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'Lean 4.0': How can digital technologies support lean practices?

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ABSTRACT

Digital technologies, such as advanced analytics, autonomous vehicles or the Internet of Things, are often touted as means to substantially improve operations. While this potential has been frequently highlighted and evidenced from single case applications, we still lack a deeper theoretical understanding of the underlying mechanisms how digital technologies can support process improvement in general, and lean practices more specifically. In this paper, we use a qualitative study based on focus group design to understand how manufacturing and supply chain management professionals perceive the potential of digital technologies in support of lean practices. We identify eight digital waste reduction mechanisms that illustrate how digital technologies can support lean practices. These include a cluster of mechanisms that augment operational execution in terms of speed and precision of execution, as well as flexibility in space and time. Furthermore, we identify a second cluster of mechanisms that augment decision-making through visibility, feedback, engagement, and prevention. In terms of managerial implications, our findings provide firms with a structured approach how to identify those digital technologies that can most effectively support their respective process improvement activities.

1. Introduction

Digital technologies are powerful innovations that have rightfully captured the imagination of practitioners and scholars alike how they could support and enhance operations (see for example Frank et al. (2019), Benitez et al. (2020), Dalenogare et al. (2018) or Wee et al. (2015)). A growing number of studies are at hand that have studied the digital technologies that are commonly clustered as 'Industry 4.0' (see, for example Buer et al. (2018), Culot et al. (2020) or Weking et al. (2019)), and some have linked these technologies directly to process improvement through lean practices (Gillani et al., 2020; Wagner et al., 2017). For example, Wagner et al. (2017) argue that digitalization will not only support lean, but it will also enlarge its scope. The common view is that digitalization will enhance operational improvements, and in turn, improve operational performance (see, for example: Davies et al., 2017; Kolberg and Zühlke, 2015; Li et al., 2020; Moeuf et al., 2020; Tortorella et al., 2019 and 2020).

While a consensus view may be emerging, much of this discourse remains conceptual in nature and lacks empirical confirmation. Most contributions either provide a conceptual discussion of the potential relation between Lean and Industry 4.0 (see, for example Buer et al. (2018) or Núñez-Merino et al. (2020)) or refer to projected future benefits (see, for example: Rosin et al. (2020) and Tortorella et al. (2019)). We took this gap as starting point and initially conducted an exploratory survey of European manufacturing plants in 2019 (Cifone et al., 2019). Our aim was to understand whether, and how, firms seize the opportunities that digital technologies present to improve their operational performance using lean practices. To this effect we targeted lean companies with at least one plant in Europe leading us to a final dataset comprehending 105 plants corresponding to 88 different companies. Questions were related mainly to lean practices implementation (Shah and Ward, 2003), to digital technology implementation, and to operational performance (Shah and Ward, 2003) that were realised after any integration of lean practices and digital technologies. Our survey findings demonstrate that while the majority of plants show a high degree of lean maturity, they still have not embraced digitalization to a comparable degree. As such, it was not possible to provide a quantitative empirical perspective of the extent that digital technologies can support lean practices. While there is nascent evidence suggesting that digital technologies can indeed support lean practices (see Section 2.3), the exact mechanisms enabling new technologies to reduce wastes are still not entirely clear. These mechanisms are important to understand as

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they offer companies the opportunity to identify appropriate technologies to best address the different lean wastes. In addition, the mechanisms offer researchers new perspectives to further investigate the different conceptual links between new digital technologies and lean practices. The current study continues this line of inquiry using a qualitative research design to obtain detailed insights into how digital technologies enable lean practices, or in short, enable a 'Lean 4.0'. To this effect we selected a focus-group-based research design and conducted 12 in-depth sessions across two countries with 48 experience managers. We aimed at assessing what potential manufacturing and supply chain management professionals see for digital technologies to support lean, while also assessing the respective perceived importance of each of the six digital technology clusters.

Our findings first and foremost confirm that, as has been suggested before, digital technologies offer significant potential to support and enhance lean within manufacturing. Extending previous studies, we identify eight digital waste reduction mechanisms how digital technologies can support lean: firstly, those that *enhance operational execution*, and secondly those that *enhance operational decision making*. Our findings contribute a theoretical view towards understanding the true impact of Industry 4.0 technologies can have on process improvement in general, and lean practices in particular. We are advancing a largely conceptual debate on the relationship between Industry 4.0 and lean by providing empirical evidence of the likely implications digital technologies will have on lean practices. Our findings also have direct managerial relevance as a guideline by firms wishing to adopt digital technologies, showing which technologies most effectively can support certain improvements on the shop-floor.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on Lean, Industry 4.0 as well as the relationship between the two concepts. Section 3 shows the research methodology, discussing the digital technologies we adopted in our study, the focus group design, and the coding process that lead us to unveil the digital waste reduction mechanisms. Then, we present our results and discussion in Section 4. The paper ends with the conclusions in Section 5, which highlights the implications of the study, limitations and future research directions.

2. Theoretical background

In this section, we set out by briefly reviewing the established lean concepts and practices in the context of process improvement within the manufacturing firms. We then proceed to identifying the technology clusters that are most relevant in this context. Finally, we synthesize the relationship between these two streams of the literature.

2.1. Lean manufacturing: concepts and practices

The concept of lean production, and its evolution over time, have been widely researched and discussed in the operations management literature over the past three decades, and its key tenets thus must not be repeated here (for historical overviews see Holweg (2007), Hines et al. (2004) and Fujimoto (1999); for reviews of key lean tools and practices see Monden (1998), Shah and Ward (2007, 2003), Liker (2004), Womack et al. (1990), Hopp and Spearman (2020, and Cusumano et al. (2021))tor.

Lean production can be conceptualised at various levels: its guiding *philosophy*, the *principles* that guide its implementation, and the underlying *practices* that lead to actual process improvement. At its core, the lean philosophy is to improve processes by removing muda (waste), muri (overburden) and mura (unevenness) from the process. The most common way to state the lean philosophy is through Taiichi Ohno original seven wastes in manufacturing (often abbreviated as TIMWOOD – Transportation, (excess) Inventory, Motion, Waiting, Overproduction, Overprocessing and Defects), which later have been expanded to also include 'Skills', or wasted human talent and ideas. Muda, together with mura and muri, provide the original, and still the most succinct, way how to conceptualise lean (Bicheno and Holweg, 2016). All lean practices, as for example outlined by Shah and Ward in their seminal papers (Shah and Ward, 2003, 2007) in essence are focussed on addressing one or several of these wastes. It is for that reason that we adopt the eight wastes for our study, in order to understand how digital technologies can help reduce these eight wastes from manufacturing processes. In other words, using the fundamental concept of the eight wastes allows us to identify the actual digital waste reduction mechanisms how the various technologies support their reduction within the manufacturing process.

This conceptual framing also represents a limitation that future research should seek to overcome. Specifically, further studies may wish to link specific lean practices, as for example identified by Monden (1998), Shah and Ward (2003), Liker (2004), and many others, to see how digital technologies can support, enhance, or possibly impede the main lean practices. It is likely that certain digital technologies will support lean practices better than others, and it will be important to understand these differential effects in the long term – even though they may exceed the scope of this initial study.

2.2. Industry 4.0

Contrary to lean production, digital technologies and their growing role within operations practices are a nascent phenomenon (Schniederjans et al., 2020). Companies have always used new technologies to advance their processes, with the shipping container being probably the most successful example of a technical revolution that significantly improved supply chain processes and shaped global trade flows (Levinson, 2010). However, it is important to note that digital technologies not always fulfil the expectations they are said to achieve. An example is Radio Frequency Identification (RFID) technology that has triggered high expectations for process improvement in retailing operations, but so far, have only been able to partially fulfil (Gaukler and Seifert, 2007).

The most recent wave of digital technologies is often referred to as 'Industry 4.0', a term that was coined within German industrial policy in 2011 (BMBF-Internetredaktion, 2016; Kagermann et al., 2011). Most prominently, Industry 4.0 was recognized as the 'Fourth Industrial Revolution (4IR)' by the World Economic Forum (Schwab, 2016). Because of its novelty, there is neither a world-wide accepted definition of it nor a proper classification of technologies under its umbrella (Culot et al., 2020). Different authors provide indeed both their own definition of Industry 4.0 as well as of technologies (Buer et al., 2018; Moeuf et al., 2017; Weking et al., 2019). Generally speaking, Industry 4.0 represents the further digitalization of the manufacturing world (Dalenogare et al., 2018; Weking et al., 2019). It is recognized as the convergence of several different technologies (Raj et al., 2020). Even though most technologies were already well-known in the manufacturing world before the explicit definition of Industry 4.0 (Culot et al., 2020; Tortorella et al., 2020a), their low-cost availability as well as their increase of power are some of its enablers.

The industry 4.0 concept has equally captured the attention of scholars, focusing on the increase in operational capabilities (Bai et al., 2020). Specifically, most studies focus on how these augmented capabilities improve firm performance (Gillani et al., 2020). Within the Industry 4.0 the advent of Internet of Things (IoT), cloud services, big data, advanced analytics enable the creation of cyber-physical systems (CPS), which is the keystone and the real innovation of Industry 4.0 (see, for example: Frank et al., 2019 and Wang et al., 2016). The ultimate aspiration of Industry 4.0 is the creation of a network among humans and objects connected through real-time data (Lopes de Sousa Jabbour et al., 2018; Osterrieder et al., 2020; Wagner et al., 2017). Such networks will cover the whole supply chain, facilitating relationships among all different stakeholders (Benitez et al., 2020; Dalenogare et al., 2018) resulting in a horizontal integration among involved actors as a process-related element of Industry 4.0 (Shahin et al., 2020). Industry 4.0 is portrayed as a way for companies to reach unprecedented level of innovation (Moeuf et al., 2020) and of operational performance (Gillani et al., 2020; Tortorella et al., 2019). These drastic advances in technologies for operations and supply chain management have indeed the greatest impact on companies operational success (Chiarini et al., 2020). Among others, Industry 4.0 facilitates companies in strengthening or building a flexible and agile supply chain, in fully customizing of products and in achieving higher efficiency within their process (see, for example Gillani et al., 2020; Osterrieder et al., 2020; Wang et al., 2016). Exploiting advanced analytics and big data, companies can detect possible future patterns regarding customers, suppliers or production assets and therefore to enhance their reactive capability to any change (Weking et al., 2019). On the other hand, companies can – leveraging CPS – create a modular and changeable production system, that in turn allows the production of highly customized products (Tortorella et al., 2020).

In summary, virtually all technologies associated within Industry 4.0 (i.e., Internet of Things, advanced analytics, robotics, additive manufacturing, augmented reality and others) are seen to play a strong role in enhancing operational efficiency (Buer et al., 2018; Dalenogare et al., 2018; Frank et al., 2019). Yet the actual mechanisms *how* these improvements can be realised is far less clear, as is the way in which Industry 4.0 will be integrated into existing operations management approaches, such as lean practices.

2.3. Synthesis: Integrating Lean and Industry 4.0

The integration of lean and Industry 4.0 into the 'Lean 4.0' concept is increasingly being discussed in the concurrent practitioner, as well as the academic literature (e.g. Buer et al., 2018). There are several differing perspectives on how this might be achieved, while two main perspectives are emerging in this debate (Núñez-Merino et al., 2020). The first perspective describes lean as a basis for the implementation of Industry 4.0 (Hambach et al., 2017). Indeed, since lean practices are aimed at waste reduction along the process (Womack and Jones, 2003), having a streamlined and in-control process might represent a prerequisite for any process digitalization (Buer et al., 2018). Companies with a higher associated level of lean implementation benefit the most in embracing Industry 4.0 and in grasping its potentials (see for example: Hoellthaler et al., 2018; Rossini et al., 2019). In other words, lean implementation is not a binary prerequisite, yet amplifies the positive effects of digitalization (Chiarini et al., 2020).

The second stream of research refers to Industry 4.0 as being a necessary complement to 'traditional' lean (Kolberg and Zühlke, 2015; Tortorella et al., 2020). Here, it is argued, that today's market requirements are complex with customers demanding highly personalized products, which may hinder traditional lean to still be fully effective. Industry 4.0 could be used for lean to keep up with the pace of customisation (Rosin et al., 2020; Sanders et al., 2016). In this sense, Industry 4.0 represents the means that lean can exploit to adapt to new trends in the manufacturing world, preserving its process' robustness.

Irrespectively, the strong interest in the topic from the academic community is evident, while the novelty still makes it difficult to assess the impact of Lean 4.0 for most companies. To the best of authors' knowledge, available scientific studies are mostly focused on theoretical research (see, for example Buer et al., 2018; Shahin et al., 2020) or on the possible impact of Lean 4.0 on companies performance (see, for example: Rosin et al., 2020; Rossini et al., 2019; Tortorella et al., 2021a, b). A conclusive analysis of what Lean 4.0 is and the roles that Industry 4.0 technologies will play in the waste reduction fight is still outstanding.

This research marks a first attempt at studying the mechanisms explaining how digital technologies can enhance lean. The scope is limited to industrial operations management, comprising manufacturing, logistics and supply chain operations, since this marks the traditional application space for lean. We do see equal potential for digital technologies in service and other non-manufacturing operations yet. For the purpose of this study a tight boundary was necessary in order to identify tangible mechanisms. The main gap we seek to address is that, to date, we neither understand the mechanisms how digital technologies can actually support lean, nor know if there is any indication how important each of these technologies is in comparison. To this effect, we designed a focus-group-based research approach, which we report on in the next section.

3. Methodology

The lack of digital maturity was a key outcome of our preliminary survey (Cifone et al., 2019), we hence amended our focus towards identifying the potential mechanisms that describe how digital technologies can support lean, what we refer to as 'digital waste reduction mechanisms' in short. We initially considered a case study design, yet this was discounted as most digital technology implementations were found to still be at a pilot stage, rendering any comparative or even longitudinal analyses difficult. Hence, we decided to pursue our investigation by means of qualitative research, opting for a focus group design. Firstly, we select six main technologies that are impactful for process improvement. Although many emerging technologies have become available to support lean, we focused on technology clusters that were already widely discussed in practice and literature. This way we ensure that experts had sufficient exposure and potential knowledge on their functionally, application and potential impact. Secondly, we conducted twelve focus group sessions with industry experts from the manufacturing and logistics sectors.

3.1. Technology selection

As we are interested in the technologies' benefits that aim at process improvement, we carefully screened for relevant technologies in this context. We performed a thorough selection of literature, mostly comprehending practitioners' articles, white papers as well as reports issued by large technology and big consultancy firms. The reason for using these sources is their immediate focus on the *application* of digital technology and their relative timeliness. Not including scientific literature must not be considered as a limitation in this context: as suggested by Bokrantz et al. (2017), these publications cover a broad scope of issues, they appeal greatly to industrial management field and they are highly reputable. The initial research was carried out via web search starting in February 2018, with frequent updates up until August 2019, using the keywords of: 'industry 4.0', 'bundles industry 4.0', 'smart manufacturing', 'industry 4.0 technologies', 'digital technologies 4.0' and 'industry 4.0 categories'. We collected documents in English, which provided us with a set of 38 practitioner publications and reports (for example 'Time to accelerate in the race toward Industry 4.0' by the Boston Consulting Group, 2016, or 'Industry 4.0: How to navigate digitalization of the manufacturing sector' published by McKinsey, 2015) that are available from the authors on request. For each document, we collected the list of Industry 4.0 technologies or drivers mentioned, and then merged them all so to focus only on the most prominent technologies in our scope of analysis (see Appendix A).

We discovered that even though there is still considerable ambiguity as to which technologies go under Industry 4.0 umbrella, alongside great variation in the terminology itself, a consensus view emerged with six technologies as the ones potentially most relevant for process improvement. Technologies identified, briefly described below, are (in alphabetical order): additive manufacturing, advanced analytics, autonomous vehicles, Internet of Things (IoT), robotics and virtual and augmented reality (V/A reality). Out of these technologies, cybersecurity clearly sit at a higher level, being concerned with overarching safety, privacy, security and knowledge protection concepts (Anderl, 2014). Other emerging technologies such as robotic process automation (RPA), blockchain or smart contracts might have important implications for lean as well but are often still fuzzy and less well-known outside a small pool of true subject matter experts. Therefore, we opted to exclude them for the study.

Advanced analytics are methodologies and tools used to analyse and extract values from data, that nowadays are available in a huge amount that is too difficult to be managed by traditional data-processing application software (Lorenz et al., 2016; Schlaepter et al., 2015; Pozzi et al., 2021). They comprehend techniques such as machine learning (ML), artificial intelligence (AI), data mining and simulation (Davies, 2015; Hoberg 2020).

Autonomous vehicles offer the possibility of having a completely autonomous or semi-autonomous type of transportation for both short and long distances. They constitute a radical innovation that could assist in the efficient management of production lines, handling of warehouse inventories and supporting intra- and inter-logistics services (Blanchet et al., 2014).

Additive manufacturing refers to the process of manufacturing products by adding material layer upon layer from 3D models, without the need to use any specialised tools (Chan et al., 2018; Weller et al., 2015). In general, it allows unprecedented freedom in products development, enabling thus the production of highly customized products (Heinen and Hoberg, 2019; Holmström et al., 2016, 2019). Nowadays, it is particularly suitable for small batches, while it cannot achieve the high output rates required for mass production (Friesike et al., 2018).

Internet of Things is mainly built upon the interconnectivity among objects, such as electronic devices, smartphones, machines, modes of transportation, enabled by the internet (Dalenogare et al., 2018; Schlaepter et al., 2015). According to Atzori et al. (2017) and Alqahtani et al. (2019), the main IoT technologies are RFID platforms, pervasive computing platforms, cyber-physical systems, sensors networks and M2M systems. The exchange of information between objects generates a huge amount of data, which can be subsequently analysed to increase added value for companies (Lopes de Sousa Jabbour et al., 2018; Hoberg and Herdmann, 2018; Weißhuhn and Hoberg 2021).

Robotics have been long prevalent in modern manufacturing, and their use continues to grow. Nowadays, the availability of new generations of robots has opened new perspectives for automation (Frank et al., 2019). Indeed, they are equipped with high-performance sensors and thus increasingly do not need safety fences anymore, being able to fairly interact with the environment (Stadnicka and Antonelli, 2019).

Virtual and augmented realities are interactive experiences where real-world objects are either represented completely 'virtually', or else are 'augmented' by computer-generated perceptual information (Stankovic et al., 2017). Virtual Reality is indeed an immersive three-dimensional computer-built environment that can be explored and with which it is possible to interact using devices or wearables, such as viewers, gloves, earphones (Frank et al., 2019). On the other hand, augmented reality consists of the enrichment of existing environment with digital information, as additional animations or digital contents that enable the user to have a deeper knowledge of what surrounds him or her (Elia et al., 2016; Rüssmann et al., 2015).

3.2. Focus group design

Focus groups have been successful applied in varying contexts (Stewart et al., 2007) by collecting data from group of individuals for a topic defined by the research team (Morgan, 1993). Based on the interaction with the individuals during the focus group, the research aims to draw from complex personal experiences, beliefs, perceptions and attitudes of the participants (Nyumba et al., 2018). In prior operations literature, focus groups have been applied to gain insights into the value of innovative technologies such as additive manufacturing for example (Wagner and Walton, 2016). The process for designing focus-group-based research begins with identifying the main aim and defining the key research objectives of the study (Morgan et al., 1998). In our research, the objectives are twofold. First, we aim to identify the mechanisms that link digital technologies to lean wastes, exploring the potential mechanisms that allow new technologies to reduce waste and thus enhance lean. Second, we aim to obtain the experts' assessment on the importance the new technologies have to address waste across its different dimensions. For this purpose, we used the classic eight wastes of lean concept already discussed in Section 2.1 that are: transportation, inventory, motion, waiting, overproduction, overprocessing, defects, and skills (Bicheno and Holweg, 2016). For each of the wastes, we obtained the experts' assessment on how the new technologies described in the previous paragraph can support its reduction.

We decided to run two focus groups for each of the six technology clusters. By running each focus group in two countries, we aimed to correct for potentially different maturity levels and country-specific experiences with the technologies. All twelve focus group sessions were conducted at Politechnico di Milano, Italy, and Kühne Logistics University, Germany, between May 2019 and December 2019. For each of the focus group sessions we recruited five to ten experts using contact databases provided by Politecnico di Milano and the German logistics association (BVL), ensuring that the participants had operational responsibilities in their organisation. The databases, as well as the two countries where focus groups have been performed, were selected in favour of convenience sampling to allow for closer control of participants' responsibilities, as well coherence in the national contexts of their firms. We looked for covering a spread set of industrial experts' background, and this is the most relevant criteria. The choice of Germany and Italy was really driven by the location of the authors and the access to experts. However, we could have leveraged any experts in more mature economies. Initially, we were not sure if the depth of the discussion would differ between Italy and Germany but ultimately we did not observe a difference. Participating experts had an average work experience of 14 years and were commonly having roles such as supply chain manager, operations manager or senior consultant. Further, we invited selected academics to our focus groups based on their operations knowledge and/or prior industry expertise. Appendix B provides details of the experts' profiles and the composition of the focus groups (note that some experts were involved in different focus groups).

3.3. Execution and coding

Each of the twelve focus group sessions was conducted based on the methodology outlined in the left part of Fig. 1. To test and fine-tune the methodology and the software used, a pilot focus group was conducted with four participants in May 2019 before the main study. While up to three researchers were present in each of the sessions, one researcher was present across every session to ensure consistency in terms of process and timing.

Each session started with a presentation of the objectives and an outline of the methodology. Next, a researcher briefly explained the technology under discussion and defined the scope. For example, advanced analytics includes all different predictive analytics, machine learning, or deep learning tools while blockchain or robotic process automation was not intended to be included in the discussion. Participants had the opportunity to ask questions to ensure a common understanding of the sub-technologies that should be considered. In a next step, a brief recap of the eight wastes including examples was given by the researcher. Again, participants had the opportunity to ask questions to verify their understanding. The entire introduction was supported by a short slides set that was also provided beforehand to the participants.

Following the introduction, the workshop started with the first individual task for the participants. Appendix B provides details of all focus groups items. All participants were asked to identify potential mechanisms that enable the technology to reduce the first waste, e.g. for the technology 'advanced analytics' to reduce the waste 'transportation'. A challenge in typical focus group discussions is to encourage more reticent participants to take part in the discussions and bring their ideas forward (Lloyd, 2011). To discourage this behaviour we asked the participants to provide their initial input via laptop/tablet into the

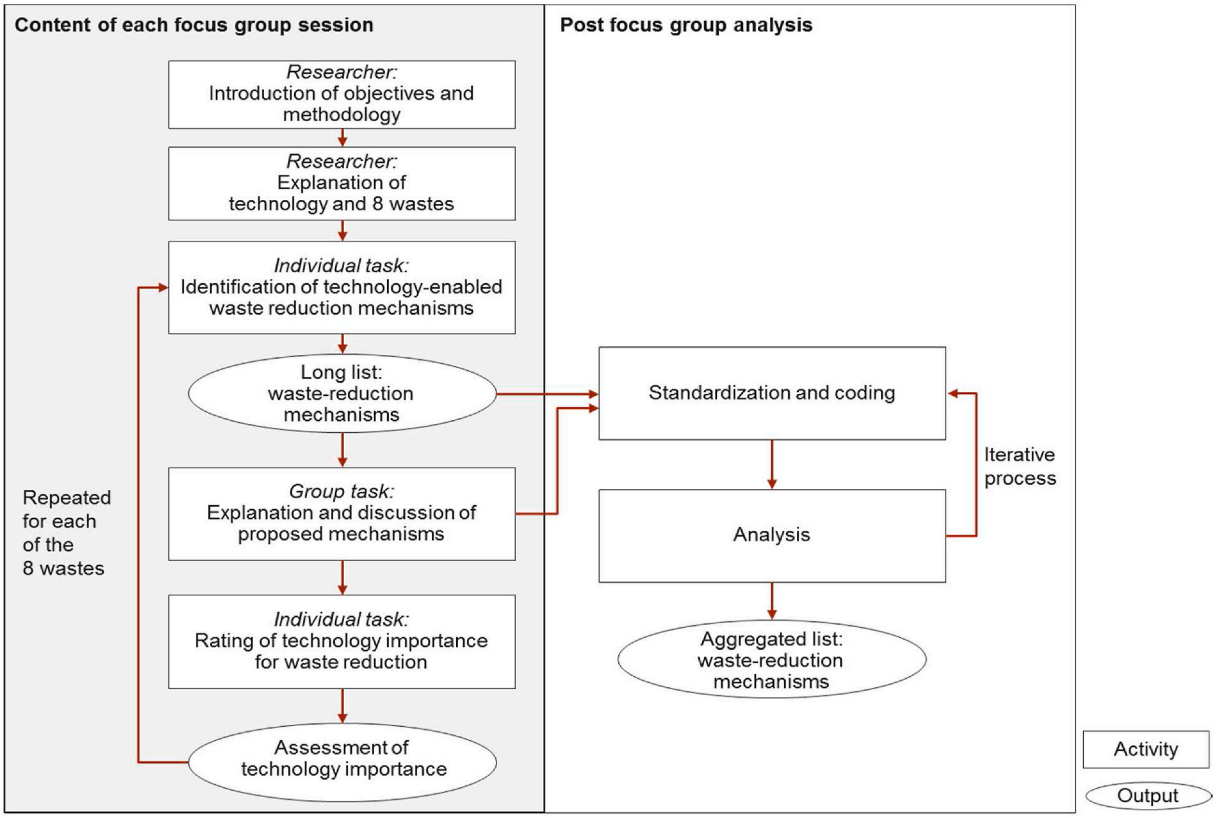

Fig. 1. Methodological process for focus groups.

software PollEV, using its web interface. We encouraged participants to provide the three main mechanisms they could identify for each combination of waste and technology. All mechanisms provided were added to a long list that was then shown to the participants. For example, in the first focus group on ‘advanced analytics’, participants provided 13 mechanisms to address the waste ‘transportation’. These included statements such as ‘less transportation since products can be made where demanded [due to better forecasting]’, ‘less transport due to better use of capacity based on space optimization’ or ‘better layout reduced transport lengths in plant’.

Based on the long list we initiated the group discussion. The researcher read out each mechanism and asked the participant who provided the statement to explain his/her reasoning. Since the statements were anonymous, each participant had the same chance to be called up and present his/her ideas. Then other participants were asked to comment on their agreement/disagreement with the mechanism. During the discussion, a researcher was taking notes for the further analysis. In line with the GDPR, we obtained consent to capture the comments made by participant through an observer taking notes during the sessions. Participants did feel uncomfortable about being recorded, thus rendering a verbatim transcription impossible. While this is certainly a limitation, the sessions were run before the Covid-19 pandemic in person, allowing for a rich discussion with and amongst the participants.

Once all mechanisms were addressed (typically several statements were heading into similar directions and could be skipped) the process moved on the next individual task. Here, the participants were asked to turn back to their laptop/tablet to provide their individual ratings on the importance of the technology to reduce the waste under consideration using the PollEV software. They could rate the technology on scale from ‘No impact – 1’ to ‘High impact – 5’. This activity provided the assessment of the technology importance. This process was then repeated for each of the eight wastes. The focus group sessions took between 90 and 120 min each. After the end of the session, participants were invited to food and drinks for informal feedback. Based on the discussions, participants confirmed that they felt that the interaction in the focus group represented their views well.

The analysis of the twelve focus groups outlined in the right part of Fig. 1 is aimed at unveiling the meaning of data collected by extracting main themes emerging from data, named digital waste reduction mechanisms. Data collected during focus groups come both from the long list of mechanisms recorded in PollEv from participants and from the notes taken by a researcher during the group discussion in each session. A single document containing all data was imported into NVivo 11, a qualitative data management software (Creswell, 2003) that supported us in managing vast amount of data, in tracking the analysis process and in re-coding (Cullen and Webster, 2007).

Contents were then coded independently by three researchers, exploiting both manual and electronic coding and following systematically the ‘free coding approach’ proposed by Campbell et al. (2013). This approach is based on an iterative process where codes emerge inductively from empirical data as significant themes and final nodes are gradually built up. It was considered appropriate for this research due to its exploratory characteristic (Frankfort-Nachmias and Nachmias, 1982), instead of using a deductive approach which defines codes *a priori*. The aim was to cluster the long list of mechanisms provided by experts during focus groups, highlighting emerged macro themes, namely digital waste reduction mechanisms.

For the purpose of an external audit, we used peer-debriefing and inter-coder agreement. Peer-debriefing relies on the discussion of emerged themes with other researchers belonging to authors’ departments (Bokrantz et al., 2019). They work as outsider to criticize and discuss both data collection and analysis with the other coders (Corley and Gioia, 2004). After peer-debriefing sessions, we revised and slightly changed the final emerged clusters of mechanisms. On the other hand, inter-coder agreement must be considered when multiple researchers code the whole set of data. Even if any structured way on how to perform inter-coder agreement assessment is available for inductive approach (Campbell et al., 2013), one well-known approach consists in reaching the consensus coding among researchers. Researchers were indeed asked to agree on codes, revising them and the emerged clusters of mechanisms accordingly (Bokrantz et al., 2019). Similarly, it is still not available any formal assessment of coding reproducibility for inductive coding, while they have been typically created for deductive contexts (Campbell et al., 2013; Krippendorff, 1980). Moreover, to enhance trustworthiness of our data and assess the reproducibility of our coding, two further external researchers coded data collected and examined matching of results as proposed by Bokrantz et al. (2019).

The coding and analysis process produced eight main clusters, specifically eight digital waste reduction mechanisms, that will be discussed in detail in the subsequent section. Since we look for mechanisms through which technologies may reduce wastes, we discarded any codes that do not fit to any waste. In this context we created a further category called 'Other' where codes not specifically related to wastes have been clustered (e.g. revenue improvement levers or levers impacting investments), which were not considered further in our analyses. In total, 93 responses (15 %) were thus excluded from the analysis.

4. Discussion

Overall, it quickly emerged that the industry experts were generally well-aware of the various digital technologies and their applications in a manufacturing context, and that many initial pilot implementations were already underway in their respective organisations. The most prominent theme that emerged across all sessions was the role of data, and more specifically, how the digital transformation in general provided better and more timely data, which in turn then enabled many of the waste reductions that were discussed subsequently. In this section, we will outline the main findings from the focus groups.

4.1. *Differential impact of technologies on the eight wastes*

Across the twelve focus groups we found that all six technology clusters as well as all eight wastes were consistently mentioned in the discussion, yet to varying degrees. For example, advanced analytics, IoT, robotics and V/A technologies were mentioned considerably more often than autonomous vehicles and additive manufacturing, for example, as shown in Table 1. Even more stark was the differential response when it came to the eight wastes, whereby we found almost 1:3 difference between the lowest, overprocessing, and the highest, overproduction. In itself these descriptive findings are of course not conclusive, yet provide a strong indication that across the 48 possible technology-waste combinations there are certain combinations that are perceived to be considerably more promising than others. This is an important indication for our initial hypothesis, namely that not all technologies are equally helpful or supportive of lean efforts. In other words, as Table 3 shows, there is a strong perception within practice that the impact of the various digital technologies on process improvement varies greatly. The differential perception is also mirrored in the importance participants associated with each technology-waste combination. As Table 1 shows, the ratings of importance on a 5-point Likert scale varied greatly across combinations, from 4.6 to 1.4.

Combined, these descriptive findings of the frequencies and perceived importance provide very strong evidence indeed that digital technologies do not uniformly support lean improvements, yet that certain technologies support the reduction of certain wastes, while some technologies have an overall small impact and/or no impact at all. In the following, we will turn our attention to the mechanisms that link the technologies to the reduction of the respective wastes, in order to elucidate the reasons for this differential impact.

4.2. *Identification of mechanisms*

To identify these digital waste reduction mechanisms, we coded the respective responses into clusters, as outlined above in Section 3.3 In total, out of the 594 individual response items recorded, we identified eight mechanisms how the six digital technologies support the reduction of the respective wastes. These eight digital waste reduction mechanisms are listed in Table 2, including their definitions and frequencies, as well as examples provided by experts during focus groups sessions.

Having identified the clusters in the responses from the focus groups makes it possible to show graphically how different technologies can contribute to the reduction of wastes in manufacturing. Fig. 2 shows the results of our focus groups in a Sankey chart – linking the six technology clusters on the left with the eight wastes on the right, showing the connections via the eight mechanisms we identified.

In addition to the first finding, that digital technologies are perceived to support lean improvements to a varying degree, this analysis show there are eight common mechanisms that link all six technologies to all eight wastes. These mechanisms are shared across all digital technologies, although again, they are seen to support lean to a varying degree each. Overall, the eight digital waste reduction mechanisms identified span across two generic ways how to improve operations: first, technologies that are *execution-enhancing*, this includes precision and speed of execution, as well as flexibility in time and space. Examples include additive manufacturing that adds flexibility in space and time, or improved precision of execution due to more accurate definition of needs. Second, there are technologies that are *decision-enhancing*, which includes visibility, feedback, engagement and prevention. Examples include machine learning that can update planning and schedules, as well as improved feedback from the process itself, amongst others by preventing mistakes through better information. It is worth highlighting

Table 1
Frequencies and importance of technology-waste combinations in the focus group research.

		Transportation	Inventory	Motion	Waiting	Overproduction	Overprocessing	Defects	Skills	Total
Frequency	Advanced Analytics	16	27	10	18	29	5	18	12	**135**
	Autonomous Vehicles	9	12	12	17	4	2	14	12	**82**
	Additive Manufacturing	12	19	2	7	29	9	12	5	**95**
	IoT	18	26	14	11	24	10	10	10	**123**
	Robotics	19	11	16	14	19	11	13	9	**112**
	V/A Reality	12	21	16	8	16	9	20	15	**117**
	Total	**86**	**116**	**70**	**75**	**121**	**46**	**87**	**63**	**664**
Importance	Advanced Analytics	3.9	4.1	2.3	3.1	3.6	3.1	3.9	3.0	**3.4**
	Autonomous Vehicles	3.6	2.9	4.6	4.0	2.1	2.5	3.7	3.7	**2.6**
	Additive Manufacturing	3.1	2.9	1.4	2.4	2.8	2.6	2.8	2.6	**3.6**
	IoT	3.7	4.0	3.3	3.7	3.7	2.7	4.3	3.8	**3.4**
	Robotics	3.0	2.8	4.0	3.9	2.6	3.5	4.5	3.0	**3.4**
	V/A Reality	2.9	2.5	3.4	2.9	2.5	2.0	3.4	2.7	**2.8**
	Average	**3.4**	**3.2**	**3.2**	**3.3**	**2.9**	**2.7**	**3.7**	**3.1**	

Table 2
Overview of eight digital waste reduction mechanisms.

	Mechanism	Definition	Explanation	Examples	Frequency
1	Visibility	Technologies exploited in order to improve the planning phase. Based on information available in real time and to a greater visibility.	Ability to (i) manage demand *ex ante*, forecasting it, and anticipate customers' needs, (ii) analyse data *ex post* to better plan the activities, (iii) avoiding stocks and WIP, and (iv) reducing batch size.	Advanced analytics to improve demand forecast, IoT to automatically balance production lines.	161
2	Precision of execution	Technologies exploited in order to improve process accuracy and reliability (characteristics of the process).	Ability to (i) ensure a process is well controlled, (ii) manage the variation in process outcome, (iii) manage the quality of the output of a process, and (iv) ensure process safety.	Autonomous vehicles to reduce human errors, Additive manufacturing to produce very complex products by design.	108
3	Speed of execution	Technologies exploited in order to speed up processes.	Ability to enable time reduction in terms of (i) lead time, (ii) setup time, and (iii) delivery time.	Autonomous vehicles with route planning utilization to reduce transportation time, Robotics to synchronize operations and reduce setup time.	100
4	Feedback	Technologies exploited in order to improve feedback system and to identify defects and process errors in real time.	Ability to create feedback to human operators or systems by (i) data provided for analysis, (ii) visualization of results and (iii) guidance on output achieved.	V/A Reality to identify defects and errors, IoT to create a self-correcting system.	95
5	Engagement	Technological capabilities exploited in order to enrich employees' job.	Ability to provide employees with (i) tools/possibilities to dedicate their effort to value-added activities, (ii) systems that enable their well-being, and (iii) approaches that increase their motivation.	Robotics to reduce non-value added movements from operators, V/A Reality for more effective training.	86
6	Flexibility in time	Technologies exploited in order to customize output and to fulfil customers' request. The production can be linked to actual demand, as required.	Ability to increase flexibility in terms of (i) responding to changing volumes (volume flexibility), (ii) ability to reschedule (mix flexibility), and (iii) flexibility to changing product requirements (product flexibility).	Additive manufacturing to produce with smaller lots, Advanced analytics to better follow customers' requirements.	44
7	Flexibility in space	Technologies exploited in order to design and manage the assets properly as to enable a more responsive system and a local production.	Ability to exploit greater flexibility in terms of (i) production location and (ii) factory layout.	IoT to support locations decision, Robotics to create a more compact layout.	41
8	Prevention	Technologies exploited in order to anticipate defects or the need for intervention, as well as to carry out preventive maintenance.	Ability to prevent disruptions due to (i) better anticipation of disruptions, (ii) preventive maintenance, and (iii) more timely and effective execution of countermeasures.	Advanced analytics to predict tool degradation, Additive manufacturing to efficiently create ad hoc spare parts.	29

Table 3
The ten most often mentioned technology-mechanism-waste links.

#	Individual link	Frequency
1	Advanced Analytics-Visibility-Overproduction	18
2	Advanced Analytics-Visibility-Inventory	17
3	Additive Manufacturing-Flexibility in time-Overproduction	12
4	IoT-Visibility-Inventory	12
5	V/A Reality-Engagement-Skills	12
6	IoT-Visibility-Overproduction	11
7	Advanced Analytics-Engagement-Skills	10
8	Additive Manufacturing-Visibility-Inventory	10
9	Autonomous Vehicles-Engagement-Skills	10
10	Advanced Analytics-Precision in execution-Waiting	9

that the two cluster of mechanisms identified do not represent an absolute categorisation: indeed, they are grouped according to their main characteristics, while specific features of each digital waste reduction mechanism may even fit both clusters.

More specifically, digital technologies provide greater *visibility* of the process. In particular, new data sources offered by IoT technology as well as analytics capabilities enhance visibility along the different processes. This mechanism is illustrated, for example, by responses items like 'Advanced analytics to improve demand forecast' and 'IoT to automatically balance production lines'. In one focus group there was a vivid discussion of all the potential data sources (e.g. weather, holiday plans or price discounts) and AI approaches (e.g. machine learning, decision trees) that can be leveraged to improve demand forecasting in operations planning. Based on the improved demand forecast, replenishment orders and workforce planning (among many other decisions) can be improved. In another focus group, the idea of using IoT sensors at the different production stages to improve the line balancing was raised. Again better visibility can be achieve based on IoT data (e.g. yield rates, throughput times) to decide on product routing and volumes.

In line with greater visibility, the *precision of execution* can be advanced using comprehensive, more accurate, and more timely data, less error-prone and less variable processes. For example, augmented reality glasses can guide the picker to the right shelf and integrated cameras and optical pattern recognition technology will enable the glasses to automatically validate the item picked in warehouses that cannot be easily automated.

Next, the *speed of execution* can be improved, as information are made available at the workplace without time-consuming delays. Much more data is gathered and shared in real-time and new flexible assets reduce production and transportation times. All this relates to blue-collar processes in operations as well as white collar processes such as planning. For example, new planning tools using supplier's data integrated via cloud platforms can enable much faster decision making and reduce time lags.

Furthermore, technologies can be exploited to increase employees' *engagement*. Analytics solutions for example enable employees to spend less time on data cleaning and crunching, and more time on problem-solving activities. Tacit knowledge and data gathered in blue-collar contexts can be captured and leveraged for process improvement. One commonly cited application are robots in manufacturing that will further reduce simple, repetitive tasks (e.g. loading parts in/out of machines) and enable employees to leverage their experience towards improving the process – as opposed to simply operating it.

Flexibility in time refers to the potential to both customize processes to fulfil customers' request as required and produce on demand. Additive manufacturing technologies enable firms to manufacture goods without the need to first create tools and without the need to achieve certain batch sizes. Likewise, real-time rescheduling of delivery trucks enables firms to respond to urgent customer request and change priorities. Similarly, *flexibility in space* exploits technologies to design and manage the assets properly and to enable a more responsive system. Here goods

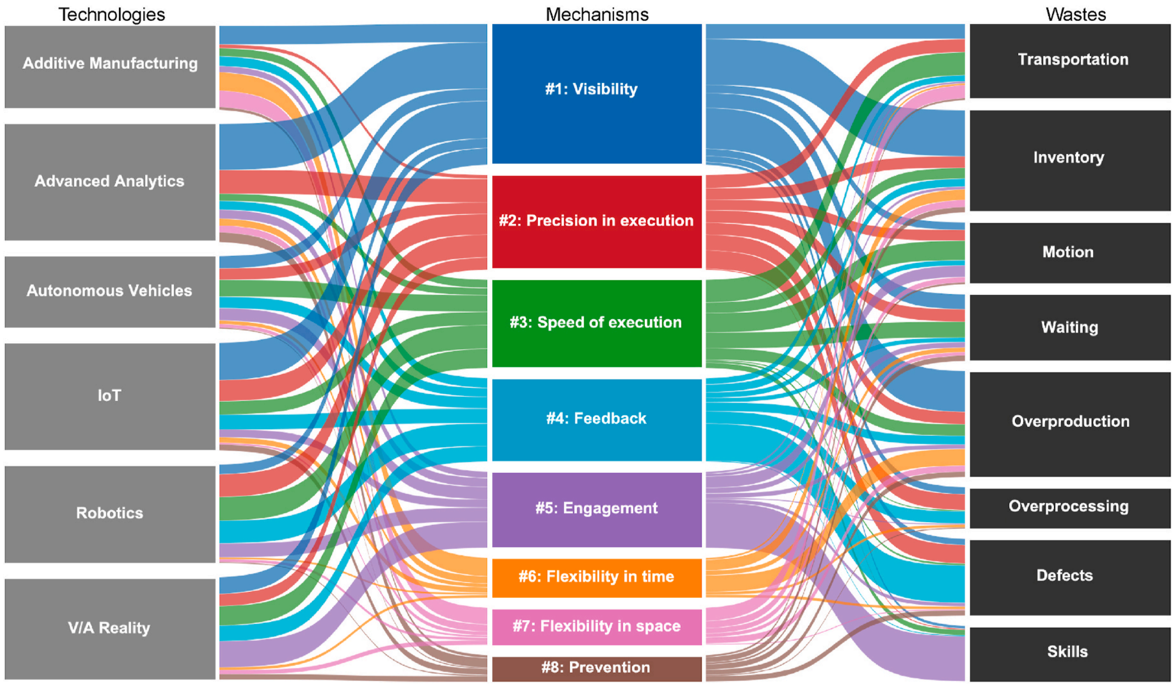

Fig. 2. Sankey chart of the linkages between technologies, mechanisms and wastes.

can be moved without much effort to avoid movement of workers (e.g. due to Kiva robots in Amazon warehouses) or movement of goods can be minimized (e.g. due to local 3D printing).

Finally, *prevention* exploits technologies to anticipate the need for intervention and to avoid them. Preventive maintenance enabled by sensors and analytics ensure that the production equipment can be repaired before a critical failure occurs. Augmented reality solutions for operators provide guidance on how to execute processes even if the SOP documentation is only available far from the workspace. Likewise, new exoskeletons use in car manufacturing or warehouses support the ergonomics of workers and reduced fatigues and injuries.

It is worth noting that the digital improvement mechanisms above closely relate to the existing literature on process improvement within manufacturing and the wider supply chain, confirming the broad theoretical concepts of lead-time reduction, the reduction of undesired variation, as well as the benefits of increased flexibility and visibility of the process (Holweg et al., 2018). Digital technologies, for example, reduce the lead-time for the production processes as well as the lead-time of data or feedback to be received by the process controller, thus greatly enhancing the quality and speed of any corrective action. Equally, being able to receive more timely and better data reduces undesired variation, which in turn again improves the ability to plan and adjust the process, as needed. The improvements in flexibility that are enabled by digital technologies follow the same volume, mix and product categories identified by Slack (1987).

Thus we argue that digital technologies do not provide any *new* improvement mechanisms *in their own rights*, yet in effect do present an *augmentation* and *new combination* of existing theoretical concepts that are well documented within the operations and supply chain management literatures. In theoretical terms, this is probably the most important finding, as it clearly allows for an explanation of these new technologies in terms of the existing operations management theory.

4.3. Relative importance of mechanisms

In order to identify the most promising avenues how digital technologies can support operations, we can show the technology-mechanism-waste connections as a Pareto chart, see Fig. 3. Out of the total 594 individual response items in our data, 214 links are mentioned (out of a theoretically possible pool of 384). While it does not fall into a classic 80/20, there are clearly linkages that are perceived more important than other. Specifically, the first 20 % of links represent 49 % of all responses. The top ten represent 18 % of the overall responses, while 50 % of links represent 79 % of all mentions.

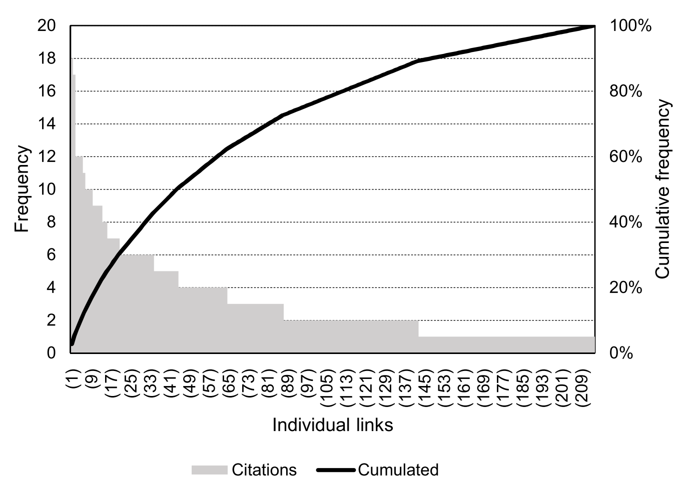

Fig. 3. Pareto analysis of individual technology-mechanism-waste links.

Within these, the ten most important technology-mechanism-waste combinations are as shown in Table 3. What is striking here, again, is the general importance of data as enabler of improvements. Specifically, it is the availability of better and more timely data, as well as the ability to use that data via advanced analytics to improve operational outcomes, which in turn reduces one or several wastes in manufacturing.

These findings are of direct managerial relevance, as the linkages identified in Table 3 represent those that are being perceived as most promising. In other words, these links are most likely to yield a positive return on the investment in digital technologies. They can act as guidance to firms considering the implementation of digital technologies, in order to maximise their likelihood of achieving a positive impact on the performance of their manufacturing operations.

5. Conclusion

First and foremost, our findings confirm the widely accepted notion that digital technologies represent a major opportunity to improve existing products and processes. As their rate of adoption is set to increase, understanding the mechanisms how they actually augment operational execution will become more important. In the following we set out our contributions to theory, managerial implications, and suggestions for further research.

5.1. Theoretical contributions

Our main contribution to the debate on the adoption of digital technologies is to provide insights into the actual mechanisms how digital technologies can support process improvement. Our findings thus directly contribute to the nascent debate how the Lean and Industry 4.0 concepts interact, and how their combination leads to actual performance improvements (Buer et al., 2018; Frank et al., 2019; Gillani et al., 2020; Shahin et al., 2020; Tortorella et al., 2021b). A deeper understanding of the actual mechanisms will allow future research to elucidate clear strategies which configurations are most appropriate in a given context. This, in turn, will elevate the existing debate from a generalist view that digital technologies will improve (which is the consensus view), to a more differentiated discourse as to which technologies are most likely to have the greatest impact on performance in a given context. To this effect we identify eight 'digital waste reduction mechanisms', which represent distinct modes how digital technologies impact on process improvement. We propose that digital technologies will generally work by either enhancing operational execution, or by improving operational decision-making. The former includes increased precision and speed in execution, as well as improved flexibility in time and space. The latter includes enhanced visibility, feedback, engagement and prevention. While we cannot claim exclusivity, our findings do provide us with some degree of confidence that these two clusters are central to understanding the performance improvements related to digital technology adoption.

In this context it is interesting to note that the mechanisms we have identified here closely match those previously established in the operations management literature. A reduction in uncertainty (i.e. 'improved visibility') has been highlighted as a general mechanism previously, in the same way as reductions in lead-time (i.e. 'speed of execution') and variation (i.e. 'precision of execution') (Schmenner and Swink, 1998; Holweg et al., 2018). The impact of digital technologies, in this context, can thus be explained as a general means of enhancing operational capabilities at *process* level. This bring about an interesting connotation (and one that extends beyond the remits of this paper), namely that one could posit that digital technologies have an equally positive impact on other process improvement methodologies like Six Sigma, the Theory of Constraints, or even more general approaches like Business Process Reengineering.

5.2. Managerial implications

Our findings have further implications for practice. As firms seek to harness the potential of digital technologies in their improvement efforts, we can support the view that there is synergy by merging within a wider 'Lean 4.0' strategy (Chiarini et al., 2020; Núñez-Merino et al., 2020; Tortorella et al., 2021a). Yet beyond this general insight, our findings provide more specific guidance which technology can support a given desired improvement outcome. Firms seeking to adopt such approach should be aware that each digital technology serves a bespoke set of mechanisms. In this sense, any digital transformation should start by considering which is the objective a company is willing to achieve, rather than what is technically feasible. By firstly defining the lean wastes companies are trying to tackle, going through the digital waste reduction mechanisms, they can clearly understand which technology is most suited to support their objective. Aligning their desired improvement goals with the mechanisms that each technology enables will result in the greatest success. As Toyota would also argue, simply investing in any technology, without a clear understanding of how it will support lean efforts, bears the danger of being a waste in its own right. Even though the practitioner literature generally may suggest as much, it is clear that Industry 4.0 technologies are clearly a means to an end, not an end in itself.

5.3. Limitations and future research

Our study contributes to a nascent yet important debate in the operations management literature. As the Industry 4.0 applications in practice will become mainstream, the ability to study these will improve drastically. At this early point in the wider digital transformation of manufacturing operation, our qualitative study provides important insights – these, however, should be considered within the limitations of our study. First and foremost, we limit our study to the improvement achieved by reducing wastes in existing processes. We consciously disregarded all the mechanisms (15 % of responses) that were out of this scope, as for example how the Internet of Things may be vehicle for the creation of new business models or how Additive Manufacturing may enable the creation of new products. A second limitation of our study is related to how we quantify importance of 'digital waste reduction mechanisms'. Indeed, we measured it by considering their relative frequencies, that is, in terms of how many times they were mentioned by experts during our focus groups. It will be important to also assess the actual value of mechanisms within the context of actual implementations. It is conceivable, for example, that a mechanism mentioned only once yet has a greater impact on waste reduction than mechanisms mentioned more frequently. Finally, we had to limit ourselves to technologies that could already be well evaluated by available experts. For this reason we excluded the potentially relevant technology blockchain.

Two important areas for future research emerge: first, our analysis is based on perception of our focus group participants. As digital technology implementations mature, and move from pilot projects to mainstream applications, our findings need to be confirmed empirically by studying actual implementations. Second, the role of skills, and the potential de-skilling and impediments to process improvement related to digital technologies need to be analysed further. While the impact of digital technologies on skills was vividly debated within the focus groups, it was very interesting to note that much of that discussion centred around the skills needed for a given task. The common perception was that digital technologies, like augmented reality, not only prevent mistakes (for example via poka-yoke), but also lower the skills needed for executing a given task. In other words, digital technologies *lower* the skill level needed for task execution, and in turn, may lead to more task automation in the future. However, the notion of *wasted* or *unused* human skills was very difficult to grasp for participants, and only on one occasion did the discussion refer to the potential issue that digital technologies – by simplifying the task at hand – may be detrimental to process improvement. By adding a digital technology one can potentially add a barrier that reduces engagement with the process, and in turn, hinders worker engagement with process improvement. In this context, it is important to better understand the general role that technology might play in this context (Neumann et al., 2021). Using technology to substitute for skills, for example via poka-yoke devices implemented via augmented reality, could also create barriers for workers to act freely, to be empowered, within the process. As such it has two opposing effects: one the one hand it immediately reduces defects by preventing errors, but in the long run may also hinder improvement activities by reducing empowerment (i.e. the scope to act). This area of tension is an important area for future research in our view, and highlights the general point that a much more differentiated understanding of the role of digital technologies in operations and supply chain management is needed.

Appendices.

Appendix A. Sources used in the review of the 'grey' literature

Table 4
Overview of 'grey' literature considered in the review

ID	Title	Year	Author	Company
1	Time to accelerate in the race toward Industry 4.0	2016	M. Russmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, A. Bause	The Boston Consulting Group
2	Industry 4.0: The Capgemini Consulting View	2014	J. Bechtold, C. Lauenstein, A. Kern, L. Bernhofer	Capgemini
3	Industry 4.0: challenges and solutions for the digital transformation and use of exponential technologies	2015	D. Schlaepter, M. Koch, P. Mzerkofer	Deloitte
4	Industry 4.0: The future of productivity and Growth in Manufacturing Industries	2015	M. Russmann, M. Lorenz, P. Gerbert, M. Waldner, J. Justus, P. Engel, M. Harnisch	The Boston Consulting Group
5	Industry 4.0: How to navigate digitalization of the manufacturing sector	2015	D. Wee, R. Kelly, J. Cattell, M. Breunig	McKinsey
6	Industry 4.0: Digitalization for productivity and growth	2015	R. Davies	European Parliament
7	Industry 4.0: Building the digital enterprise	2016	R. Geissbauer, J. Vedso, S. Schrauf	PwC
8	Crafting the future: a roadmap for industry 4.0 in Mexico	2015	M. Rios, O. Correa, E. Acuna, A. Gonzalez	Mexican Ministry of Economy
9	Information economy report	2017	A. Guterres, M. Kituyi	United Nations Conference on Trade and Development
10	Redefine your company based on the company you keep	2018	P. Daugherty	Accenture
11	Shaping the Future of Construction: Breakthrough in Mindset and Technology	2018	World Economic Forum and The Boston Consulting Group	World Economic Forum and The Boston Consulting Group
12	Industry 4.0 and Smart manufacturing market report 2018–2023	2018	M. Wopata, J. Rickert, K. Lueth, P. Scully	IoT Analytics
13	Planning for the warehouse of the future	2018	M. Veenman, U. Tagscherer, E. Schärtl, A. Herold	Swisslog
14	The post-digital era is upon us: are you ready for what's next?	2019	P. Daugherty, M. Carrel-Billiard	Accenture
15	Top 50 emerging technologies: growth opportunities of strategic imperative	2016	R. Kumar, L. O'Connor, A. S, A. Shukla	Frost & Sullivan
16	Emerging technologies: changing how we live, work and play	2019	M. Makhija	Ernst & Young
17	Industry 4.0 for the future of manufacturing in the EU	2016	M. Tiraboschi	European Commission
18	A reality check for today's C-suite on industry 4.0	2018	P. Harris, M. Hendricks, E. Logan, P. Juras	KPMG
19	Industry 4.0 – opportunities and challenges for SMEs in the North Sea Region	2018	Interreg North Sea Region	Interreg North Sea Region
20	HFS Blueprint guide: Industry 4.0 services	2017	P. Jain, T. Mondal	Accenture
21	Industry 4.0: engaging with disruption	2018	Ernst & Young - India	Ernst & Young
22	Industry 4.0: Go fourth insights into the next industrial revolution	2018	D. Peters	Irwin Mitchell
23	Industry 4.0 and ICS sector report	2018	European Cyber Security Organisation	European Cyber Security Organisation
24	Industry 4.0: India Inc. gearing up for change	2018	AIMA and KPMG	AIMA and KPMG
25	Industry 4.0: The new industrial revolution. How Europe will succeed	2014	M. Blanchet, T. Rinn, G. Von Thaden, G. De Thieulloy	Roland Berger
26	India's Readiness for Industry 4.0 – A focus on automotive sector	2017	C. Swarnima, P. Mehra, A. Daso	Grant Thornton
27	Industry X.0: Combine and Conquer - Unlocking the power of digital	2017	D. Abood, A. Qilligan, R. Narsalay	Accenture
28	The 2018 World Manufacturing Forum Report: Recommendations for the Future of Manufacturing	2018	World Manufacturing Forum	World Manufacturing Forum
29	Industry 4.0: Making your business more competitive	2017	Senior experts at CGI	CGI Group Inc.
30	Man and Machine in Industry 4.0	2015	M.Lorenz, M. Rubmann, R.Stack, K. L. Lueth, M. Bolle	The Boston Consulting Group
31	Industry 4.0: opportunities behind the challenge	2017	M. Stankovic, R. Gupta, J. E. Figueroa	United Nations Industrial Development Organization
32	National Policy on Industry 4.0	2018	Ministry of International Trade and Industry	Ministry of International Trade and Industry
33	Readiness for the Future of Production Report 2018	2018	World Economic Forum	World Economic Forum
34	Accelerating clean energy through Industry 4.0	2017	United Nations Industrial Development	United Nations Industrial Development Organization
35	SAP Leonardo Digital manufacturing	2017	J. Tulusan, P. Hidvegi	SAP Leonardo
36	Unlocking Industry 4.0 Potential	2018	Deloitte	Deloitte
37	Industry 4.0 as an evolution, not a revolution	2019	N. Enose, S. Ramachandran	Infosys
38	2019 Manufacturing: Trends Report	2018	Microsoft	Microsoft

Table 5
Frequency of technologies mentioned in the 'grey' literature reviewed

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	Total
Advanced Analytics		X	X	X	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		**35**
Digital Manufacturing	X	X	X	X	X	X	X	X	X		X	X	X		X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	**34**
Internet of Things	X	X	X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	X		X	X	X	X	X		X	X	X	X	X	X	X	X	X	X	X	**35**
Robotics	X	X	X	X	X	X		X	X		X	X	X		X	X	X	X	X	X	X	X	X	X	X	X	X		X	X		X	X			X		X	**28**
V/A reality	X		X	X	X	X	X			X	X	X		X	X	X		X	X	X		X	X	X		X	X			X	X	X	X	X				X	**26**
Cybersecurity				X			X			X				X	X		X	X	X	X				X	X	X						X				X			**14**
Autonomous Vehicles	X		X	X							X	X	X						X			X			X	X	X			X		X							**12**
Block chain										X				X		X					X						X				X		X	X	X				**9**
Horizontal & Vertical System Integration				X				X											X							X				X		X				X			**7**
Mobile Device					X		X				X																X		X										**5**
Smart Sensors						X	X				X														X														**4**
Biotechnology & Nanotechnology			X														X																X						**3**
Smart Materials																	X								X								X						**3**
Predictive Maintenance	X																													X						X			**3**
Process Automation																X	X				X																		**3**
Social Business Media	X																											X											**2**
Geoengineering			X																														X						**2**
Neurotechnology			X																														X						**2**
Energy Storage					X																										X								**2**
Quantum Computing														X																			X						**2**
Advanced Materials																																X						X	**2**
Digital Twins																																					X	X	**2**

Appendix B. Focus group overview and participant profiles

Table 6
Focus groups participants demographic

NUMBER OF PARTICIPANTS			
Blinded for peer review		*Blinded for peer review*	Total
Advanced Analytics	6	6	12
Autonomous vehicles	7	5	12
Additive manufacturing	10	6	16
IoT	5	7	12
Robotics	6	5	11
V/A Reality	6	6	12
PARTICIPANTS PROFILE			
Expert	*Role*	*Years of experience*	*Sector*
1	Head of technical department	6	Metal products
2	Consultant	37	Consultancy
3	Process Manager	na	Metal products
4	Consultant	3	Academia
5	Consultant	4	Academia
6	na	na	
7	na	na	
8	Head of sales	8	Automotive
9	Senior Partner	30	Consultancy
10	Project manager	7	Logistics and supply chain
11	Project manager	8	IT
12	Consultant	13	Consultancy
13	Process Manager	6	Household appliance industry
14	Sales manager	10	Logistics and supply chain
15	Consultant	13	Consultancy
16	Lawer	6	Consultancy
17	Operations Manager	4	Logistics and supply chain
18	Procurement manager	15	Aerospace
19	Supply chain manager	15	Chemical
20	Consultant	3	Academia
21	Production manager	20	Chemical
22	Process engineer	5	Automotive
23	Logistics Manager	19	Food and beverage
24	Consultant	29	Consultancy
25	Process Engineer	4	Automotive
26	Head of manufacturing	21	Automotive
27	After Sales Manager	35	Machinery
28	Process Manager	19	Food and beverage
29	Process manager	16	Logistics and supply chain
30	Operations Manager	20	Machinery
31	Logistics Expert	17	Food and beverage
32	na	33	na
33	Consultant	2	Academia
34	na	na	na
35	na	na	na
36	na	na	na
37	Supply Chain Manager	8	Logistics and supply chain
38	na	na	na
39	Process Manager	7	Logistics and supply chain
40	Account Manager	16	Logistics and supply chain
41	Manager	18	PR organization
42	Project manager	15	Logistics and supply chain
43			
44	Sales Manager	8	Logistics and supply chain
45	Consultant	8	Logistics and supply chain
46	Consultant	3	Academia
47	Head of logisitcs	20	na
48	Consultant	25	Consultancy

Appendix C. Focus group items

Table 7
Focus group items

INDIVIDUAL TASKS	
1	Which are the three mechanisms most impacting on transportation?
2	Which is the overall impact on transportation? (No impact; Low impact; Average impact; Good impact; High impact)
3	Which are the three mechanisms most impacting on excess of inventory?
4	Which is the overall impact on excess of inventory? (No impact; Low impact; Average impact; Good impact; High impact)
5	Which are the three mechanisms most impacting on motion?

(*continued on next page*)

Table 7 (*continued*)

INDIVIDUAL TASKS	
6	Which is the overall impact on motion? (No impact; Low impact; Average impact; Good impact; High impact)
7	Which are the three mechanisms most impacting on waiting?
8	Which is the overall impact on waiting? (No impact; Low impact; Average impact; Good impact; High impact)
9	Which are the three mechanisms most impacting on overprocessing?
10	Which is the overall impact on overprocessing? (No impact; Low impact; Average impact; Good impact; High impact)
11	Which are the three mechanisms most impacting on overproduction?
12	Which is the overall impact on overproduction? (No impact; Low impact; Average impact; Good impact; High impact)
13	Which are the three mechanisms most impacting on defects?
14	Which is the overall impact on defects? (No impact; Low impact; Average impact; Good impact; High impact)
15	Which are the three mechanisms most impacting on skills?
16	Which is the overall impact on skills? (No impact; Low impact; Average impact; Good impact; High impact)
17	Which will be the overall role of *Technology under discussion* on Lean 4.0? (No importance; Low importance; Average importance; Good importance; High importance)

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