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Digitization of manufacturing: The role of external search

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Abstract

Purpose: Manufacturers seek to innovate and improve processes using new digital technologies. However, knowledge about these new technologies often resides outside a firm's boundaries. We draw on the concept of absorptive capacity and the literature on open innovation to explore the role of external search in the digitization of manufacturing.

Approach: We developed and distributed a survey to manufacturing firms in Switzerland, to which we received 151 complete responses from senior managers. We used multiple linear regressions to study the relations among the breadth and depth of external search, firms' adoption of digital technologies, and operational performance outcomes.

Findings: External search depth was found to relate positively to higher adoption of computing technologies and shop floor connectivity technologies. No significant correlation was found between external search breadth and firms' adoption of digital technologies. Regarding performance outcomes, there is some evidence that increased adoption of digital technologies relates positively to higher volume flexibility, but not to increased production cost competitiveness.

Practical implications: Manufacturing firms that aim to digitize their processes can benefit from inbound open process innovation, but its utility varies for different clusters of digital technologies. Generally, the findings suggest that firms should build strong ties with a few external knowledge partners rather than surface relations with many.

Originality: This study contributes to the growing literature on the digitization of manufacturing with an analysis of the relation between firms' external search and their adoption of digital technologies. It adds early empirical insights to the literature on open process innovation.

Keywords: Process innovation, Open innovation, Digitization, Absorptive capacity, Industry 4.0

1. Introduction

Digitization has become one of the trendiest topics in manufacturing (Feng and Shanthikumar, 2018; Holmström *et al.*, 2017). It has even been suggested that digital technologies are defining a new industrial revolution (Kagermann, 2015; Schwab, 2017). Digitization presents new opportunities for radical and incremental process innovation (Brynjolfsson and Schrage, 2009; Robertson *et al.*, 2012; Shih, 2018). It promises to deliver both decreased production costs and increased flexibility—two competitive capabilities that have traditionally been seen as trade-offs (Boyer and Lewis, 2002). Due to these potentials, many manufacturers are strategically working to introduce new digital technologies into their factories (Olsen and Tomlin, 2020; World Economic Forum, 2019). One significant challenge is that firms often lack knowledge about these new digital technologies and their potentials and drawbacks. To innovate their processes, they often require technological knowledge that may be absent or exist only at a rudimentary level within the firm. Hence, they must search for it externally. In this paper, we study these mechanisms by investigating the role of external search in the digitization of manufacturing.

To study this topic, we draw on the concept of absorptive capacity (cf. Cohen and Levinthal, 1990; Todorova and Durisin, 2007; Zahra and George, 2002), which explains how and how well firms are able to insource external knowledge and put it to use. This theoretical perspective is foundational for the business practice known as *open innovation*, i.e., the ability to innovate based on knowledge exchange with external parties (Bogers *et al.*, 2017; Chesbrough, 2003). The open innovation literature predicts that firms innovate more successfully when they adopt an open strategy for developing innovations (Reichstein and Salter, 2006; Robertson *et al.*, 2012; Trantopoulos *et al.*, 2017; Vega-Jurado *et al.*, 2009). *Open* refers to the free exchange of knowledge (ideas, solutions, technologies, etc.) with external parties as opposed to no or a very limited exchange of knowledge (i.e., closed innovation) (Chesbrough, 2003; Enkel *et al.*, 2009). When engaging in open innovation, firms actively search for and access knowledge outside their boundaries and convert it into actionable ideas (Laursen and Salter, 2014).

Digitization of manufacturing involves a number of process innovations. Yet, while open innovation has been much discussed in the product innovation literature (Chesbrough, 2003; Enkel *et al.*, 2009; Gassmann *et al.*, 2010; West and Bogers, 2017), it has received scarce attention in the process innovation literature (Trantopoulos *et al.*, 2017; von Krogh *et al.*, 2018). Manufacturers that strategically apply *open process innovation* (von Krogh *et al.*, 2018), innovate their processes by accessing external knowledge sources, for example, customers, suppliers, competitors, technology vendors, research institutions, or firms in other industries. The reasons for engaging in external search are numerous, including a lack of internal capabilities and resources, rapid technological change, and an increasing fragmentation of global value chains (Chesbrough, 2003; Kagermann, 2015; Pisano, 1997; Trantopoulos *et al.*, 2017).

The primary objective of this paper is to reveal the relation between external search activities and the digitization of manufacturing. We investigate whether open process innovation is a valuable concept for manufacturers seeking to implement digital technologies. However, implementing technology for the sake of technological maturity itself does not necessarily increase the competitiveness of the firm (Deuse *et al.*, 2015). Therefore, as a secondary objective we also investigate the relation between the level of adoption of digital technologies and operational performance. The two research questions are:

> **RQ1:** How does manufacturers' external search for knowledge relate to their adoption of digital technologies?
>
> **RQ2:** How does the adoption of digital technologies relate to operational performance?

To research these questions, we develop a survey questionnaire and distribute it to registered members of an industry association for manufacturers in the electrical and mechanical engineering industries in Switzerland.

2. Theoretical background

In this section, we first elaborate on the role of digital technologies for process innovation in manufacturing. One major challenge is the exponential growth and development of new digital technologies, which makes it extremely difficult for manufacturing firms to stay on top of all the new opportunities for innovation (Kagermann, 2015). Hence, manufacturers must learn to effectively access and make use of knowledge that resides outside of its firm boundaries. Helpful perspectives to study this phenomenon are the rich literature on open innovation and the concept of absorptive capacity, which are introduced in this section.

2.1 Role of digital technologies in process innovations

The management of process innovations has a long history in manufacturing research and is seen as one of the most crucial factors for competitiveness (Adner and Levinthal, 2001; Becheikh *et al.*, 2006; Schroeder *et al.*, 1989). The Organisation for Economic Co-operation and Development (2005) defines process innovation as “the implementation of a new or significantly improved production or delivery method” (p. 49). Process innovations are crucial for the success of a firm, especially in the manufacturing sector; not only do process innovations lead to performance improvements, but they are also needed to manufacture new products (Frishammar *et al.*, 2012). Considering the advent of a fourth industrial revolution (also referred to as Industry 4.0) (Kagermann, 2015; Schwab, 2017), process innovations based on new digital technologies are expected to transform manufacturing.

Process innovation often requires implementing new information and communication technologies (Trantopoulos *et al.*, 2017). One particularly important type of process innovation in manufacturing involves the use of advanced manufacturing technologies (Khazanchi *et al.*, 2007). Today, digitization is integrated in all such advanced manufacturing technologies (Chui *et al.*, 2018). Several studies have indicated that digitization can have a significant impact on the competitiveness of manufacturing firms (Bauernhansl, 2014; Brynjolfsson and McAfee, 2016; Kang *et al.*, 2016; Sendler, 2018). Digital technologies come in many forms, including computing, communication, connectivity, and information processing capabilities (Bharadwaj *et al.*, 2013). Numerous attempts have been made to summarize and cluster new digital technologies (for example, the major consultancy firms have published white paper reports with varying degrees of content overlap), but there is no general agreement on which technologies to include or exclude within the frame of the digitization of manufacturing (Tortorella *et al.*, 2019).

Consider the following 12 digital technologies ranging from the factory floor to supply chains. On the factory floor, advanced *robotics*, *additive manufacturing*, and *machine-to-machine (M2M) communication* transform how products are made and processes are organized, largely enabled by the digital components of these hardware-related technologies (Frank *et al.*, 2019). Furthermore, the factory worker can be supported by technologies such as *mobile devices*, *augmented reality*, and *drones* (Kagermann *et al.*, 2013). *Identification solutions*—such as barcodes, sensors, radio-frequency identification (RFID), or near field communication (NFC)—allow for contactless tracking of products and processes in production (Xu *et al.*, 2018). Taken together, these data comprise *big data*, which can be mined and analyzed with conventional statistics or *machine learning* algorithms (Brinch, 2018; Kache and Seuring, 2017; Matthias *et al.*, 2017; Monostori *et al.*, 2016). The data can be used to create *digital twins* of products, processes, and assets, which allow for cheaper experimentation and problem solving (Kagermann, 2015). Sending the data to Internet-enabled *cloud computing* can be used for remote analytics and new product–service offerings (Ahmad and Schroeder, 2002; Hartmann *et al.*, 2016; Vanpoucke *et al.*, 2017). Finally, *blockchain technologies* can help manage data flow between firms in the supply chain. These 12 digital technologies were included at the outset of this study.

2.2 Open innovation and open process innovation

Due to the variety of digital technologies and their embedded complexities, it is difficult—if not impossible—for firms to possess knowledge about all opportunities enabled by digital technologies (World Economic Forum, 2018). The literature on open innovation suggests that firms can access knowledge outside their boundaries and thereby innovate processes by following an open strategy (Reichstein and Salter, 2006; Robertson *et al.*, 2012; Trantopoulos *et al.*, 2017). The term open innovation was coined by Chesbrough (2003). While the concept has been criticized for not being original (Dekkers *et al.*, 2019; Trott and Hartmann, 2009), others have argued that it represents a "new paradigm to manage innovation" (Chesbrough and Bogers, 2014, p. 18). Since its first mention in the literature, open innovation has attracted much research (Bogers *et al.*, 2017), mostly related to product innovation activities, with less focus on process innovation (Crossan and Apaydin, 2010; Trantopoulos *et al.*, 2017).

Recently, von Krogh *et al.* (2018) argued that open innovation also applies to process innovations, and introduced the term *open process innovation*. There is some evidence that those firms that are more open in seeking external knowledge sources tend to be more innovative in their processes than closed firms (Reichstein and Salter, 2006; Terjesen and Patel, 2017; von Krogh *et al.*, 2018). In the operations management literature, for instance, Wagner and Bode (2014) found that an open relationship between a supplier and a buyer can have positive effects on the buyer's process innovation activities.

2.3 Absorptive capacity

To learn about new technologies, a firm must access external knowledge sources (Cohen and Levinthal, 1990). The firm's task is to acquire this knowledge, assimilate it, then transform the new technologies within the current knowledge base and exploit the technologies to improve their processes (Trantopoulos *et al.*, 2017; Zahra and George, 2002). This process can be explained by the concept of *absorptive capacity* (Cohen and Levinthal, 1990). Whereas the first two tasks of acquiring and assimilating knowledge refer to *potential* absorptive capacity, the latter two tasks of transformation and exploitation refer to the *realized* absorptive capacity (Zahra and George, 2002). A central task for manufacturers seeking more process innovation is to increase the capacity to absorb knowledge from within or outside of the firms' boundaries.

One way to increase a firm's absorptive capacity is to invest in internal research and development (Robertson *et al.*, 2012). Even though this internal perspective for creating absorptive capacity was prevalent in the work of Cohen and Levinthal (1990), the theory has evolved into a more dynamic perspective through the work of Zahra and George (2002), among others. Lichtenthaler and Lichtenthaler (2009), for example, built on absorptive capacity to provide an capability-based framework for open innovation. They differentiated the location of knowledge—either internal or external—and the subsequent tasks in the innovation process of knowledge exploration (i.e., searching for knowledge about new digital technologies), retention (i.e., absorbing knowledge about technologies), and exploitation (i.e., implementing new digital technologies). Possessing absorptive capacity is a necessary enabler for retention and exploitation (Robertson *et al.*, 2012). Thus, a modern understanding of absorptive capacity also refers to the exploration of external knowledge (i.e., located outside the firms' boundaries).

In view of the concept of absorptive capacity, the literature on open innovation can explain the knowledge flow across firms' boundaries. Open innovation activities can be differentiated into in-flow (outside-in) and out-flow (inside-out) knowledge transfer (Enkel *et al.*, 2009). To allow for an in-flow of knowledge, a firm must first search external sources of knowledge from which to absorb knowledge. Laursen and Salter (2006) differentiated the search process into two dimensions: the search breadth and the search depth. Following the literature on open innovation (Bogers *et al.*, 2017; Chesbrough, 2003; Enkel *et al.*, 2009; von Krogh *et al.*, 2018), both external search breadth and depth are important concepts when predicting process innovation performance of a manufacturing firm.

3. Hypothesis development

Armed with the insights from the theoretical background concerning digitization of manufacturing, open innovation, and absorptive capacity, we can now develop our hypotheses. Figure 1 summarizes the research model. We first develop the hypotheses related to the role of external search (breadth and depth) in the adoption of digital technologies in manufacturing (Hypotheses 1 and 2 in Figure 1). Subsequently, we develop hypotheses related to the effect of search on different types of technologies (Hypotheses 3a and 3b) and the technology adoption and performance outcomes (Hypotheses 4 and 5).

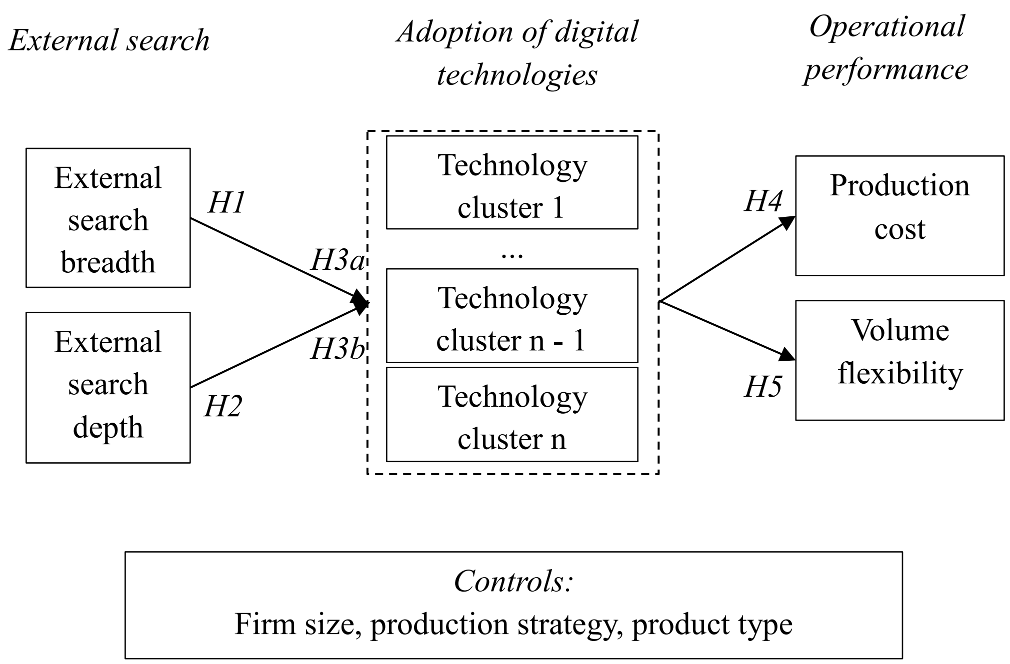

Figure 1. Research model.

3.1 External search breadth and adoption of digital technologies

The search breadth describes the amount and variety of external sources that a firm searches in their innovation processes (Laursen and Salter, 2006). Search breadth allows firms to draw ideas from a wide range of different knowledge sources.

To illustrate, consider BMW, an automotive company famous for its innovation capabilities. To drive process innovation at scale, BMW searches broadly for external knowledge. For example, when innovating their internet-of-things platform (referred to as the open manufacturing platform), BMW relied on knowledge from external firms such as Microsoft (Majchrzak *et al.*, 2019). Note also that the main objective of this platform is to enable process innovation by sourcing knowledge from many external partners. At the same time, BMW cooperated with another information technology company, NVidia, to innovate automated guided vehicles for their production plants, increasing the speed and flexibility of material handling. Furthermore, BMW regularly organizes large-scale open hackathons to engage students and independent teams all over the world to solve business problems. These three examples illustrate how BMW searches broadly outside their own firm's boundaries to insource process innovation ideas

Arguably, a broad external search is especially important when it comes to the digitization of manufacturing. Developing process innovations based on digital technologies, such as those illustrated in the BMW example, requires knowledge of fields that a traditional manufacturer does not possess (e.g., specialized software development) (Vega-Jurado *et al.*, 2009)—not even in advanced firms such as BMW. However, a broad external search involve a great deal of uncertainty, as it is not clear a priori which sources will provide successful innovations. It is therefore important to engage with various sources to increase the likelihood of successful innovation (Piening and Salge, 2015). This ex ante uncertainty can result in failed projects that may lead firms to refrain from accessing external sources in the future (Levinthal and March, 1993).

In the literature on product innovation, there is some evidence that the relationship between external search breadth and product innovation performance follows an inverted U-shape (e.g., Laursen and Salter, 2006). However, process innovations are essentially different from product innovations (Terjesen and Patel, 2017). Hence, the effect of search breadth on process innovation is not settled. In view of the concept of absorptive capacity, the breadth of sources searched should correlate with the number of innovations adopted. Zahra and George (2002), for example, argued that the greater a firm's exposure to a wide diversity of external sources, the more potential absorptive capacity it will develop. In support of this, Leiponen and Helfat (2010) found a positive linear relationship between a firm's search breadth and adoption of process and product innovations. Following this line of reasoning, we hypothesize the following:

Hypothesis 1: Breadth in external search relates positively to the adoption of digital technologies.

3.2 External search depth and adoption of digital technologies

The search depth describes the intensity with which sources are searched. In contrast to search breadth, search depth investigates the deep interrelations between the searching firm and the external sources (Laursen and Salter, 2006). Evaluating these interrelations provides an opportunity to understand how strongly the firm uses these sources when innovating its processes. Search depth leads not only to stronger connections but also leverages the own learning and thereby knowledge of the firm (Terjesen and Patel, 2017).

When engaging deeply with a source, a firm increases its absorptive capacity because it learns how to leverage knowledge to solve specific problems (Zahra and George, 2002). The effect of external search depth on innovation performance has also been addressed in the prior literature (Laursen and Salter, 2006). In contrast to the literature on product innovation, there is some evidence that the effect is linear for process innovation (not an inverted U-shape): deeper interactions with external sources improve the process innovation performance (cf. Terjesen and Patel, 2017). Considering this and the concept of absorptive capacity, we hypothesize:

> **Hypothesis 2:** Depth in an external search relates positively to the adoption of digital technologies.

3.3 External search and clusters of digital technologies

The hypothesized relationship between external search and the adoption of digital technologies is likely to depend on the technology that the firm seeks to implement. Again, absorptive capacity offers an explanation. A firm holds various levels of existing internal knowledge (Cohen and Levinthal, 1990) and different technologies require different types of knowledge. Hence, it is to be expected that different digital technologies are affected differently by external search depth and breadth.

The internal knowledge base is expectedly larger for technologies closely related to the core competency of the firm than for those that are new to the firm. It is expected that firms do not need to search broadly for knowledge in areas in which they have built in-house expertise. However, for new technologies that are less familiar to the firm—for example, computing technologies such as big data analytics (cf. Kagermann, 2015; Wee *et al.*, 2015)—the required knowledge for process innovation is often not available internally, which motivates manufacturers to seek broadly externally. This leads to the next hypothesis:

Hypothesis 3a: External search breadth relates less [more] to the adoption of digital technologies that are more [less] familiar to the firm.

This situation changes for search depth. To illustrate, many manufacturers have used automation technologies for a long period of time. Hence, due to their relatively high internal knowledge about these technologies, they can be more selective when seeking the necessary external knowledge, and they need to investigate deeper to gain new knowledge. According to the concept of absorptive capacity, the firms' external search will be more effective for these old technologies because the firm possesses more capacity to absorb them. At the surface, this may seem counterintuitive since firms are less likely to search externally for knowledge they possess internally, but when they search, they will search deeply. Thus, the next hypothesis states:

Hypothesis 3b: External search depth relates more [less] to the adoption of digital technologies that are more [less] familiar to the firm.

3.4 Adoption of digital technologies and operational performance

Manufacturers implement digital technologies to increase competitiveness through process innovation. Continuous developments in these technologies enable manufacturers to reduce the cost per parts produced by improving either the quality or the productivity of the processes (cf. Kache and Seuring, 2017; Kusiak, 2017; Shih, 2018; Wee *et al.*, 2015). Besides cost reduction, digital technologies assist manufacturers in increasing their flexibility. Being able to meet more dynamic market demands by flexibly shifting between manufacturing of different products and their volumes has been foreseen to be a more important competitive differentiator in the coming years (Deuse *et al.*, 2015; Kagermann, 2015). Digital technologies can enable manufacturers to produce customized lower-volumes products at competitive costs compared to mass production. In this regard, we formulate two hypotheses:

Hypothesis 4: Adoption of digital technologies relates positively to a higher production cost competitiveness.

Hypothesis 5: Adoption of digital technologies relates positively to higher volume flexibility.

4 Methodology

To test these hypotheses, we collected original data through a survey research design. Surveys are appropriate when the theory for the examined phenomenon is mature (Forza, 2002; Malhotra and Grover, 1998). Both of the examined concepts, open innovation, and digitization, have received considerable attention in the literature (cf. Bogers *et al.*, 2017; Kagermann, 2015). However, their interaction has been less studied (Trantopoulos *et al.*, 2017).

4.1 Data collection and sampling

For the empirical analysis, we developed a survey and administered it among manufacturers in Switzerland (the survey is included in Appendix B). The questionnaire was based on an initial literature review as well as input from industry experts. Peer researchers and senior academics reviewed the draft and further tested it with a purposive sample of manufacturing firms. We used the subsequent feedback to develop the questionnaire in several rounds iteratively.

For sample selection and distribution, we cooperated with Swissmem, an association of Swiss manufacturers in the machining, electronics, and metal industries. Swissmem agreed to distribute the survey to all its members with at least one manufacturing location in Switzerland (N = 1000). Hence, the risk of selection bias stemming from a non-random sample selection was mitigated. The survey was distributed between November 2017 and February 2018 via email. Reminders were sent after four weeks. As an incentive for participation, all responding firms were provided with a customized report to benchmark their current status compared to the industry average.

After three rounds of reminders, 184 responses were received (response rate of 18.4%). The responses were checked for logical errors, and those that had missing values for information on their external search were cleaned. After data cleaning and row-wise exclusion of responses that were not filled out completely, 151 responses were included in the final sample. Three out of four respondents (75.5%) were firm leaders (chief executive officers or managing directors), which indicates that the respondents possessed a good understanding of all the survey questions. The remaining respondents held senior management positions in their divisions. Following the classification of the European Union, 13% of the firms were large (more than 250 employees worldwide), and 87% were small or medium sized (250 employees or less) (European Union, 2012). Almost half of the firms (49%) were privately owned. Table 1 shows the composition of the different industries within the sample. The main responses came from the machinery sector. This was expected, as this sector was the biggest group in the association.

Table 1. Industry composition of the sample

Manufacturing Industry	Frequency	%
Machinery	52	34.44
Basic metals	29	19.21
Electronics	16	10.60
Electrical equipment	11	7.28
Textiles/apparel	7	4.64
Automotive	5	3.31
Other	31	20.53
Total	**151**	**100.00**

4.2 Variable definitions

Table 2 summarizes the variable definitions used in the survey. The details of each operationalization are provided in the following subsections.

Table 2. Variable definitions

Variable	Operational Definition	Scale
Search breadth	Number of external knowledge sources searched; counts all sources that have been used at least rarely (2–7 on a 7-point Likert scale)	0–3
Search depth	Number of external knowledge sources used extensively; counts all sources that have been used at least often (5–7 on a 7-point Likert scale)	0–3
Digital maturity	Mean value of the adoption level of the different digital technologies	1–6
Production cost	The cost of production relative to competitors	1–7
Volume flexibility	The flexibility to produce different volumes of products in manufacturing	1–7
Size	Small firms: less than or equal to 250 employees Large firms: more than 250 employees	1 = small 0 = large
Production strategy	Main production strategy used by the firm	MTS, ATO, MTO, ETO
Market type	The market the firm serves	B2B, B2C, B2P

MTS = Make-to-stock; ATO = Assemble-to-order; MTO = Make-to-order; ETO = Engineer-to order

4.2.1 External search

In line with previous research (cf. Garriga *et al.*, 2013; Laursen and Salter, 2006; Trantopoulos *et al.*, 2017), we operationalized openness in process innovation by the variables *Search Breadth* and *Search Depth*. The survey asked the respondents to provide the degree to which the firm collaborated with external sources to develop process innovations. This was measured for each of the external sources: research institutes, consultancies, and other firms (cf. Laursen and Salter, 2006; Reichstein and Salter, 2006; Trantopoulos *et al.*, 2017; Un and Asakawa, 2015). The degree was measured on a 7-point Likert scale (1 = never, 2 = very rarely, 3 = rarely, 4 = sometimes, 5 = often, 6 = very often, and 7 = extensively).

The first variable, *Search Breadth*, describes the firm's efforts to acquire external knowledge for process innovations from different external sources. Therefore, all sources that the firm accessed to a degree of 3 (rarely) or higher were considered. Hence, this variable summarizes the number of sources that were accessed broadly.

The second variable, *Search Depth*, describes the number of sources extensively searched by the firm. This variable was constructed by summarizing the sources that the firm used to a degree of 5 (often) or higher. Differentiating external search breadth and depth by the degree of usage by the firm is in line with other literature on external search (for a similar approach, see Laursen and Salter, 2006; Terjesen and Patel, 2017; Trantopoulos *et al.*, 2017).

Both independent variables were calculated in the range from 0 (none) to 3 (high). The Cronbach's alpha of the external knowledge sources that were combined for the two independent variables was 0.60, which is acceptable.

4.2.2 Digital maturity

Many authors have measured the adoption of digital technologies by comparing the stage of implementation in a firm (cf. Tortorella and Fettermann, 2018). This stage of implementation can be referred to as the maturity of that firm regarding a certain technology (Frank *et al.*, 2019; Schumacher *et al.*, 2016). Maturity models typically describe a limited number of development stages toward a target state and use anchored Likert scales (Netland and Alfnes, 2011). They are useful for assessing the current maturity level of a firm related to a specific set of practices as well as for setting target states (Becker *et al.*, 2009).

To identify relevant technologies, we thoroughly reviewed the academic and practitioner literature. Individual technologies that were mentioned at least twice by two different outlets were added to a long list of digital technologies. Further, we combined technologies that have different names but belong to the same technology class (e.g., unmanned aerial vehicles [UAVs] and drones). After the literature review, the preselected technologies were reviewed by two senior academics in the field and discussed with a panel of 28 experts from manufacturing firms and consultancies. The industry experts had different educational backgrounds and job titles and were dedicated to different hierarchical levels (e.g., chief operating officer, plant manager, project manager, and research and development manager). We used the feedback to narrow down the list to 12 digital technologies: additive manufacturing, augmented reality, big data analytics, blockchain, cloud computing, drones, identification solutions (RFID, NFC, etc.), machine learning, M2M communication, mobile devices on the shop floor level (e.g., tablets and smartphones), robotics, and digital twin (Kang *et al.*, 2016; Mittal *et al.*, 2017; World Economic Forum, 2017). The overall construct had a Cronbach's alpha of 0.75.

To develop the scale for *Digital Maturity*, we drew on the literature and practice of maturity models for digitization and, more generally, Industry 4.0 (Schuh *et al.*, 2017; Schumacher *et al.*, 2016; Tortorella and Fettermann, 2018) We used a 6-point Likert scale (1 = irrelevant, 2 = under surveillance, 3 = research and development, 4 = prototype implemented, 5 = first applications, and 6 = fully implemented). In accordance with other maturity models, the construct of *Digital Maturity* was calculated by the methods used to adopt the different digital technologies.

4.2.3 Identifying technology clusters

Factor analysis helps to identify underlying dimensions within a larger number of variables. We followed the common method for identifying when the eigenvalue is less than 1 (Tabachnick and Fidell, 2013). The factors were extracted using the principal axis and varimax rotation method. The method returned three distinct factors with an eigenvalue above 1. Considering that Pedhazur and Pedhazur Schmelkin (1991) suggested at least 50 observations per factor, the three factors were a good fit for the sample size. We employed the common cutoff value of 0.5 (Tabachnick and Fidell, 2013). After the first extraction, five items that did not meet the threshold value (mobile devices, digital twin, machine learning, additive manufacturing, and drones) were removed (results are illustrated in Appendix A). The result was three distinct factors covering seven digital technologies, as shown in Table 3.

Table 3. Factor analysis of technology clusters

Technology	Factor Loadings		
	Cluster 1	Cluster 2	Cluster 3
	Computing	Shop floor connectivity	Operator enhancement
Big data	0.73		
Blockchain	0.58		
Cloud computing	0.57		
Robotics		0.78	
M2M communication		0.59	
Identification technologies		0.51	
Augmented reality			0.72
Cronbach's alpha	0.62	0.67	-

The first technology cluster shown in Table 3 covers the digital technologies big data, blockchain, and cloud computing (Cronbach's alpha = 0.62). These technologies relate to non-physical computing technologies, and hence this cluster was labelled "computing." The second technology cluster covers robotics, M2M communication, and identification technologies (Cronbach's alpha = 0.67). These technologies relate to shop floor manufacturing processes and hence were labelled "shop floor connectivity." The last cluster consists only of augmented reality since drones were dropped due to a sub-threshold loading. The third cluster was labelled "operator enhancement." Considering the Cronbach's alpha values in the last row, the reliability of the clusters was acceptable. For the following analysis, only the technologies listed in Table 3 were considered. The overall Cronbach's alpha for all seven technology items was 0.68.

4.2.4 Operational performance

Production Cost and *Volume Flexibility* were defined as the outcome variables in Hypotheses 4 and 5. For both items, a single measure was used in the survey. Using a single measure in contrast to a multi-item scale helped reduce the length of the survey instrument. According to Forza (2002, p. 159), "when objective constructs are considered, a single direct question would be appropriate." Both production cost and volume flexibility are objective measures. For the production cost measure, the respondents were asked to evaluate the production cost relative to their main competitors. Similarly, a question in the survey was used to measure the volume flexibility relative to the respondent firm's main competitors. Both variables ranged from 1 (much worse) to 7 (much better).

4.2.5 Control variables

We expected that the size of the firm would affect the degree and effectiveness of openness. Large firms have the budgets to develop digitization resources in-house, which may make them less dependent on external knowledge compared to small firms. The size of the firm is also likely to impact the dependent variables. Larger firms can create economies of scale that lower production costs but have also shown a tendency to grow organizational inertia that reduces flexibility. To control for firm size, we differentiate between large firms and small and medium-sized enterprises (SMEs). *SME* was introduced as a binary variable, which took the value of 1 if the firm was small or medium sized (i.e., less than 250 employees) and 0 otherwise.

Another factor that might influence openness and the level of adoption of digital technologies, production costs, and volume flexibility is the firm's production strategy. Olhager and Selldin (2004) differentiated four different production strategies: make-to-stock (MTS), make-to-order (MTO), assemble-to-order (ATO), and engineer-to-order (ETO) strategies. MTS firms satisfy customer demand with products from stock, while ATO firms assemble pre-manufactured parts upon customer request. In contrast, MTO firms only procure and manufacture products upon incoming orders. This policy leads to low inventory cost and high flexibility, but also to longer delivery times (Kalantari *et al.*, 2011). Finally, ETO firms produce products individually for customers, from design to shipment. ETO and ATO can be seen as sub-categories of MTO (Olhager and Selldin, 2004). In this study, *Production Strategy* was a categorical variable that could assume the characteristics of MTS, ATO, MTO, or ETO.

Finally, the type of market the firm serves was regarded as a potential confounding variable that could jointly affect the independent and dependent variables in the model. The categorical *Market Type* variable distinguished between consumer goods (business to consumer [B2C]), industrial goods (business to business [B2B]), and public goods (business to public [B2P]).

4.3 Descriptive statistics

Table 4 shows the descriptive statistics for the data. The average digital maturity of the firms in the sample was 2.58, with the most advanced firm ranking at 5.33. On average, the sampled firm accessed knowledge from 2.26 sources. However, the average number of extensive uses of a source was 0.58. Notably, each of the variables had a sound distribution.

Table 4. Descriptive statistics

Variable	n	Mean	Std. Dev	min	max
Digital maturity	151	2.58	0.95	1	5.33
Search depth	151	0.58	0.77	0	3.00
Search breadth	151	2.26	0.98	0	3.00
Production cost	120	4.28	1.26	1	7.00
Volume flexibility	120	4.72	1.01	1	7.00
Size	151	0.87	0.34	0	1.00
Order processing	150	3.09	0.95	1	4.00
Market type	151	1.95	0.29	1	3.00

Table 5 shows the correlation matrix for the regarded values. The correlations were calculated with the Pearson method using complete observations only.

Table 5. Correlation matrix

	1	2	3	4	5	6	7	8
1 Digital maturity	1.00							
2 Search depth	0.23**	1.00						
3 Search breadth	0.17*	0.35**	1.00					
4 Production cost	0.12	0.00	0.09	1.00				
5 Volume flexibility	0.21*	0.14*	0.09	0.26**	1.00			
6 Size	-0.23*	0.13	-0.19**	-0.14	0.05	1.00		
7 Production strategy	-0.21*	0.11	-0.02	0.00	-0.05	0.17	1.00	
8 Market type	-0.05	-0.04	-0.01	-0.09	0.02	0.1	0.22**	1.00

**p < 0.01; *p < 0.1

5. Results

The data analysis followed two steps. In the first step, we examined the correlations between the adoption of digital technologies (digital maturity) and search breadth and depth using linear regressions. In the second step, we used linear regressions to analyze the effect of digital maturity on two operational performance variables: volume flexibility and production cost.

5.1 Relation between external search and the adoption of digital technologies

Table 6 shows the results from the regression of the two independent variables, search breadth and search depth, on digital maturity. In the first model, we only included the main variables. In the second model, we added the control variables to the regression model. In the third model, the effects of the different clusters were investigated. For each of the clusters in Model 3, the full model was regressed on the average digital maturity of the clusters.

Table 6. The relation between external search and digital maturity

Variables	Model 1	Model 2	Model 3		
	Digital Maturity	Digital Maturity		Digital Maturity	
	All	All	Cluster 1	Cluster 2	Cluster 3
Constant	2.17***	2.86***	2.76***	2.76***	1.65***
Search breadth	0.11	0.05	0.13	0.10	0.13
Search depth	0.26*	0.35**	0.28*	0.50**	0.04
SME		-0.54*	-0.24	-0.64	-0.31
Market type					
Cons. goods (def.)					
Industrial goods		-0.01	-0.36	0.09	0.02
Public goods		0.25	-0.60	0.18	-0.34
Production strategy					
MTS (def.)					
ATO		0.32	-0.32	0.83	0.05
MTO		-0.08	-0.74*	0.54	0.07
ETO		-0.32	-0.70*	0.02	0.27
R^2	0.07	0.16	0.17	0.17	0.04

***p < 0.001; **p < 0.01; *p < 0.05

The first model showed a significant positive relation between search depth and digital maturity and a positive but not significant relation between search breadth and digital maturity. This model explained 7% of the variance (R^2). The second model added the controls for size, market type, and production strategy, which significantly improved the model performance (R^2 increased to 16%). In this model, search depth remained significant, and search breadth remained nonsignificant. For search depth, a one-unit increase was related to an increase of 0.35 for digital maturity. For Model 2, no significant relation was found for the control variables, with the exception of a weak significance for firm size (as expected, SMEs tended to have a lower digital maturity than large firms).

5.2 Relation between external search and technology clusters

The remaining columns, which depict Model 3, demonstrate the result for the same variables but split between the three identified technology clusters. In this model, search depth was significantly correlated with the level of implementation of computing technologies (Cluster 1) and the shop floor connectivity technologies (Cluster 2). An increase of one unit in search depth increased the digital maturity by 0.28 for the first cluster and 0.50 for the second cluster. No significant relationship was found between search breadth and digital maturity in these two clusters. For Clusters 1 and 2, the model explained 17% of the variance, which indicates an acceptable performance. For Cluster 3, neither search breadth nor search depth showed a significant relation with digital maturity. The low R^2 of 4% indicates that this model did not perform well (recall that there was only one technology in this cluster).

To test whether Cluster 1 and 2 are significantly different from each other, we performed several sub-sample tests. A challenge when splitting a limited sample size into smaller sub-samples is the loss of statistical power. For example, following the method proposed by Clogg *et al.* (1995), we calculated the z-value to test the difference. As expected, due to the small sample size, the result was not statistically significant (p-value = 0.11). Hence, although the effect for Cluster 2 was more pronounced than for Cluster 1, we cannot rule out that this occurred by chance.

Regarding control variables, it appears that firms relying on an order-driven production strategy (MTO and ETO) reported lower levels of computing technologies than firms relying on a forecast-driven model (MTS). All other controls were nonsignificant.

5.3 Relation between the adoption of digital technologies and operational performance

Table 7 reports the results of the regressions for the adoption of digital technologies on the two operational performance measures: production cost (Model 4) and volume flexibility (Model 5).

Table 7. Regression on operational performance and digital maturity

Variables	Model 4 Production Cost	Model 5 Volume Flexibility
Constant	4.58***	3.64***
Digital maturity	0.16	0.27**
SME	-0.26	0.35
Market type		
Cons. goods (def.)		
Industrial goods	0.12	0.49
Public goods	-0.64	-0.29
Production strategy		
MTS (def.)		
ATO	-1.31*	-0.64
MTO	-0.39	-0.30
ETO	-0.59	-0.38
R^2	0.11	0.09

As can be seen in Table 7, we find a positive but nonsignificant relation between digital maturity and lower production costs. However, a positive and significant relationship was found between digital maturity and volume flexibility. Higher digital maturity was positively correlated with higher volume flexibility. The model explains 9% of the variance. No significance was found for any of the control variables except for the ATO production strategy in Model 4.

6. Discussion

This study examines the role of external search for process innovations related to the digitization of manufacturing. In this section, we discuss the implications of the findings for research and industrial practice.

6.1 Contributions to the literature

This paper makes three distinct contributions to the emerging literature on open process innovation (e.g., Terjesen and Patel, 2017; Trantopoulos *et al.*, 2017; von Krogh *et al.*, 2018):

1. Adding empirical evidence of the relations between external search depth and process innovation,
2. Providing a nuanced view on how external search relates to the adoption levels of different clusters of digital technologies, and
3. Adding empirical evidence to the relations between digitization of manufacturing and operational performance.

6.1.1 Relations between external search and process innovation

We find that a *deeper* external search related to a higher adoption of most digital technologies, and the effect was more pronounced for shop floor connectivity technologies than for computing technologies. This was evidenced by the statistically significant acceptance of Hypothesis 2. Because the results were not significant for external search breadth (Hypothesis 1), we cannot conclude if a broader external search is beneficial for process innovation. A potential explanation for the nonsignificant results for search breadth may be that it follows a nonlinear relationship that the models did not pick up. For example, Laursen and Salter (2006) found an inverted U-shaped relationship between external search breadth and product innovation. Overall, it seems that external search depth is more important for the digitization of manufacturing than external search breadth.

Terjesen and Patel (2017) found that external search depth followed a linear relationship with process innovation. The positive effect of search depth on process innovation has also been noted in other previous studies (Trantopoulos *et al.*, 2017). However, our research design differs from previous studies and can, therefore, add important nuance to the literature. Most importantly, we use an arguably better measurement of digital maturity (our process innovation measure). Earlier studies have mainly examined the relationship between search depth and process innovations directly (cf. Reichstein and Salter, 2006; Vega-Jurado *et al.*, 2009). Many of the existing studies measured process innovation simplistically, usually by a binary dummy variable that captures whether a firm has introduced a process innovation in the previous years (cf. Leiponen and Helfat, 2010; Reichstein and Salter, 2006; Terjesen and Patel, 2017; Vega-

Jurado *et al.*, 2009). Alternatively, process innovation has been measured by cost reduction connected to the process innovation (cf. Trantopoulos *et al.*, 2017). This study provides a more nuanced measure of process innovation that captures the extent to which the innovation has been scaled in the firm—in this case, the level of adoption of digital technologies.

The process innovations studied in this paper involved knowledge-intensive digital technologies. Arguments of the absorptive capability perspective can perhaps explain the nonsignificant results of search breadth: having many diverse sources makes it difficult to absorb knowledge (Cohen and Levinthal, 1990; Terjesen and Patel, 2017). By not engaging deeply with external knowledge partners—which is difficult to do when there are many partners—the focal firm struggles to increase its absorptive capacity. For example, it struggles to build up internal knowledge. This may have been exaggerated for the shop floor connectivity technologies of Cluster 2 (e.g., equipping sensors on machines), which explains the more pronounced results for search depth. In line with Greco *et al.* (2015) we argue that a broad search is insufficient for process innovations related to digitization of manufacturing. Only when engaging deeply with external partners can the firm build absorptive capacity for the underlying technological requirements for successful implementation.

6.1.2 Relations between external search and clusters of digital technologies

As there were no statistically significant differences between external search breadth and the maturity of the three technology clusters, Hypothesis 3a was rejected. However, the research contributes a nuanced view on the strength of the effect of search depth on the adoption of digital technologies dependent on the specific type of technology sought to be implemented. Although the difference was not statistically significant (suggesting that Hypothesis 3b cannot be accepted), the strength of the relationship between external search depth and technologies related to shop floor connectivity (Cluster 2) was more pronounced than it was for computing (Cluster 1). That is, an increase in search depth appeared to be correlated with a higher increase in the digital maturity for Cluster 2 than Cluster 1. Further, for operator enhancement (Cluster 3; i.e., virtual reality technologies), the model did not show good performance, indicating that external search is not an essential driver of its adoption.

We speculate that these results might have been caused by the different pre-existing knowledge and capabilities required for the adoption of these technologies. The absorptive capacity perspective suggests that higher levels of pre-existing knowledge support the absorption of new knowledge (cf. Cohen and Levinthal, 1990; Robertson *et al.*, 2012; Zahra and George, 2002). The technologies in Cluster 2 were on average already at a higher maturity level in the firms (average of 2.84). These technologies (e.g., robotic, M2M communication, and identification technologies) have been employed in manufacturing for several years already, and firms are therefore experienced in using them. Technologies in Cluster 1 (computing), however, have only just become popular in manufacturing (e.g., big data analytics). Manufacturing firms may therefore not yet possess extensive internal knowledge about Cluster 1 technologies (evidenced by a lower average maturity level of 2.21), making external search—counterintuitively—less effective for Cluster 1 technologies than for Cluster 2.

6.1.3 Relations between digitization and operational performance

A third contribution to the literature concerns the effect of adopting digital technologies. Even though digitization is a strategic priority for many firms, there is limited scientific evidence on the relationship between the adoption of digital technologies and operational performance (Tortorella and Fettermann, 2018). This study contributes empirical evidence to this discussion. While we found support for the relationship between digital maturity and volume flexibility (as predicted in Hypothesis 5), no statistically significant evidence was found for the relationship with production cost competitiveness (Hypothesis 4). The positive relationship with volume flexibility is in line with scholars who view digitization as potentially leading to more customized products being developed without production efficiency losses versus mass production (Deuse *et al.*, 2015; Kagermann, 2015).

We can only speculate why we did not find support for Hypothesis 4. This may be surprising considering that firms regard digitization as a strategy to reduce production costs in order to keep high-cost manufacturing locations (Brynjolfsson and McAfee, 2016). Two potential explanations for this finding may be that cost advantages are not realized in the short term or that digitization help maintains competitive parity when competitors continue on their digitization journeys. However, more research is needed to provide answers to this question. Overall, our results support the perspective that digitization of manufacturing is first and foremost a strategy for increasing flexibility in manufacturing

6.2 Managerial implications

We summarize three implications for practitioners. First, external search plays an important role when engaging in the digitization of manufacturing. In particular, practitioners need to search deeply, not broadly. This research suggests that firms are better off engaging in a few deep relationships instead of many broad ones. Second, following the absorptive capacity perspective, practitioners should evaluate their internal knowledge before searching externally because a higher knowledge base seems to increase the effectiveness of an external search. Third, digitization was found to be more strongly correlated with volume flexibility than cost reduction. Hence, treating digital technologies as a means of achieving short-term financial benefits can result in unfulfilled expectations.

6.3 Limitations and future research

All cross-sectional survey-based studies have limitations, and this one is no exception. First, the small number of respondents (sample size of 151) limits the sophistication of the statistical analyses. Second, the operationalization of several constructs could have been different or more elaborate. For example, external search could include further sources such as users (e.g., Hippel, 2001) or start-up firms (e.g., Kurpjuweit and Wagner, 2020; Weiblen and Chesbrough, 2015). Future research could provide a more nuanced analysis of the role of different types of external knowledge sources. Third, there are, as always, limitations regarding representativeness and generalization. This research was conducted in Switzerland, one of the world's most advanced countries with a high degree of adoption of digital technologies. While we expect that the same results may hold true in other countries, this cannot be tested with these data. A fourth limitation is that we used static values for the variables, and thus claims can only be made regarding correlation. Future research could implement a longitudinal design that captures causation. Quasi-experiments with panel data may be especially well-suited to providing more robust scientific evidence. Unfortunately, such data could not be accessed in this study.

7. Conclusion

This study provides a better understanding of how open process innovation relates to the digitization of manufacturing. External search depth for process innovations was found to be related to a higher degree of adoption of digital technologies in a firm. Search breadth, however, did not appear as a statistically significant driver for the adoption of digital technologies. Generally, this suggests that firms should search deeply, not broadly, when seeking to increase their adoption of digital technologies. The effect of external search depth is more pronounced for certain technology clusters. Search depth is particularly helpful for connectivity and shop floor connectivity technologies. Finally, we found that a higher adoption level of digital technologies correlates positively with increased volume flexibility, but no statistical evidence was found for an improved production cost competitiveness. Overall, we see open process innovation as a promising concept for both researchers and practitioners.

References

Adner, R. and Levinthal, D. (2001), “Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation”, *Journal of Manufacturing Science and Engineering*, Vol. 47 No. 5, pp. 611–628.

Ahmad, S. and Schroeder, R.G. (2002), “Refining the product-process matrix”, *International Journal of Operations & Production Management*, Vol. 22 No. 1, pp. 103–124.

Bauernhansl, T. (Ed.) (2014), *Industrie 4.0 in Produktion, Automatisierung und Logistik*, Springer, Wiesbaden.

Becheikh, N., Landry, R. and Amara, N. (2006), “Lessons from innovation empirical studies in the manufacturing sector: A systematic review of the literature from 1993–2003”, *Technovation*, Vol. 26 5-6, pp. 644–664.

Becker, J., Knackstedt, R. and Pöppelbuß, J. (2009), “Developing Maturity Models for IT Management”, *Business & Information Systems Engineering*, Vol. 1 No. 3, pp. 213–222.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A. and Venkatraman, N.V. (2013), “Digital Business Strategy: Toward a Next Generation of Insights”, *MIS Quarterly*, Vol. 37 No. 2, pp. 471–482.

Bogers, M., Zobel, A.-K., Afuah, A., Almirall, E., Brunswicker, S., Dahlander, L., Frederiksen, L., Gawer, A., Gruber, M., Haefliger, S., Hagedoorn, J., Hilgers, D., Laursen, K., Magnusson, M.G., Majchrzak, A., McCarthy, I.P., Moeslein, K.M., Nambisan, S., Piller, F.T., Radziwon, A., Rossi-Lamastra, C., Sims, J. and Ter Wal, A.L.J. (2017), “The open innovation research landscape. Established perspectives and emerging themes across different levels of analysis”, *Industry and Innovation*, Vol. 24 No. 1, pp. 8–40.

Boyer, K.K. and Lewis, M.W. (2002), “Competitive priorities: Investigating the need for trade-offs in operations strategy”, *Production and Operations Management*, Vol. 11 No. 1, pp. 9–20.

Brinch, M. (2018), “Understanding the value of big data in supply chain management and its business processes”, *International Journal of Operations & Production Management*, Vol. 38 No. 7, pp. 1589–1614.

Brynjolfsson, E. and McAfee, A. (2016), *The second machine age: Work, progress, and prosperity in a time of brillant technologies*, W. W. Norton & Company, New York.
Brynjolfsson, E. and Schrage, M. (2009), "The new, faster face of innovation", *The Wall Street Journal* August 17.
Chesbrough, H. and Bogers, M. (2014), "Explicating open innovation: Clarifying an emerging paradigm for understanding innovation", *New Frontiers in Open Innovation. Oxford: Oxford University Press, Forthcoming*, pp. 3–28.
Chesbrough, H.W. (2003), *Open innovation: The new imperative for creating and profiting from technology*, Harvard Business School; Maidenhead: McGraw-Hill, Boston, Mass.
Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P. and Malhotra, S. (2018), "Notes from the AI frontier. Insights from hundreds of use cases", *McKinsey Global Institute*.
Clogg, C.C., Petkova, E. and Haritou, A. (1995), "Statistical Methods for Comparing Regression Coefficients Between Models", *American Journal of Sociology*, Vol. 100 No. 5, pp. 1261–1293.
Cohen, W.M. and Levinthal, D.A. (1990), "Absorptive capacity: A new perspective on learning and innovation", *Administrative science quarterly*, Vol. 35 No. 1, pp. 128–152.
Crossan, M.M. and Apaydin, M. (2010), "A Multi-Dimensional Framework of Organizational Innovation: A Systematic Review of the Literature", *Journal of Management Studies*, Vol. 47 No. 6, pp. 1154–1191.
Dekkers, R., Koukou, M.I., Mitchell, S. and Sinclair, S. (2019), "Engaging with open innovation: A scottish perspective on its opportunities, challenges and risks", *Journal of Innovation Economics*, Vol. 28 No. 1, p. 193.
Deuse, J., Weisner, K., Hengstebeck, A. and Busch, F. (2015), "Gestaltung von Produktionssystemen im Kontext von Industrie 4.0", in Botthof, A. and Hartmann, E.A. (Eds.), *Zukunft der Arbeit in Industrie 4.0*, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 99–109.
Enkel, E., Gassmann, O. and Chesbrough, H. (2009), "Open R&D and open innovation: exploring the phenomenon", *R&D Management*, Vol. 39 No. 4, pp. 311–316.
European Union (2012), *Evaluation of the SME definition*, Sevenoaks, Kent.
Feng, Q. and Shanthikumar, J.G. (2018), "How Research in Production and Operations Management May Evolve in the Era of Big Data", *Production and Operations Management*, Vol. 27 No. 9, pp. 1670–1684.
Forza, C. (2002), "Survey research in operations management: a process-based perspective", *International Journal of Operations & Production Management*, Vol. 22 No. 2, pp. 152–194.
Frank, A.G., Dalenogare, L.S. and Ayala, N.F. (2019), "Industry 4.0 technologies: Implementation patterns in manufacturing companies", *International Journal of Production Economics*, Vol. 210, pp. 15–26.
Frishammar, J., Kurkkio, M., Abrahamsson, L. and Lichtenthaler, U. (2012), "Antecedents and Consequences of Firms' Process Innovation Capability. A

Literature Review and a Conceptual Framework", *IEEE Transactions on Engineering Management*, Vol. 59 No. 4, pp. 519–529.
Garriga, H., Krogh, G. von and Spaeth, S. (2013), "How constraints and knowledge impact open innovation", *Strategic Management Journal*, Vol. 34 No. 9, pp. 1134–1144.
Gassmann, O., Enkel, E. and Chesbrough, H. (2010), "The future of open innovation", *R&D Management*, Vol. 40 No. 3, pp. 213–221.
Greco, M., Grimaldi, M. and Cricelli, L. (2015), "Open innovation actions and innovation performance", *European Journal of Innovation Management*, Vol. 18 No. 2, pp. 150–171.
Hartmann, P.M., Zaki, M., Feldmann, N. and Neely, A. (2016), "Capturing value from big data – a taxonomy of data-driven business models used by start-up firms", *International Journal of Operations & Production Management*, Vol. 36 No. 10, pp. 1382–1406.
Hippel, E. von (2001), "Innovation by user communities: Learning from open-source software", *MIT sloan management review*, Vol. 42 No. 4, p. 82.
Holmström, J., Holweg, M., Lawson, B., Pil, F. and Wagner, S. (2017), "The digitization of manufacturing", *Special Issue in the Journal of Operations Management: Call for Papers.*
Kache, F. and Seuring, S. (2017), "Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management", *International Journal of Operations & Production Management*, Vol. 37 No. 1, pp. 10–36.
Kagermann, H. (2015), "Change through digitization — Value creation in the age of Industry 4.0", in Albach, H. and Meffert, H. (Eds.), *Management of Permanent Change*, pp. 23–45.
Kagermann, H., Wahlster, W. and Helbig, J. (2013), "Securing the future of German manufacturing industry: Recommendations for implementing the strategic initiative industrie 4.0.", *Final report of the Industrie, 4.0*.
Kalantari, M., Rabbani, M. and Ebadian, M. (2011), "A decision support system for order acceptance/rejection in hybrid MTS/MTO production systems", *Applied Mathematical Modelling*, Vol. 35 No. 3, pp. 1363–1377.
Kang, H.S., Lee, J.Y., Choi, S., Kim, H., Park, J.H., Son, J.Y., Kim, B.H. and Noh, S.D. (2016), "Smart manufacturing: Past research, present findings, and future directions", *International Journal of Precision Engineering and Manufacturing-Green Technology*, Vol. 3 No. 1, pp. 111–128.
Khazanchi, S., Lewis, M.W. and Boyer, K.K. (2007), "Innovation-supportive culture: The impact of organizational values on process innovation", *Journal of Operations Management*, Vol. 25 No. 4, pp. 871–884.
Kurpjuweit, S. and Wagner, S.M. (2020), "A New Model for Managing Corporate-Startup Partnerships", *California Management Review*, Vol. 62 No. 4, (in press).
Kusiak, A. (2017), "Smart manufacturing must embrace big data", *Nature*, Vol. 544 No. 7648, pp. 23–25.

Laursen, K. and Salter, A. (2006), “Open for innovation. The role of openness in explaining innovation performance among U.K. manufacturing firms”, *Strategic Management Journal*, Vol. 27 No. 2, pp. 131–150.

Laursen, K. and Salter, A.J. (2014), “The paradox of openness: Appropriability, external search and collaboration”, *Research Policy*, Vol. 43 No. 5, pp. 867–878.

Leiponen, A. and Helfat, C.E. (2010), “Innovation objectives, knowledge sources, and the benefits of breadth”, *Strategic Management Journal*, Vol. 31 No. 2, pp. 224–236.

Levinthal, D.A. and March, J.G. (1993), “The myopia of learning”, *Strategic Management Journal*, Vol. 14 S2, pp. 95–112.

Lichtenthaler, U. and Lichtenthaler, E. (2009), “A Capability-Based Framework for Open Innovation: Complementing Absorptive Capacity”, *Journal of Management Studies*, Vol. 46 No. 8, pp. 1315–1338.

Majchrzak, A., Netland, T.H. and Srai, J. (2019), “Innovation in Next-Generation Production Platforms”, *World Economic Forum*.

Malhotra, M. and Grover, V. (1998), “An assessment of survey research in POM: from constructs to theory”, *Journal of Operations Management*, Vol. 16 No. 4, pp. 407–425.

Matthias, O., Fouweather, I., Gregory, I. and Vernon, A. (2017), “Making sense of Big Data – can it transform operations management?”, *International Journal of Operations & Production Management*, Vol. 37 No. 1, pp. 37–55.

Mittal, S., Khan, M.A., Romero, D. and Wuest, T. (2017), “Smart manufacturing: Characteristics, technologies and enabling factors”, *Proceedings of the Institution of Mechanical Engineers*, Vol. 65.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W. and Ueda, K. (2016), “Cyber-physical systems in manufacturing”, *CIRP Annals*, Vol. 65 No. 2, pp. 621–641.

Netland, T.H. and Alfnes, E. (2011), “Proposing a quick best practice maturity test for supply chain operations”, *Measuring Business Excellence*, Vol. 15 No. 1, pp. 66–76.

Olhager, J. and Selldin, E. (2004), “Supply chain management survey of Swedish manufacturing firms”, *International Journal of Production Economics*, Vol. 89 No. 3, pp. 353–361.

Olsen, T.L. and Tomlin, B. (2020), “Industry 4.0: Opportunities and Challenges for Operations Management”, *Manufacturing & Service Operations Management*, Vol. 22 No. 1, pp. 113–122.

Organisation for Economic Co-operation and Development (2005), *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data,* 3rd Edition, OECD Publishing, Paris.

Pedhazur, E.J. and Pedhazur Schmelkin, L. (1991), “Exploratory factor analysis”, *Measurement, design and analysis: An Integrated Approach*, Vol. 627.

Piening, E.P. and Salge, T.O. (2015), “Understanding the Antecedents, Contingencies, and Performance Implications of Process Innovation: A Dynamic Capabilities Perspective”, *Journal of Product Innovation Management*, Vol. 32 No. 1, pp. 80–97.

Pisano, G.P. (1997), *The development factory: Unlocking the potential of process innovation*, Harvard Business School Press, Boston, Massachusetts.

Reichstein, T. and Salter, A. (2006), “Investigating the sources of process innovation among UK manufacturing firms”, *Industrial and Corporate Change*, Vol. 15 No. 4, pp. 653–682.

Robertson, P.L., Casali, G.L. and Jacobson, D. (2012), “Managing open incremental process innovation. Absorptive Capacity and distributed learning”, *Research Policy*, Vol. 41 No. 5, pp. 822–832.

Schroeder, R.G., Scudder, G.D. and Elm, D.R. (1989), “Innovation in manufacturing”, *Journal of Operations Management*, Vol. 8 No. 1, pp. 1–15.

Schuh, G., Anderl, R., Gausemeier, J., Hompel, M. ten and Wahlster, W. (2017), *Industrie 4.0 Maturity Index: Die digitale Transformation von Unternehmen gestalten*, Herbert Utz Verlag, München.

Schumacher, A., Erol, S. and Sihn, W. (2016), “A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises”, *Procedia CIRP*, Vol. 52, pp. 161–166.

Schwab, K. (2017), *The fourth industrial revolution,* First U.S. edition, Crown Business, New York.

Sendler, U. (2018), *The Internet of Things*, Springer Berlin Heidelberg, Berlin, Heidelberg.

Shih, W. (2018), “Why High-Tech Commoditization Is Accelerating_MIT SMR”, *MIT sloan management review*, Vol. 59 No. 4, pp. 52–58.

Tabachnick, B.G. and Fidell, L.S. (2013), *Using multivariate statistics, Always learning,* 6. ed., internat. ed., Pearson, Boston, Mass.

Terjesen, S. and Patel, P.C. (2017), “In Search of Process Innovations. The Role of Search Depth, Search Breadth, and the Industry Environment”, *Journal of Management*, Vol. 43 No. 5, pp. 1421–1446.

Todorova, G. and Durisin, B. (2007), “Absorptive capacity: Valuing a reconceptualization”, *Academy of Management Review*, Vol. 32 No. 3, pp. 774–786.

Tortorella, G.L. and Fettermann, D. (2018), “Implementation of Industry 4.0 and lean production in Brazilian manufacturing companies”, *International Journal of Production Research*, Vol. 56 No. 8, pp. 2975–2987.

Tortorella, G.L., Giglio, R. and van Dun, D.H. (2019), “Industry 4.0 adoption as a moderator of the impact of lean production practices on operational performance improvement”, *International Journal of Operations & Production Management*, Vol. 39 6/7/8, pp. 860–886.

Trantopoulos, K., Krogh, G. von, Wallin, M. and Woerter Martin (2017), “External Knowledge and Information Technology: Implications for Process Innovation Performance”, *MIS Quarterly*, Vol. 41, pp. 287–300.

Trott, P. and Hartmann, D. (2009), “Why 'Open Innovation' is old wine in new bottles”, *International Journal of Innovation Management*, Vol. 13 No. 04, pp. 715–736.

Un, C.A. and Asakawa, K. (2015), “Types of R&D Collaborations and Process Innovation. The Benefit of Collaborating Upstream in the Knowledge Chain”, *Journal of Product Innovation Management*, Vol. 32 No. 1, pp. 138–153.

Vanpoucke, E., Vereecke, A. and Muylle, S. (2017), “Leveraging the impact of supply chain integration through information technology”, *International Journal of Operations & Production Management*, Vol. 37 No. 4, pp. 510–530.

Vega-Jurado, J., Gutierrez-Gracia, A. and Fernandez-de-Lucio, I. (2009), “Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry”, *Industrial and Corporate Change*, Vol. 18 No. 4, pp. 637–670.

von Krogh, G., Netland, T.H. and Wörter, M. (2018), “Winning with open process innovation”, *MIT sloan management review*, Vol. 59 No. 2, pp. 53–56.

Wagner, S.M. and Bode, C. (2014), “Supplier relationship-specific investments and the role of safeguards for supplier innovation sharing”, *Journal of Operations Management*, Vol. 32 No. 3, pp. 65–78.

Wee, D., Kelly, R., Cattel, J. and Breunig, M. (2015), “Industry 4.0: How to navigate digitization of the manufacturing sector”, *McKinsey & Company*, Vol. 58.

Weiblen, T. and Chesbrough, H.W. (2015), “Engaging with Startups to Enhance Corporate Innovation”, *California Management Review*, Vol. 57 No. 2, pp. 66–90.

West, J. and Bogers, M. (2017), “Open innovation. Current status and research opportunities”, *Innovation*, Vol. 19 No. 1, pp. 43–50.

World Economic Forum (2017), *Technology and innovation for the future of production: Accelerating value creation*, Geneva, Switzerland.

World Economic Forum (2018), *The Future of Jobs Report: 2018*, Geneva, Switzerland.

World Economic Forum (2019), *Fourth Industrial Revolution: Beacons of Technology and Innovation in Manufacturing*, Geneva, Switzerland.

Xu, L.D., Xu, E.L. and Li, L. (2018), “Industry 4.0: state of the art and future trends”, *International Journal of Production Research*, Vol. 56 No. 8, pp. 2941–2962.

Zahra, S.A. and George, G. (2002), “Absorptive Capacity: A Review, Reconceptualization, and Extension”, *Academy of Management Review*, Vol. 27 No. 2, pp. 185–203.

Appendix A: Factor analysis

Table A-1. Factor analysis for all 12 technologies

	Factor 1	Factor 2	Factor 3
Big data	0.70	0.06	0.12
Blockchain	0.62	-0.06	0.04
Cloud computing	0.58	0.12	0.02
Digital twin	0.38	0.22	0.29
Robotics	0.04	0.70	0.03
M2M communication	0.28	0.63	0.08
Identification technologies	0.42	0.46	0.23
Machine learning	0.31	0.40	0.24
Additive manufacturing	-0.14	0.35	0.13
Augmented reality	0.18	0.03	1.00
Drones	0.01	0.13	0.22

Appendix B: Survey Questions

Which industry does your company operate in? [Industry]
Please tick the industrial sector in which your company is operating. If more than one category is correct, please choose the most dominant one.

- o 10 - Manufacture of food and animal feed
- o 11 - Manufacture of beverages
- o 12 - Manufacture of tobacco products
- o 13 - Manufacture of textiles
- o 14 - Manufacture of clothes
- o 15 - Manufacture of leather and related products and shoes
- o 16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
- o 17 - Manufacture of wood and wood products and the manufacture of pulp, paper, and paper products
- o 18 - Publishing, printing, and reproduction of recorded media
- o 19 - Manufacture of coke and refined petroleum products
- o 20 - Manufacture of chemical products
- o 21 - Manufacture of pharmaceuticals
- o 22 - Manufacture of rubber and plastic products
- o 23 - Manufacture of other non-metallic mineral products
- o 24 - Metal production and metal processing
- o 25 - Manufacture of metal products
- o 26 - Manufacture of computer, electronic, and optical products
- o 27 - Manufacture of electrical equipment
- o 28 - Mechanical engineering
- o 29 - Manufacture of automotive and automotive components
- o 30 - Manufacture of other transport equipment
- o 31 - Manufacture of furniture
- o 33 - Repair and installation of machinery and equipment
- o 32 - Production of other goods, namely:

How many people are employed by your company in Switzerland? [SME]
Please state the number of FTE (full-time equivalents) within the following functional areas. If you do not have the exact number, please give your best estimate. Please give the rounded up answer in whole numbers without separation marks.

Manufacturing & assembly: ________
Service (e.g. maintenance, refit, etc.): ________
Research & development, projecting: ________
Other (e.g., purchase, administration, etc.): ________

What is the primary type of goods produced by your company? [Market type]

- o Consumer goods (B2C)
- o Industrial goods (B2B)
- o Goods for public institutions (B2G)

Which concept for order processing is mainly applied by your company? [Production strategy]

- o Make-to-stock (MTS)
- o Assemble-to-order (ATO)
- o Make-to-order (MTO)
- o Engineer-to-order (ETO)

What is the current status of your company regarding the following technologies that can be used for Industry 4.0 and digitalization activities? [Digital maturity]

	Not relevant	Observing	Researching and developing	Working on the implementation	Already in first use	Fully implemented
Additive manufacturing (3-D printing)	O	O	O	O	O	O
Augmented reality solutions	O	O	O	O	O	O
Autonomous vehicles or transport systems	O	O	O	O	O	O
Big data analytics	O	O	O	O	O	O
Blockchain	O	O	O	O	O	O
Cloud computing	O	O	O	O	O	O
Digital twin (product)	O	O	O	O	O	O
Digital twin (process)	O	O	O	O	O	O
Drones (commercial UAWs)	O	O	O	O	O	O
Identification or communication solutions (RFID, NFC, etc.)	O	O	O	O	O	O
Machine learning (deep learning)	O	O	O	O	O	O
Machine-to-machine communication (M2M)	O	O	O	O	O	O
Robotics	O	O	O	O	O	O

How has your company developed process innovations during the last three years? [Search breadth/depth]

Please choose one or more from the following.

	Never	Very Rarely	Rarely	Sometimes	Often	Very often	Extensively
Your company together with other companies	O	O	O	O	O	O	O
Your company cooperating with consulting companies	O	O	O	O	O	O	O
Your company cooperating with research institutions (universities, public research facilities, etc.)	O	O	O	O	O	O	O

How has the performance of your company changed in comparison to its competitors during the last three years? [Production costs/volume flexibility]

Please indicate the development of the following factors.

	Much worse	Worse	Slightly worse	No change	Slightly better	Better	Much better
Production costs	O	O	O	O	O	O	O
Flexibility (volume)	O	O	O	O	O	O	O