technologies to meet changing customer expectations (e.g. perfect quality, low cost, increased variety). A recent phenomenon, the 4th Industrial Revolution, has brought the I4.0 that reshapes operations considerably (López-Gómez *et al.*, 2018). I4.0 is about infinite variety, and it emphasizes technological advancements that pervade processes and people’s skills as well.

Academic discussion examining the relationship between the selected PRs has also been fertile (Tortorella *et al.*, 2019). Scholars usually reach the conclusion that companies using lean methods are also more likely to implement I4.0 technologies (Tortorella and Fettermann, 2018; Demeter *et al.*, 2021; Kolberg and Zühlke, 2015). Dombrowski *et al.* (2017) even consider lean as one of the foundations of I4.0. These findings reflect path dependency, a concept underpinning DCs theory. It claims that company's "current position is often shaped by the path it has travelled" (Teece *et al.*, 1997, p. 522). Demeter *et al.* (2021) explicitly rely on this concept as they explain why firms with mature lean systems turn to I4.0.

H2. The level of deployment of lean methods influences the level of deployment of Industry 4.0.

2.2.3 The link between functional-level capabilities and shop floor-level routines. Regarding the influence of PDCs on PRs, one should start with the DC view. It claims that DCs are the drivers of resource renewal (Teece, 2018). So, by this resource renewal at functional level, not only POCs (see H1) but also the specific manifestations of resource configurations (PRs) are influenced. In the DC sub-stream, we found links between DCs and lean management (Hansen and Moller, 2016) or I4.0 technology implementations (Demeter *et al.*, 2021). We expect that PDCs positively influence the deployment of both lean methods (H3a) and I4.0 (H3b).

To understand the influence of POCs on PRs, one must highlight their different organizational roles and their relations to the available resource stocks. First, POCs' positive influence on PRs stems from the fact that POCs are at functional (closer to firm) level and PRs are closer to shop floor execution level. Hence, the direction in their relationship is a structural issue, already considered in the proposed framework. Second, production capability sub-stream of POM describes how the two concepts interlinked regarding resource stocks. Peng *et al.* (2008) consider the bundles of PRs (first-order factors) as operational capabilities (second-order factors). Wu *et al.* (2010) also separate operational practices (like just in time) from operational capabilities. They consider practices as recipes, or documented knowledge, which does not guarantee the same outcome in every case due to differences in the tacit operational capabilities behind (see the results of Toyota vs. many other companies applying lean management). POCs contain the actual physical and intellectual resource stock alongside the dimensions like facilities, technologies, processes and skills (Danneels, 2016). PRs are specific practices alongside the same dimensions, and they are followed on the shop floor to exploit the resource stock. If we rely on this interpretation, then we can state that higher-level general resource stocks, like POCs, positively influence lower-level specific resource configurations, like lean (H3c) or I4.0 (H3d).

H3. Production capabilities positively influence shop floor production routines.

H3a. Production dynamic capabilities positively influence the deployment of lean methods.

H3b. Production dynamic capabilities positively influence the deployment of Industry 4.0.

H3c. Production ordinary capabilities positively influence the deployment of lean methods.

H3d. Production ordinary capabilities positively influence the deployment of Industry 4.0.

To summarize, the resource renewal will result in the "new" actual resource stock (H1), which can be exploited by the specific PRs (H3), whereby different PRs with specific resource configurations can also stimulate each other (H2).

2.2.4 Dimensions of performance implications. The reviewed literature demonstrates that high and improving capabilities and routines lead to improvements in both operational and business measures. While SM is almost exclusively interested in business measures, POM is usually scrutinizing operational implications. To intertwine these different emphases, we assume a textbook-wise link between the two dimensions of performance, namely, that operational performance improvements contribute to better business performance (Slack and Brandon-Jones, 2018). More specifically, higher quality through error-free activities, better time performance through fast throughput and reliable processes and higher flexibility through ability to change all can contribute to higher productivity and thus lower costs, and, in parallel, increase customer value (and market performance).

H4. Operational performance improvement contributes to better business performance.

Revealing factors that influence operational performance (improvements) is a central topic in both production capabilities and PRs literature. Scholars usually hypothesize that each of these capability layers impacts traditional operational performance measures like cost, quality, flexibility, services and time. At production capability level, Swink and Hegarty (1998) and Wu *et al.* (2010) empirically demonstrated the positive links between production (ordinary and dynamic) capabilities and operational measures. At shop floor routine level, both lean (Chavez *et al.*, 2013; De Toni and Tonchia, 1996) and I4.0 (Felsberger *et al.*, 2020; Szász *et al.*, 2021) were proved to enhance operational performance. These conclusions are expressed by H5, whereby production capabilities appear in H5a and H5b, and PRs are linked to H5c (lean) and H5d (I4.0).

H5. Operational performance improvement is influenced by each layer of capabilities.

H5a. Operational performance improvement is positively influenced by production dynamic capabilities.

H5b. Operational performance improvement is positively influenced by production ordinary capabilities.

H5c. Operational performance improvement is positively influenced by the deployment of lean methods.

H5d. Operational performance improvement is positively influenced by the deployment of Industry 4.0.

As presented, SM literature considers improved market (like market share, sales) and financial (like profitability) measures as proxies for competitive advantage as a result of DCs. In the empirical research, the direct influence of DCs on these performance measures becomes blur (Laaksonen and Peltoniemi, 2018). In line with the theoretically reasoning, one argues that DCs influence OCs, and then the use of the renewed resource stock leads to higher performance. Even if we also follow this logic, we still argue that the continuous reconfiguration of the resource stock (PDCs) to fit better to the market requirements will lead to higher business performance directly.

Although findings about PRs' performance impacts are dominated by operational measures, the financial and market implications are also regularly assessed (Fullerton and Wempe, 2009; López-Gómez *et al.*, 2018). However, several authors warn that the direct positive link of these PRs to business performance is not straightforward at all. Regarding lean, it is not evident how operational excellence can be transformed to business excellence in lean firms (Losonci and Demeter, 2013). Considering digitalization, Björkdahl (2020) concluded that firms have not yet been able to achieve any performance increase with digital transformation. Altogether, the literature suggests that the current resource stocks are dominantly linked to improved operational performance measures, and the link to business performance is controversial.

H6. Business performance is influenced only by functional level capabilities.

H6a. Business performance is positively influenced by production dynamic capabilities.

H6b. Business performance is positively influenced by production ordinary capabilities.

2.2.5 The research model. Our model (Figure 2) answers the following general research questions:

RQ1. How are the layers of production capabilities interlinked (H1, H2 and H3)?

RQ2. How do they contribute to different dimensions of firm performance (H4, H5 and H6)?

In this research, we take PDCs as the key vehicle of the resource renewal process, which influences the exploitation of resource configurations. Regarding the current resource stocks, besides the general resource configuration (i.e. POCs), we also consider two seminal PRs, namely, lean practices and in I4.0. We investigate the links between these concepts, assuming, according to path dependency, that PDCs influence the POCs (H1) and lean methods provide the basis for I4.0 (H2). Afterward, implications of production level exploitation and exploration efforts are assessed related to the shop floor production routines (H3). The relation between the performance dimensions is also examined, assuming that improved operational performance leads to better business performance (H4). Finally, the performance implications of the capabilities and routines are assessed. When we turn to this part, the effect of the capabilities and routines on the operational performance is analyzed (H5). Since better resource renewal processes and the exploitation of the current resource stock can make the difference between the companies, we propose that better functional level capabilities can lead directly to higher competitive advantage (H6).

3. Research methodology

First, we provide insights to the analyzed survey and research sample. Then we present the applied research technique. Finally, the measures are described.

3.1 The survey and the research sample

The Competitiveness Research Center organizes research programs about firms' competitiveness in every 4–6 years since the mid-1990s in Hungary. The last round has started in 2018. The survey-based program focuses on firms with at least 50 employees in selected industries.

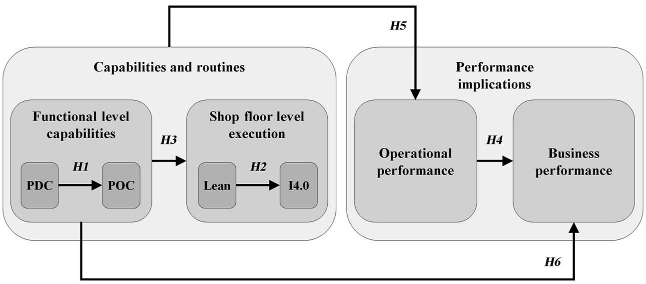

Figure 2.
The research model

The sampling frame for this last survey was based on the Hungarian Statistical Office's enterprise database and contained 4,295 firms. Sample stratification was performed by size (50–99, 100–249 and > 250 employees), industries and regional dimensions. The data collection was organized between December 2018 and July 2019. Data were collected by TÁRKI, a professional company specialized in empirical social science research. Altogether, 2,062 companies were contacted and 234 companies filled the questionnaires. To ensure the reliability of the collected data, a data cleaning process was also applied. We have eliminated companies with incomplete questionnaires and inconsistent or missing financial data. Financial data about the sample companies were obtained from Bisnode, a financial service firm. After data cleaning, the final sample included 209 companies, of which 113 of them represented the manufacturing sector. To assess the nonresponse bias, we have compared size and industry of firms of the sample frame and final sample. We concluded that the final sample is representative of the national economy in the examined industries and size categories.

The survey-based program targets top managers. Three questionnaires are designed to learn about functional areas like production (production manager), trade/marketing (sales/marketing manager) and finance (financial manager). One questionnaire covers strategy, organization and human resources and it is filled-in by the CEO. The fifth questionnaire contains the main characteristics of the company, institutional factors and competitiveness measures. Before completing the questionnaire, full anonymity was guaranteed for the participating companies.

Our research sample includes 86 manufacturing companies of the 113 due to missing data at construct level (for details see Table 1). In the final sample (N = 86), we have 17 large and

Industry (Nace rev. 2)	Number of companies	Number of employees 50–99	100–249	>250	Frequency (%)
Manufacture of fabricated metal products (25)	*22*	15	6	1	25.58
Manufacture of machinery and equipment (28)	*8*	2	5	1	9.30
Manufacture of rubber and plastic products (22)	*8*	4	0	4	9.30
Food production (10)	*7*	2	2	3	8.14
Manufacture of other transport equipment (30)	*4*	1	1	2	4.65
Manufacture of electrical equipment (27)	*4*	1	3	0	4.65
Printing and other reproduction activities (18)	*4*	2	2	0	4.65
Manufacture of nonmetallic mineral products (23)	*4*	3	1	0	4.65
Manufacture of chemicals and chemical products (20)	*3*	1	2	0	3.49
Manufacture of wearing apparel (14)	*3*	1	1	1	3.49
Manufacture of motor vehicles (29)	*3*	0	1	2	3.49
Manufacture of furniture (31)	*3*	3	0	0	3.49
Repair and installation of industrial machinery, equipment and tools (33)	*3*	0	1	2	3.49
Manufacture of computer, electronic and optical products (26)	*2*	1	0	1	2.33
Manufacture of textiles (13)	*2*	1	1	0	2.33
Manufacture of basic metals (24)	*2*	2	0	0	2.33
Pharmaceutical production (21)	*1*	0	1	0	1.16
Other manufacturing (32)	*1*	1	0	0	1.16
Manufacture of paper and paper products (17)	*1*	1	0	0	1.16
Manufacture of leather and related products, footwear (15)	*1*	0	1	0	1.16
TOTAL	*86*	*41*	*28*	*17*	*100.00*

Table 1. Distribution of the sample by manufacturing industries

69 middle-sized firms. We have tested the nonresponse bias (Armstrong and Overton, 1977) by comparing the first and the last 30 answers with a standard *t*-test, and no significant difference is revealed.

We set up a 50% threshold limit for missing data in each construct. Therefore, one latent construct for a particular firm must have at least half of the items. Firms with missing items in a construct above the threshold were omitted. For firms below the threshold, missing values were replaced with the variable average. Fortunately, from the 1,978 data points (86 firms * 23 manifest variables), we have only 25 missing data, which means 1.26% of the whole data set. In all, 80.2% of the companies have no missing data. The maximum missing ratio is 8.7%, so it means that for any firm, out of the 23 manifest variables only 2 are missing. In case of 19 manifest variables, we have no missing values. The three lean-related manifest variables have the most missing values (4, 9 and 11 missing items). In case of one I4.0 manifest variable, we have only 1 missing value.

3.2 The applied research technique

The empirical analysis is based on the partial least squares structural equation modeling (PLS-SEM). We chose this method, because of the following characteristics:

(1) SEM can handle complex interrelations;

(2) SEM is able to assess indirect and total effect on the constructs of interest;

(3) SEM can be applied in small data sets;

(4) SEM the factor and the regression analysis can be deployed at the same time, which is necessary in this research, since the main variables are constructed from several variables;

(5) SEM can handle non-normally distributed data, which is an important feature, because data from surveys typically show skewed distribution (Hair *et al.*, 2017).

In the survey, Likert scales (from 1 to 5) were used, which also supported the application of the PLS-SEM method (Hair *et al.*, 2017; Kazár, 2014). The covariance-based (CB) SEM) is a similar method of the PLS-SEM, but during the method selection process the characteristics of the latter one were better for our research model. First, our aim was to identify if the PDCs are the basis of the POCs and shop floor-level routines. In addition, we examined if the capabilities and the routines can have performance implications. Thus, we had the aspiration to identify some key driver constructs. Based on the methodological recommendations (Sarstedt *et al.*, 2016; Rigdon *et al.*, 2017), in this situation PLS-SEM is preferred over CB-SEM. In addition, our sample size is small, and in this case also the PLS-SEM is the better option to choose. We do not assume circular relationships, which can be examined only with CB-SEM, thus for our research model the PLS-SEM fits well. To make sure the final sample size of 86 is suitable for the SEM-PLS analysis, a power analysis (Faul *et al.*, 2008) was done. The post hoc power analysis shows that at 5% statistical significance level (a) the statistical power (1-β) of our analysis is 90.20%, which is fair (the probability of type II errors (β) is 9.8%).

For the analysis, the variance-based PLS-SEM method is used (Henseler *et al.*, 2016). In total, we have made 7 latent constructs based on 23 manifest variables (indicators). The 7 latent constructs are developed as part of a reflective model, where all constructs are the cause (and not the consequence) of the manifest variables (Henseler *et al.*, 2016). In the procedures, we followed the recommendations and best practices of Hair *et al.* (2017). In the model, two main parts can be distinguished: the external model and the internal model. The external model describes the relationship between the manifest variables and the latent variables, and the internal model shows the relationship between the latent variables. The external model must be evaluated first, and, if this is appropriate, we can move on to the evaluation of the internal model (Hair *et al.*, 2017; Kazár, 2014).

3.3 Measures

We have developed measures for PDCs, POCs, PRs and firm performance indicators.

In the first step, we formed the PDC construct (see Table 2). In our research, we have adapted Danneels' (2016) measures. PDCs are made from four elements: (1) building new facilities, (2) introduction of new services or production processes, (3) introducing new technology and (4) building the expertise.

The POC (Danneels, 2016) latent variable contains six variables: (1) service and production facilities (work environment), (2) current technology, (3) management's capabilities (e.g. production manager, technical manager etc.), (4) service and production processes, (5) technological know-how (engineering knowledge) and (6) employees' technical abilities and competences.

Then we defined the items representing the two selected PRs' latent constructs. Items for lean methods and I4.0 were adopted from the International Manufacturing Strategic Survey (http://www.manufacturingstrategy.net). The lean latent construct is approximated by three variables (continuous improvement, restructuring (streamlining) of processes and applying the pull principle) that are the crucial building blocks of a lean production system (Losonci and Demeter, 2013). The I4.0 production routine latent construct consists of four variables: (1) digitization of operations, (2) automation of operational processes, (3) the share of digitization solutions in the products value and (4) the real-time connection. These variables essentially reflect the basic technological advances of I4.0. Similar approach was applied by Szász *et al.* (2021) and Gillani *et al.* (2020) as using IMSS data set.

In our questionnaire, all the capability-related items were assessed by the production manager of the manufacturing firm.

Finally, firm performance was linked to business performance as a proxy for competitive advantage and operations measures.

To assess business performance latent construct, we used (1) market share and (2) return on sales as manifest variables (e.g. Laaksonen and Peltoniemi, 2018). These variables reflect the perception of the CEO.

Operational performance construct is measured by cost, quality, lead time and flexibility (Szász *et al.*, 2021). In our analysis, the cost dimension is treated separately, while the other three variables together measure the differentiation dimension of operational performance. This separation is frequently applied (Chikán *et al.*, 2022; Dubey *et al.*, 2019; Szász *et al.*, 2021; Demeter *et al.*, 2017). This differentiation at functional level resembles Porter's approach of strategic focuses at firm level (Porter, 1985). This distinction leads to a sand-cone type set up of operational performance (differentiation→cost). So, this classification influences H4 (examining the link between operational and business performance) and H5 (examining the sources of operational improvements) as well. Variables related to improvements in operations measures were answered by production managers.

All the used manifest variables are measured on a 1 to 5 Likert scale. The average values above 3 for PDCs indicate that production managers think their firm made a bit more effort in exploration than their competitors (see Table 2). According to production managers' perceptions, in production routines, and especially in I4.0, firms lag their benchmark. Examining the averages related to firm performance in Table 2, the respondents saw significant development in both dimensions in the last years.

Table 2.
Descriptive statistics of the used variables

Latent variable		Manifest variable name	Minimum	Maximum	Average	Median	Standard deviation	No. of observations
Production dynamic capabilities		Creation of new facilities	1	5	3.2	3	0.9	86
		Introduction of a new service provision/production process	1	5	3.4	3	0.8	86
		Introduction of new technology	1	5	3.3	3	0.9	86
		Building the expertise needed for new technology	1	5	3.4	4	1.0	86
Production ordinary capabilities		Service and production facilities (work environment)	1	5	3.4	3	0.8	86
		Current technology	2	5	3.5	3	0.9	86
		Management's capabilities (e.g. production manager, technical manager, etc.)	2	5	3.6	4	0.7	86
		Service and production processes	1	5	3.6	4	0.7	86
		Technological know-how (engineering knowledge)	1	5	3.6	4	0.8	86
		Employees' technical abilities and competences	2	5	3.5	4	0.8	86
Lean		Continuous improvement	1	5	3.0	3	1.2	77
		Restructuring (streamlining) of processes	1	5	2.6	3	1.0	75
		Pull principle	1	5	2.7	3	1.1	82
Industry 4.0		Digitization of operation	1	5	2.5	3	1.1	86
		Automation of operational processes	1	5	2.9	3	1.1	86
		Digitization solutions determine the value of a product	1	5	2.9	3	1.0	86
		Real-time connection	1	5	2.9	3	1.0	85
Operational performance	Cost	Cost	1	5	3.2	3	0.7	86
	Differentiation	Quality	2	5	3.4	3	0.7	86
		Time	1	5	3.6	4	0.8	86
		Flexibility	2	5	3.7	4	0.7	86
Business performance		Market share	2	5	3.6	4	0.7	86
		Profit per sales ratio	1	5	3.7	4	0.9	86

Note(s): The original questions and the applied scales: *production dynamic capabilities* and *production ordinary capabilities*: compared to the competitors my company is better in . . . (1–strongly disagree, 5–strongly agree); *lean*: The level of the efforts in the last 3 years to implement . . . (1–very low efforts, 5–very high efforts); *Industry 4.0*: the current use of the . . . (1–very low, 5–very high); *operational performance (cost and differentiation)*: in the last 3 years the evolution of the . . . (1–unfavored evolution, 5–favored evolution); *business performance*: compared to the main competitor my company is better in . . . (1–strongly disagree, 5–strongly agree)

4. Data analysis and results

The proposed theoretical research model was tested empirically. First, we present the construct and measurement validity. Then we describe the structural model and the evaluation of the relationships.

4.1 The measurement model

In the first step, we use the PLS algorithm to assess the reliability and the validity of the measurement model. We start with the outer model by assessing the following metrics: indicator reliability (assessed by calculating the path loadings between the constructs and their indicators), internal consistency reliability (measured by three indicators, namely Cronbach's alpha, CR and Dijkstra-Henesler's ρA) and convergent reliability (examined by scores of AVE). If the outer model fits all the threshold levels, we can move forward to the inner model. The inner model is assessed based on the discriminant validity between constructs, using the Fornell–Larcker criterion and the heterotrait-monotrait ratio (HTMT).

Table 3 summarizes the outer model assessment. Most indicators' factor loadings are above 0.7, which in overall supports a high indicator reliability. All constructs, beside lean, have a Cronbach's alpha value above 0.6. Cronbach's alpha sometimes underestimates the construct reliability. So, to examine the reliability more precisely, we also consider CR indicator. Regarding CR indicator, all constructs are above the threshold of 0.7. While the latter two measures refer to the sum scores, the Dijkstra-Henseler ρA refers to the construct scores; thus, it is one of the most consistent reliability measures in PLS (Henseler *et al.*, 2016). Dijkstra-Henseler ρA values are above the 0.7 threshold level, except for the lean latent variable. AVE values are well over the 0.5 threshold, which indicates a good convergent reliability. Out of the seven latent variables, six fits every reliability and validity criteria and one fits at least one of them (lean), and therefore, we accept the outer model.

For the inner model, first we assess the discriminant validity of the constructs. By using the Fornell–Larcker criterion, we compared the square roots of the AVE values with the pairwise correlations between the latent constructs (see Table 4). Discriminant validity can be accepted if the square root of the AVE is higher than the pairwise correlations for each construct of the measurement model (Henseler *et al.*, 2016). This criterion of discriminant validity is fulfilled. HTMT ratios are also well below 1, the threshold, where discriminant validity cannot be accepted (Henseler *et al.*, 2016) (see Table 5). Therefore, the latent constructs truly measure different phenomena.

4.2 The structural model

We used the bootstrapping method offered by the SmartPLS software to test the structural model. The predictive capability of the model was assessed by the R-squared values. The explanatory power of our model is from weak to moderate (see Table 6).

The PDCs explain 43.6% of the POCs. Production dynamic and ordinary capabilities respectively explain 24.2% of the I4.0 routines and explain 30.4% of the lean practices. Differentiation is explained in 11.4%, while cost in 12.9%. The PDCs, POS, the two PRs and operational performance explain 13.4% of business performance.

To test the hypotheses, we applied the bootstrapping method. The number of maximum iterations was set to 300, and we generated 5,000 subsamples (Hair *et al.*, 2017). We used the t-values to assess the significance of the relationships between the constructs (Hair *et al.*, 2017). Considering the sample size, the 10% significance level is also worth mentioning. The results are summarized in Table 7. A graphical representation of the full model is shown in Figure 3.

Our first two hypotheses are related to different layers of capabilities. First, we find that at the functional level, PDCs influence POCs (regression coefficient: 0.666, $p = 0.000$), so H1 is supported.

Table 3.
Construct reliability and validity

Latent variables		Manifest variable name	Factor loadings	Cronbach's alpha	Composite reliability (CR)	Dijkstra-Henseler ρA	Average variance extracted (AVE)
Production dynamic capabilities		Creation of new facilities	0.784	0.872	0.912	0.881	0.722
		Introduction of a new service provision/production process	0.880				
		Introduction of new technology	0.861				
		Building the expertise needed for new technology	0.871				
Production ordinary capabilities		Service and production facilities (work environment)	0.770	0.821	0.870	0.829	0.528
		Current technology	0.751				
		Management's capabilities (e.g. production manager, technical manager etc.)	0.658				
		Service and production processes	0.758				
		Technological know-how (engineering knowledge)	0.671				
		Employees' technical abilities and competences	0.742				
Industry 4.0		Digitization of operation	0.686	0.835	0.887	0.880	0.664
		Automation of operational processes	0.827				
		Digitization solutions determine the value of a product	0.919				
		Real-time connection	0.811				
Lean		Continuous improvement	0.835	0.591	0.782	0.584	0.545
		Restructuring	0.671				
		Pull principle	0.634				
Business performance		Market share	0.921	0.833	0.923	0.835	0.857
		Profit as a proportion of sales	0.931				
Operational performance	*Cost*	Cost	1.000	1.000	1.000	1.000	1.000
	Differentiation	Quality	0.822	0.658	0.721	0.809	0.591
		Time	0.842				
		Flexibility	0.634				

Latent variables	Business performance	Cost	Differentiation	Industry 4.0	Lean	Production ordinary capabilities	Production dynamic capabilities
Business performance	*0.926*						
Cost (operational perf.)	0.219	*1.000*					
Differentiation (operational perf.)	0.208	0.369	*0.768*				
Industry 4.0	0.136	0.031	0.046	*0.815*			
Lean	0.085	0.200	0.217	0.427	*0.738*		
Production ordinary capabilities	0.080	0.276	0.372	0.385	0.566	*0.726*	
Production dynamic capabilities	0.301	0.088	0.274	0.430	0.367	0.666	*0.850*

Table 4. Discriminant validity assessment based on the Fornell–Larcker criterion

Latent variables	Business performance	Cost	Differentiation	Industry 4.0	Lean	Production ordinary capabilities	Production dynamic capabilities
Business performance							
Cost (operational perf.)	0.242						
Differentiation (operational perf.)	0.290	0.407					
Industry 4.0	0.162	0.052	0.135				
Lean	0.213	0.276	0.472	0.563			
Production ordinary capabilities	0.172	0.317	0.505	0.412	0.765		
Production dynamic capabilities	0.352	0.130	0.383	0.466	0.465	0.772	

Table 5. Discriminant validity assessment based on HTMT ratio

Latent variables	R^2	Adjusted R^2
Business performance	0.195	0.134
Cost (operational perf.)	0.180	0.129
Differentiation (operational perf.)	0.156	0.114
Industry 4.0	0.269	0.242
Lean	0.320	0.304
Production ordinary capabilities	0.443	0.436

Table 6. Explanatory power of the model (R^2)

Table 7.
Structural model (direct effects) and hypotheses testing

Research question	Hypothesis	Hypothesis code	Direct effects	Regression coefficient	Mean	Standard deviation	T Statistics	*p* Value	Supported (Y); rejected (N)
RQ1: How are the layers of production capabilities interlinked?	*H1*: Production dynamic capabilities directly and positively influence production ordinary capabilities	H1	Production dynamic capabilities → Production ordinary capabilities	0.666	0.666	0.073	9.085	0.000***	Y Supported
	H2: The level of deployment of lean methods influences the level of deployment of Industry 4.0	H2	Lean → Industry 4.0	0.312	0.316	0.113	2.759	0.006***	Y Supported
	H3: Production capabilities positively influence shop floor production routines	H3a	Production dynamic capabilities → lean	−0.018	−0.021	0.147	0.122	0.903	N Partially supported
		H3b	Production dynamic capabilities → Industry 4.0	0.317	0.328	0.110	2.883	0.004***	Y
		H3c	Production ordinary capabilities → lean	0.578	0.577	0.125	4.611	0.000***	Y
		H3d	Production ordinary capabilities → Industry 4.0	−0.003	−0.010	0.167	0.016	0.987	N

(*continued*)

Table 7.

Research question	Hypothesis	Hypothesis code	Direct effects	Regression coefficient	Mean	Standard deviation	T Statistics	p Value	Supported (Y); rejected (N)
RQ2: How do they contribute to different dimensions of firm performance?	*H4*: Operational performance improvement contributes to better business performance	H4	Cost → business performance	0.226	0.232	0.119	1.907	0.057*	Y Partially supported
			Differentiation → business performance	0.130	0.138	0.128	1.017	0.309	N
			Differentiation → cost	0.310	0.316	0.149	2.080	0.038**	Y
	H5: Operational performance improvement is influenced by each layer of capabilities	H5a	Production dynamic capabilities → cost	−0.173	−0.169	0.138	1.260	0.208	N Not supported
			Production dynamic capabilities → differentiation	0.093	0.093	0.205	0.455	0.649	N
		H5b	Production ordinary capabilities → cost	0.249	0.244	0.178	1.399	0.162	N
			Production ordinary capabilities → differentiation	0.335	0.324	0.201	1.669	0.095*	Y
		H5c	Lean → cost	0.070	0.071	0.156	0.451	0.652	N
			Lean → differentiation	0.057	0.066	0.169	0.334	0.738	N
		H5d	Industry 4.0 → cost	−0.034	−0.020	0.122	0.281	0.779	N
			Industry 4.0 → differentiation	−0.147	−0.147	0.145	1.014	0.311	N
	H6: Business performance is influenced only by functional-level capabilities	H6a	Production dynamic capabilities → business performance	0.460	0.458	0.129	3.573	0.000***	Y Partially supported
		H6b	Production ordinary capabilities → business performance	−0.376	−0.377	0.174	2.163	0.031**	N

Note(s): *$p \leq 0.10$; **$p \leq 0.05$; ***$p \leq 0.01$
A hypothesis is supported if all the sub-hypotheses are supported; a hypothesis is partially supported (not supported) if more (less) sub-hypotheses are supported than rejected, or their numbers are equals

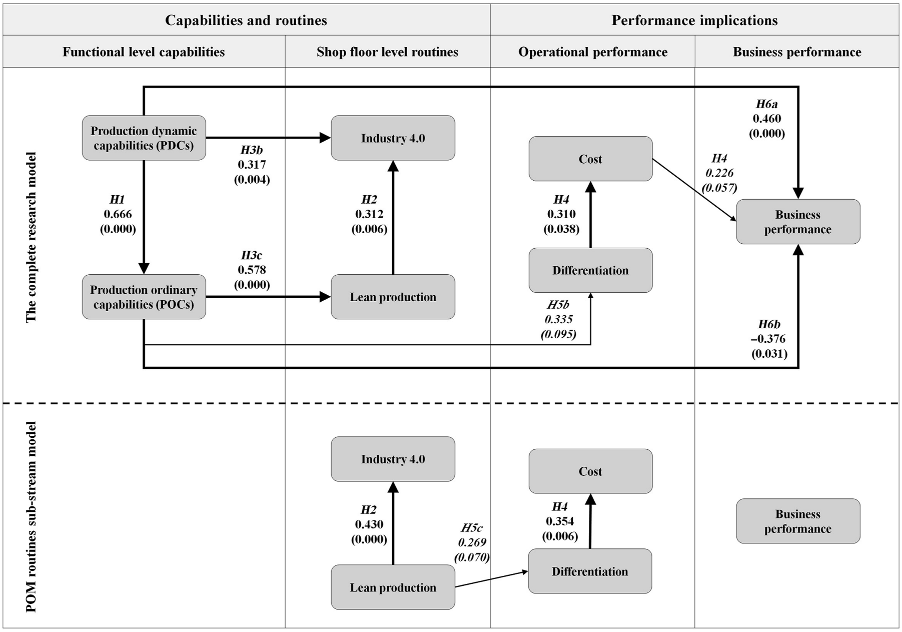

Figure 3.
Graphical representation of the structural model

Note(s): Regression coefficients and significance levels in brackets. Thick black arrows and bold values indicate effects confirmed at 5% significance level. Values in bold italics indicate the effects confirmed at 10% significance level

Second, based on our analysis, lean methods strongly support the use of I4.0 (0.312, $p = 0.006$) at the shop floor level, so H2 is also supported.

Our third hypothesis deals with the interlink between functional level capabilities and shop floor-level execution routines. We find that PDCs do not impact the deployment of lean methods (−0.021, $p = 0.903$), so H3a is not supported. Meanwhile, PDCs positively influence the use of I4.0 technologies (0.317, $p = 0.004$), so H3b is supported. Regarding the interdependencies among current resource configurations, POCs have a positive effect on the implementation of lean practices (0.578, $p = 0.000$), so H3c is supported. POCs have no influence on I4.0 (−0.003, $p = 0.987$), so H3d is not supported. To summarize, these results reveal significant links between the capability layers. Altogether, H3 is partially supported.

Next, we test the interplay between different dimensions of firm performance. Our results related to H4 reflect an accumulation-type relationship. At operational level, the differentiation is linked to cost performance (0.310, $p = 0.038$). Considering the interdependencies between the operational and business dimensions, our results underline that cost performance has a positive impact on business performance (0.226 $p = 0.057$), so H4 is partially supported. Altogether, our results support a specific manifestation of the textbook-wise impact of operational performance on business performance: differentiation → cost → business performance.

Finally, the sources of firm performance improvements are examined.

The operational implications of capabilities reveal interesting patterns (H5). All but one sub-hypotheses could be supported. POCs have a positive effect on differentiation (0.335, $p = 0.095$), so H5b is partially supported. Interestingly, the effects of the PRs on operational performance are not significant. Based on the results, we cannot support H5 that states that layers of capabilities have a positive influence on operational performance improvements.

Regarding business performance (H6), we claim that PDCs have a positive impact on business performance (0.460, p = 0.000), so H6a is supported. POCs also influence the business performance, although negatively (−0.376, p = 0.031), so H6b is not supported. Altogether, H6 is partially supported. As our results show, higher-level capabilities have direct positive (PDCs) and negative (POCs) impacts at the same time, while PRs have no impact at all.

We have applied control variables, such as size (discrete categories based on the number of employees) and technology intensity (categories based on the NACE 2 sections), but their effect was not significant.

We have analyzed a partial, POM routine sub-stream model (at the bottom of Figure 3) to learn more about the roles of PRs. So, we analyzed only the effects of the PRs on the two dimensions of firm performance. Our results of the POM routine sub-stream model showed that lean has a significant ($p < 0.10$) effect on the differentiation construct. However, no direct or indirect links to business performance measure could be revealed.

As we compare this routine-focused model with the full model (see Figure 3), we can see that the significant effect of lean methods on I4.0 remains; however, it becomes weaker. More importantly, we also realize that the linkage between lean and differentiation disappears. In the full model, the POCs is the only source of differentiation. Altogether, this comparison suggests that adding a higher-level capability layer could influence the role of lower-level routine layer significantly.

5. Discussion

Based on the shortcomings of SM and POM literature on connecting different layers of capabilities and performance measures, our main contribution is that we proposed a multilayered capability framework. This comprehensive approach enabled us to empirically assess not only the relationship between the capability layers but also their performance implications. This is either a missing step in several papers (Danneels, 2016; Teece, 2014; Swink and Hegarty, 1998), or this step is dominated by considering only a specific dimension of firm performance (business or operational).

In the following, we detail our most important findings that either confirmed previous results or brought some new theoretical insights. Finally, we develop some practical implications.

5.1 Theoretical relevance

5.1.1 How are layers of capabilities interlinked?. We proved that the proposed multilayer structure of capabilities is a viable concept.

Considering the layers, we demonstrated that the firm-level hierarchical link between DCs and OCs (Danneels, 2016) also exists at functional level (H1). PDCs play a crucial role in manufacturing firms (Danneels, 2016; Peng *et al.*, 2008) as they directly support the renewal of general POCs as stated by Chikán *et al.* (2022). Thus, we empirically proved the hypothesis of Swink and Hegarty (1998), namely, PDCs influence the POCs.

At the shop floor level, our results underline path dependency: an available PR (lean) could be the foundation for a newer initiative like I4.0 (H2). In other words, if these two PRs appear in the same company, then a “quasi-hierarchical” link between them means that I4.0-related efforts can utilize lean efforts. These results reinforce previous findings in POM (Demeter *et al.*, 2021; Dombrowski *et al.*, 2017; Kolberg and Zühlke, 2015; Tortorella and Fettermann, 2018).

Our work brings several new insights into the interplays between capabilities and routines (H3). Peng *et al.* (2008), Danneels (2016) and Wu *et al.* (2010) claim that PDCs can stimulate the use of the up-to-date PRs. We demonstrated that this assumption only holds for I4.0. We argue that production capabilities, and not only PDCs, stimulate PRs. For example, lean operations are directly driven by POCs. So, while we still acknowledge the crucial role of DCs in general and PDCs in manufacturing context, our results show that POCs, and probably also OCs, deserve more attention. POCs are critical as they have direct impact (on lean – H3c) and at the same time they also act as a transmitting vehicle of PDCs (on I4.0).

The results could also guide the way of I4.0 development. On the one hand, as path dependency predicts, lean provides a solid foundation for I4.0 (Tortorella and Fettermann, 2018; Kolberg and Zühlke, 2015; Dombrowski *et al.*, 2017). On the other hand, PDCs have a similar impact on I4.0 (H3b). In our opinion, the lean and PDCs ways could reinforce each other: lean is strong in processes and the technological novelty could come through PDCs. So, we argue that both lean and PDCs are necessary but not sufficient facilitators of I4.0 transition.

Finally, we augmented Frank *et al.*'s (2019) reasoning who claim that I4.0 solutions build on each other. We concluded that not only the existence of the core technologies helps the deployment of I4.0, but rather the presence of both PDCs and lean practices.

5.1.2 How do different layers contribute to firm performance?. Our work underlines the textbook-wise relationship between operational performance and business performance (H4). We have revealed that the two constructs, cost and differentiation, of operational performance have different roles in improving firm performance. First, our result fits the classical sand cone model, which claims that cost efficiency can be improved by increasing differentiation (e.g. quality, dependability, flexibility) (Ferdows and De Meyer, 1990). Second, the improved cost construct of operational performance directly influences the business performance (Slack and Brandon-Jones, 2018).

Regarding performance implications, we concluded that capabilities contribute to the improvement of firm performance. The multilayer approach enabled us to map different impacts of layers.

Most importantly, PDCs contribute to improved competitive advantage (H6a). This result emphasizes the strategic role of production. This functional-level evidence completes SM literature that usually considers firm-level DCs' contributions to competitive advantage (Teece *et al.*, 1997). Furthermore, given the blur empirical findings about the link between firm-level DCs and competitive advantage, we believe that our results may justify Pisano's (2017) arguments about capability-level competition at functional level. Finally, by demonstrating this positive impact, we have a valuable contribution to POM literature. This link was overlooked in POM works (Swink and Hegarty, 1998; Peng *et al.*, 2008; Wu *et al.*, 2010) that mainly considered operational indicators.

Our research revealed POCs' controversial role in business performance improvement (H6b). Traditionally, business performance and competitive advantage are related exclusively to DCs (Helfat and Peteraf, 2009; Teece *et al.*, 1997; Pisano, 2017; Winter, 2003), and not to OCs. We concluded that POCs increase differentiation performance, and by this it indirectly contributes to higher business performance as well. However, POCs also has a negative direct impact on business performance. These links altogether attribute a controversial performance improvement mechanism to POCs.

Production capabilities' direct impact on operational performance was proved (Peng *et al.*, 2008; Wu *et al.*, 2010) or assumed to exist (Swink and Hegarty, 1998). Contradicting previous POM findings, we did not find direct link between operational performance and PDCs (H5).

Our analysis underlines a very complex relationship between production capabilities (PDCs and POCs) and firm performance. PDCs' and POCs' necessary coexistence and their complex relationship explain why companies are continuously compelled to renew their operations. Exploitation can support operational-level improvement but does not contribute to sustainable competitive advantage, probably because competitors also improve their production routines.

We presented only one positive performance impact of PRs – but only in the POM sub-stream model (Figure 3). Regarding lean, the results this model underline its positive operational impact (H5b) (Chavez *et al.*, 2013; De Toni and Tonchia, 1996), and highlight that its direct link to business performance is not straightforward at all (Losonci and Demeter, 2013). The current application of I4.0 does not bring any advantages in our sample. In this regard, our findings contradict the positive impact narrative in the literature (Felsberger *et al.*, 2020; López-Gómez *et al.*, 2018). We reached the same conclusion in our SME-dominated sample as Björkdahl did (2020) examining large firms: despite I4.0 efforts, companies still struggle to gain outcomes. Most probably companies tend to apply these technologies only at an experimental level in small scale, so their impact on firm performance is still negligible or expected (Dalenogare *et al.*, 2018).

Adding the production capability layer to PRs, even this picture changes. In the multilayered capability model, the only link between lean and differentiation disappears (H5c). Given the many significant links between production capabilities and firm performance, it means that production capabilities are the real drivers of firm performance improvements. In this regard, our findings are in line with the reviewed production capability-related literature (Danneels, 2016; Wu *et al.*, 2010; Peng *et al.*, 2008). Although as we considered both operational and business performance indicators, we were able to describe a more sophisticated way of performance improvements in manufacturing firms.

Given the crucial importance of production capabilities and the weak impact of PRs, one can also speculate about the implications of our research sample dominated by SMEs. POM's narrow focus on PRs and performance is logical in large firms with dedicated resources and skills for PRs. In SMEs with less dedicated resources for PRs, the general capabilities of renewal and exploitation seem to be more important, which might give less room to PRs in general. However, the contrast between the POM sub-stream model and the multilayered model could also warn that POM narrow focus reflects a "myopic" research setup busy with only specific resources and missing "higher level" drivers.

5.2 Practical relevance

Although creating PDCs is a complex task (Teece, 2014; Spear and Bowen, 1999), manufacturing firms should build them to achieve long-term competitive advantage. PDCs include the ability to create new facilities, apply new service and production processes, introduce new technology and build the expertise needed for new technologies. So, as considering the implementation of new PRs (like I4.0), building PDCs should be the prior task, not copying the competitors' practices or introducing some "hot" practices. Furthermore, if a company starts to improve itself alongside these four components of the renewal scheme, it might see a natural co-movement of lean (processes, skills, layouts) and I4.0 (technologies, skills).

Creating PDCs from a financial point of view is worthwhile too. This is an important message, because it signals to the top management that production capabilities are critical to compete in the market. Furthermore, it was also highlighted that the application of the PRs does not represent a real advantage, even in operational indicators. It stresses production managers to find a balance between anchoring to current exploitation efforts (to improve operational performance) and renewal efforts (to improve business performance).

6. Conclusions and further research

This paper has introduced and tested a multilayer capability framework describing the relationship between production capabilities (PDCs, POCs) and specific PRs (lean and I4.0). Additionally, it revealed their implication on operational and business performance.

Based on our results, both renewal and exploitation efforts are required to improve firm performance. PDCs are in place to adapt the production function to the changing environment, and they also bear the opportunity to improve business performance. Furthermore, POCs have a tricky role. Exploiting current resource stocks has a positive impact on operational performance (and indirectly on business performance). But, in the meantime, we can also witness the potential "anchoring effects" of exploitation efforts: they have negative direct impact on business performance. In our model, PRs have no influence on firm performance. Furthermore, as indicated by path dependency, I4.0 as a new specific PR is facilitated by lean practices.

It is worth mentioning that we also introduced how adding further layers of capabilities (first PRs, then production capabilities) changes the perceived sources of firm performance improvements. This experiment warns that a myopic approach of production (and production capabilities) could lead to misleading interpretations, for example the impact of specific PRs, and recommendations for managers.

The present research has some limitations that enables possible future research. One significant limitation is that only Hungarian manufacturing firms have been analyzed, so our results are valid for the Hungarian manufacturing sector. We believe that transition economies in Central and Eastern Europe would show similar results due to similar context. Nevertheless, repeating the survey in other contexts, like in Western or Eastern countries, would strengthen the validity of our results. A further research direction is to study the potential differences between large and medium-sized firms. Although the population is dominated by mid-sized firms (as far as size is considered and not value added or sales), the theoretical considerations and scale validation efforts in the literature are biased toward large firms (Danneels, 2016). Finally, to achieve a deeper understanding about how the revealed links operate, one could conduct interviews and develop case studies with companies.

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