Synchronization of material flows in mass-customised production systems: a literature-based classification framework and industrial application

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The mass customisation strategy is needed by manufacturing companies to face the increasing variety and unpredictability of products required by customers. However, mass customisation may increase the complexity of managing manufacturing and production logistics activities, for example due to reduced product batch sizes. The synchronization of material flows within the factory is emerging as a way to address this complexity, as it enables an effective and efficient implementation of mass customisation. Indeed, the fourth Industrial Revolution introduces new digital levers, which can be combined with traditional managerial levers to achieve the synchronization of material flows within the factory. This study contributes to the rising stream of research on this topic. A systematic literature review was conducted, leading to the development of a classification framework of the levers supporting the synchronization of material flows. The identified managerial levers are: storage of materials, feeding policy, and scheduling. The digital levers are: materials tracking, process tracking, data analytics, and assistance systems. The developed framework was operationalised in four industrial cases and applied as a tool to map their levers related to the synchronization of material flows.

Keywords**:** Mass customisation; Production logistics; Cyber-Physical Production System; Synchronization.

1. Introduction

Nowadays, manufacturing companies are challenged with increasing variety and unpredictability of products required by customers, while seeking to keep high efficiency and short lead-times (Fatorakian and Kazemi 2018; Shukla, Todorov, and Kapletia 2018; Li and Huang 2021). To this end, mass customisation has emerged. It is a strategy that entails offering a wide product variety at competitive prices and within short lead times, combining products personalisation with the efficiency of mass production (Dörmer et al. 2015, Tu, Lim, and Yang 2018b; Suzic and Forza 2021).

Although beneficial from a sales perspective, mass customisation increases the complexity of managing operations within the factory (Emde and Schneider 2018; Zhang et al. 2018). Along all the stages of the product life cycle, this complexity generates unwanted effects such as more challenging product development and procurement of materials, poor economies of scale, and increased lead times in production, leading to unwanted costs of inventories, setup and changeovers, materials, operations, product quality, and customer service (Ripperda and Krause 2017; Nilsson et al. 2022; Gonnermann et al. 2022). As reported in empirical studies, the complexity due to mass customisation is particularly challenging for the manufacturing and production logistics activities performed within a factory. Manufacturing activities should successfully process increasingly smaller product batches and be ready to take immediate actions to resolve any event that might disrupt production or affect the service level to the customer (Tu, Lim, and Yang 2018b; Li 2018; Kusiak 2018; Guo et al. 2022). Production logistics should handle materials in small quantities and deliver a broad range of items to workers and machines in a timely manner (Faccio et al. 2018; Jiang et al. 2020; Adenipekun, Limère, and Schmid 2022).

Achieving the synchronization of material flows within the factory can help dealing with this complexity. In this context, synchronization is defined as the provision of the right materials to the subsequent production steps at the right moment in time or, more in general, as the coupling of work systems that are linked by material flows (Miller and Davis 1989; Chankov, Hütt, and Bendul 2016; Kong et al. 2020). While traditionally synchronization has been considered as a high-cost solution, the rapid diffusion of digital technologies in factories, due to the fourth Industrial Revolution, introduces new “digital” levers, which can be efficiently combined with traditional “managerial” levers to achieve the synchronization of material flows within the factory (D. Guo, Li et al. 2021, Li et al. 2022). To the extreme, several authors expect that factories will turn into Cyber-Physical Production Systems (CPPSs): networks of intelligent materials, machines, operators, and material handling equipment capable to analyse and exchange data gathered in real-time directly on field and take autonomous decisions (e.g., Fatorakian and Kazemi 2018; Mörth et al. 2020). In CPPSs, manufacturing and production logistics resources exploit real-time information about the status of processes, equipment, and materials, combined with updated customer requirements, to dynamically plan and control factory operations, always knowing when, where, and in what way to deliver materials and products of the right quality (Hofmann and Rüsch 2017; Tao and Qi 2019; Li and Huang 2021).

Although the research on the synchronization of material flows is still in its infancy (Jiang et al. 2020), the recent growth of contributions on "synchronization" in manufacturing within the scientific literature, as verified on widely used search databases, clearly shows the increasing interest in this topic. However, despite the surge in their number, published research works often focus on specific industrial settings (Guo et al. 2022), addressing specific managerial levers (e.g., Boysen et al. 2015; Guo et al. 2020) or digital levers (e.g., Hofmann and Rüsch 2017; Tao and Qi 2019; Li and Huang 2021) related to the synchronization of material flows. Instead, a comprehensive classification of the levers is still missing. This study addresses this gap by developing a classification framework of the managerial and digital levers supporting the synchronization of material flows within the factory. The framework, developed based on a systematic literature review, is then operationalized in four industrial cases. The aim is twofold. First, to consolidate the available knowledge on synchronization by collecting the fragmented contributions found in literature, thus introducing a framework for structuring further research on the topic. Second, to provide practitioners with a tool to comprehensively map the managerial and digital levers related to the synchronization which are – or might be – adopted within their factories.

The remainder of the paper is structured as follows. Section 2 presents the adopted methodology. Section 3 reports the results of the literature review and presents the developed framework. Section 4 describes the application of the framework to the industrial cases. Finally, Section 5 concludes and outlines directions for future research.

2. Research methodology

The research presented in this paper was conducted in two main steps. First, a systematic literature review was carried out to consolidate the knowledge on the synchronization of material flows and develop a classification framework of the levers related to the synchronization. Then, the framework was applied to four industrial cases, to illustrate its application as a tool to map the adoption of the identified levers within the factory. This methodology is deemed suitable because it allows developing and better contextualizing the available knowledge on a topic, such as the synchronization of material flows, on which literature is incomplete (Locke and Golden-Biddle 1997) and theory is not consolidated yet (Ketokivi and Choi 2014; Durach et al. 2021).

As discussed in Section 1, the extant literature features multiple fragmented examples addressing only one or few managerial and digital levers related to the synchronization, often referring to specific cases. Therefore, the review carried out in this research was aimed at the identification and classification of an exhaustive set of levers. Considering the peculiarities of the operations and supply chain management fields compared to other domains, the literature search followed the guidelines provided by Durach et al. (2017), as well as by recent studies featuring systematic literature reviews (Kembro et al. 2018; Schmid and Limère 2019; Prataviera et al. 2020). The literature search process adopted in this research is depicted in Figure 1.

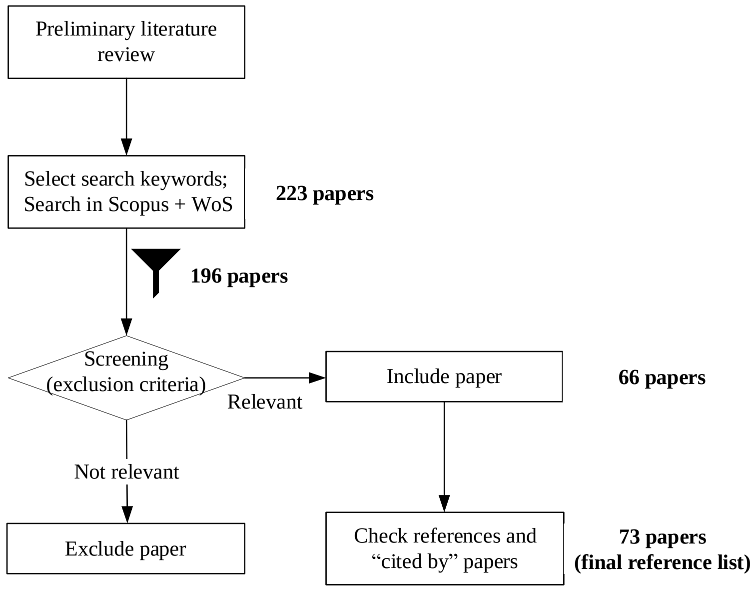

Figure 1. Literature search process (adapted from Schmid and Limère 2019)

A preliminary literature review was conducted to define the research boundaries and objectives and to set the criteria used to identify relevant literature through the systematic search. As a result, the systematic search scope included papers addressing the synchronization of material flows within the factory, encompassing both manufacturing and production logistics systems. Specifically, it focused on digital levers, based on the CPPS paradigm, and on managerial levers, intended as policies and rules governing factory operations. Therefore, the adopted search string is the following:

(factory OR production OR assembly OR "shop floor") AND (logistics OR "material handling" OR "part feeding" OR "line feeding") AND ((“cyber-physical system” AND manufacturing) OR ((policy OR rule OR decision) AND (synchronization OR "mass customi")))*

In the string, the first two groups of keywords account for the possible names used in literature to indicate the manufacturing system (e.g., production or shop floor) and the production logistics system (e.g., material handling or part feeding), respectively. The final broad group of keywords refers to the managerial and digital domains. The addition of *AND ("mass customi*" OR synchronization)* is intended to include only contributions whose focus is linked to the scope of this research.

The indicated keywords were searched in articles titles, abstracts, and keywords in Scopus and Web of Science (WoS), which are the two most used databases in this field (Prataviera et al. 2020; Mark, Rauch, and Matt 2021), looking for journal and conference papers. The initial search led to 223 papers, not including duplicate records found in both databases. This initial sample was screened to exclude search results that are not relevant for this study since they correspond to either trade journal articles, conference reviews, or documents not written in English, leading to a body of literature of 196 articles. Then, exclusion criteria were applied to remove contributions which are out of the scope of this study since they either take a supply chain perspective without a focus on the factory, they deal with warehouse management without considering the impact on the manufacturing system, or they focus on completely different domains (e.g., demand management or product design). These exclusion criteria were applied during a title and abstract screening performed by two of the authors, complemented, when needed, by a full text screening. In this way, a reference list made of 66 papers was obtained. Finally, each article in this reference list was examined and any potentially relevant references it cited were added to the body of literature to undergo the described filtering and screening process. The same was done for recent articles citing the contributions in the reference list, identified through Scopus and WoS databases. At the end of this process, a final reference list including 73 papers was considered for an in-depth investigation.

Starting from the results of the literature search, a classification framework of the levers related to the synchronization of material flows was developed, following previous works in different research fields which proposed analogous frameworks (Meyer, Främling, and Holmström 2009; Galaske et al. 2017; Modica et al. 2021). First, for each paper in the final reference list, both primary data and information on its content were collected in a database and analysed, focusing on discussions about manufacturing and production logistics activities and looking for elements related to the synchronization of material flows from a managerial or digital perspective. During the analysis, functional similarities were found among groups of digital tools or managerial policies proposed in different papers. The elements with functional similarities were clustered together in the database, obtaining seven categories of levers related to the synchronization, which were named and described. Moreover, for each category, alternative configurations were found in the reviewed literature, differing from each other for one or more features and, ultimately, for their effects on the synchronization of material flows. The configurations were included in the analysis due to the additional aim of this study to provide companies with a tool to map their level of implementation of the levers related to the synchronization. Therefore, each configuration was associated to an implementation level of the corresponding lever, where a higher implementation level indicates a better ability to support the synchronization.

In the second step, the developed framework was applied to four industrial cases. The cases were conducted in companies which, in the last three years, implemented projects to improve the synchronization of material flows in order to face the increasing complexity in manufacturing and production logistics activities within a mass customisation context. In each company, several stakeholders were involved, including plant managers, internal logistics managers, and IT experts.

When conducting the cases, the tool was first described and illustrated to the stakeholders, thus aligning terminology and interpretations. Then, the existing levers were mapped with a participatory approach: the configuration of each lever was initially mapped by the authors, based on on-site visits and open-ended interviews with the involved stakeholders, and then validated by the stakeholders.

3 Results of the literature review

The relevance of synchronization lies in enhancing the efficiency and due date performance of manufacturing and logistics systems (Chen et al. 2015; Chen et al. 2019; Luo, Yang, and Wang 2019). Its effects encompass shorter throughput times and a lower amount of inventories within the factory (Miller and Davis 1989; Hoque and Kingsman 2006; Chen et al. 2019; Guo et al. 2020). Therefore, synchronization can be measured through waiting times (Luo et al. 2017; D. Guo, Li et al. 2021; Li and Huang 2021; Guo et al. 2022). Taking a factory physics perspective (Hopp and Spearman 2011), two types of waiting times are relevant for this purpose: the ones resulting from workstations that are idle, since they are waiting for materials, tools, or information needed to start or resume their operations; and the ones resulting from materials, such as parts and work-in-process (WIP), which are stored on the shop floor waiting to be processed or assembled. These waiting times are directly linked to overall throughput times and inventory levels on the shop floor: lower waiting times indicate a better capability to deliver the right materials at the right moment in time, i.e., a better synchronization of material flows.

The reviewed literature addresses the synchronization of material flows both from a managerial and digital perspective.

In the managerial domain, a stream of research is focused on the configuration of the production logistics system replenishing workstations with materials. Different options are proposed for the number and location of logistics areas within the factory, where materials are stored and unit loads are prepared before being moved to production stations (e.g., Battini et al. 2009; Boysen et al. 2015). Moreover, some papers address feeding policies, intended as set of rules regulating the supply of materials to workstations. Several policies are presented, differing from each other for the size, content, and ensuing delivery frequency of the unit loads, and analytical models are introduced to select feeding policies solving the trade-off between the material handling effort for unit loads preparation and the resulting efficiency of production activities (e.g., Battini et al. 2009; Schmid and Limère 2019). Part of the reviewed literature also focuses on the joint optimisation of different decisions and systems within the factory (e.g., Luo et al. 2017;Li and Huang 2021). For instance, Luo et al. (2017) introduce an optimisation model for the joint scheduling of internal transportation, production, and warehousing activities, with an objective function consisting of the weighted sum of production and logistics efficiency measures as well as customer service priority measures.

In the digital domain, a broad research stream is focused on the acquisition, elaboration, and sharing of data concerning the progress of production activities, the jobs status, inventory levels, and/or the locations of materials and assets within the factory, thus leading to increased data-driven decision-making practice. Data acquisition can be enabled by different technologies, such as barcode scanning terminals (Merkel et al. 2018; Vachálek et al. 2021), RFID tags and readers (e.g., Yan, Zhang, and Fu 2019; Guo et al. 2022), or sensors and other Internet of Things (IoT) devices (e.g., Müller et al. 2018; Tu, Lim, and Yang 2018b). Regardless of the used technology, the collected data is aggregated and combined, possibly creating digital twins of the physical assets and processes (Frankò, Vida, and Varga 2020; Glatt et al. 2021). Hence, up-to-date and relevant information is made available to managers and planners and can be exploited to take prompt and informed decisions (e.g., Dai et al. 2012; Mörth et al. 2020). The collected data can also be further elaborated, either by centralised software systems or thanks to data analytics capabilities integrated within individual assets (e.g., Mörth et al. 2020), thus producing additional relevant information for decision-making. Data elaboration often relies on machine learning (Yan, Zhang, and Fu 2019; Flores-García, Jeong, and Wiktorsson 2021) and big data analysis techniques (Seitz and Nyhuis 2015) or on simulations, used to assess alternative future scenarios (Bányai 2021; Glatt et al. 2021; Vachálek et al. 2021). In some cases, this enables decentralised decision-making (e.g., Tu, Lim, and Yang 2018b). For instance, Blesing et al. (2017) describe a system in which each assembly station, interfaced with an IT system, autonomously decides whether reordering materials, based on the actual inventory level, and whether increasing the number of performed assembly tasks, thus compensating for possible delays of ensuing stations. To the extreme, Bayhan et al. (2020) propose a system in which the production sequence and the logistics activities schedules and routes are dynamically defined through negotiations among software agents, based on real-time information about customers' orders and systems states. Real-time information sharing and decentralisation of decisions can also be supported by different types of hardware devices. For instance, mobile and wearable devices, like smart glasses or smart gloves with optoelectronic scanners, can provide up-to-date information to operators who work on the shop floor and gather real-time feedback from them (Müller et al. 2018; Mark, Rauch, and Matt 2021; Guo et al. 2022). Also, manually-operated production stations and material handling vehicles can be equipped with Human-Machine Interfaces, such as tablets or displays, providing instructions to workers and information about orders and materials. In automated systems, the material handling equipment can consist of a fleet of automated guided vehicles or autonomous mobile robots that communicate with each other, with production machines, and with devices placed at the workstations or at the main intersections within the shop floor, continuously sharing information about ongoing tasks and production processes requirements, and possibly autonomously defining the schedules, routes, and order of precedence (Culler and Long 2016; Blesing et al. 2017; Zhang, Zhu, and Lv 2018). Finally, connected material handling robots can be used to form multi-product pallets starting from mono-product ones, based on requests coming from the assembly stations and thus ensuring that only the necessary amount of materials is sent to the shop floor (Bonini, Forni, and Mazzolini 2018).

3.1 A classification of the levers related to the synchronization

An overview of the results of the literature review, leading to a classification of the levers related to the synchronization of material flows, is provided in Figure 2.

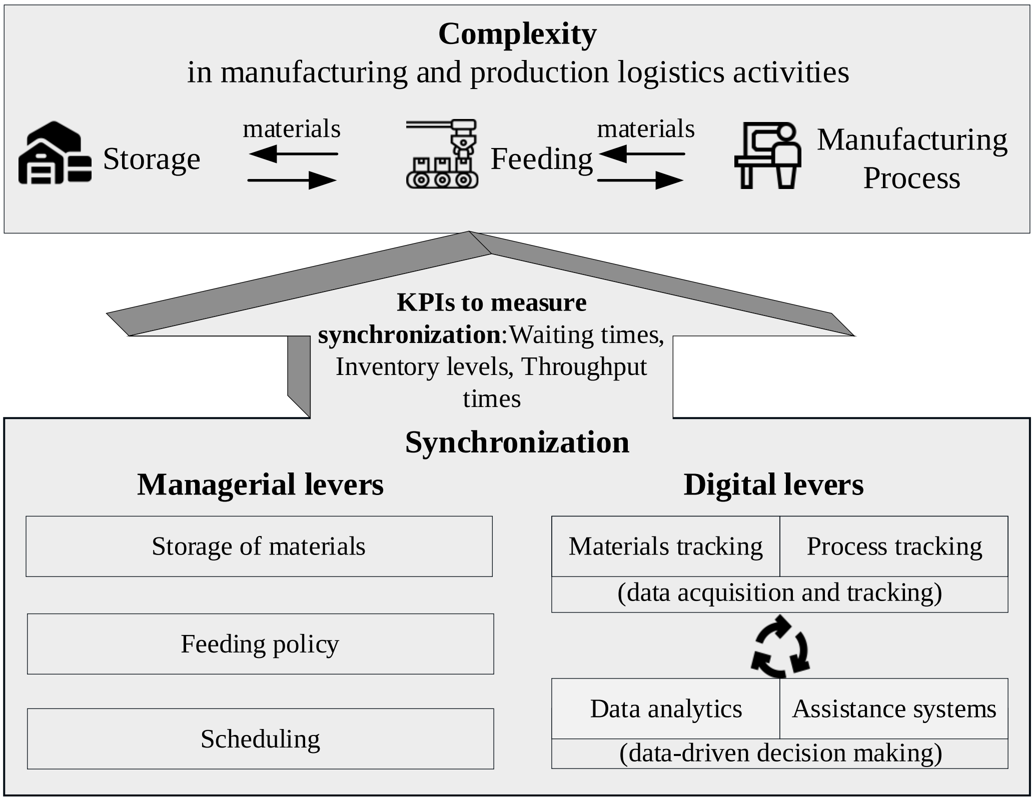

Figure 2. Synchronization to face the complexity of manufacturing and production logistics activities, related KPIs, and managerial and digital levers

To face the complexity in manufacturing and production logistics activities, the synchronization of material flows within the factory can be improved through managerial and digital levers; acting on these levers allows improving specific KPIs, such as waiting times, inventory levels, and throughput times. The literature review led to the identification of seven categories of managerial and digital levers that can be adopted in the factory to improve the synchronization of material flows, thus supporting the effective implementation of mass customisation. The managerial levers are three: (i) storage of materials, (ii) feeding policy, and (iii) scheduling. The digital levers are four: (i) materials tracking, (ii) process tracking (these refer to the acquisition of logistics and manufacturing data from the shop floor), (iii) data analytics and (iv) assistance systems (these refer to the data-driven decision making). Overall, the digital levers are more easily accessed today, due to the fourth Industrial Revolution, and can efficiently be used in combination with traditional managerial levers. Moreover, as shown in Figure 2, the digital levers influence each other (since, for example, there is no data analytics without data acquisition), but to the aim of this paper they are treated separately because each of them can individually contribute to improve the synchronization.

Table 1 indicates the relevant literature related to each lever, while a detailed description of the levers is reported in Section 3.2.

Table 1. Classification of the managerial and digital levers identified through the literature review

Type	Lever	References
Managerial	Feeding policy	Adenipekun, Limère, and Schmid 2020, 2022; Baller et al. 2020; Battini et al. 2009; Bayhan et al. 2020; Bonini, Forni, and Mazzolini 2018; Boysen and Emde 2014; Boysen et al. 2015; Cedillo-Campos et al. 2017; Hofmann and Rüsch 2017; Kilic and Durmusoglu 2015; Li and Huang 2021; Schuhmacher, Baumung, and Hummel 2017; Thoben, Wiesner, and Wuest 2017; Sali and Sahin 2016; Schmid and Limère 2019
	Storage of materials	Adenipekun, Limère, and Schmid 2020, 2022; Baller et al. 2020; Battini et al. 2009; Bayhan et al. 2020; Boysen and Emde 2014; Boysen et al. 2015; Cedillo-Campos et al. 2017; Guo et al. 2020; D. Guo, Li et al. 2021; D. Guo, Zhong et al. 2021; Kilic and Durmusoglu 2015; Luo et al. 2017; Matt 2009; Pan, Wu et al. 2021; Ruiz Zúñiga et al. 2021; Sali and Sahin 2016; Schmid and Limère 2019; Wang et al. 2021
	Scheduling	Aguirre, Méndez, and Castro 2014; Bányai 2021; Bayhan et al. 2020; Battini et al. 2009; Boysen and Emde 2014; Boysen et al. 2015; Cedillo-Campos et al. 2017; Dai et al. 2012; Groß, Gerke, and Plapper 2020; Guo et al. 2020; D. Guo, Li et al. 2021; D. Guo, Zhong et al. 2021; Guo et al. 2022; Hofmann and Rüsch 2017; Huang, Zhang, and Jiang 2008; Li and Huang 2021; Lin et al. 2020; Luo et al. 2017; Matt 2009; Müller et al. 2018; Schmid and Limère 2019; Tu, Lim, and Yang 2018b; Thoben, Wiesner, and Wuest 2017; Tu et al. 2009; Tu, Lim, and Yang 2018b; Vachálek et al. 2021; Zhang et al. 2018
Digital	Materials tracking	Bányai 2021; Bányai et al. 2019; Bayhan et al. 2020; Blesing et al. 2017; Bonini, Forni, and Mazzolini 2018; Cammardella et al. 2017; Cozmiuc and Petrisor 2018; Dai et al., 2012; Ferrer et al. 2018; Frankò, Vida, and Varga 2020; Gräßler and Pöhler 2018; Groß, Gerke, and Plapper 2020; Guo et al. 2020; D. Guo, Zhong et al. 2021; Guo et al. 2022; Hofmann and Rüsch 2017; Huang, Zhang, and Jiang 2008; Ivanov et al. 2021; Kalaiarasan et al. 2020; Li and Huang 2021; Luo et al. 2017; Mark, Rauch, and Matt 2021; Müller et al. 2018; Pan, Wu et al. 2021; Schiffer, Wiendahl, and Saretz 2019; Schuhmacher, Baumung, and Hummel 2017; Seitz and Nyhuis 2015; Thoben, Wiesner, and Wuest 2017; Tu, Lim, and Yang 2018°, 2018b; Tu et al. 2009; Yan, Zhang, and Fu 2019; Zhang et al. 2018; Zhou et al. 2020
	Process tracking	Bányai et al. 2019; Bayhan et al. 2020; Blesing et al. 2017; Culler and Long 2016; Dai et al., 2012; Di Pace et al. 2020; Dias and Toscano 2018; Figueiras et al. 2021; Flores-García, Jeong, and Wiktorsson 2021; Frankò, Vida, and Varga 2020; Glatt et al. 2021; Gräßler and Pöhler 2018; Groß, Gerke, and Plapper 2020; Guo et al. 2020; D. Guo, Li et al. 2021; D. Guo, Zhong et al. 2021; Guo et al. 2022; Z. Guo et al. 2021; Hofmann and Rüsch 2017; Huang, Zhang, and Jiang 2008; Ivanov et al. 2021; Jiang et al. 2020; Jiang et al. 2021; Kalaiarasan et al. 2020; Karabegović, Turmanidze, and Dašić 2020; Li and Huang 2021; Lin et al. 2020; Luo et al. 2017; Merkel et al. 2018; Mörth et al. 2020; Müller et al. 2018; Neal et al. 2019; Pan, Wu et al. 2021; Pan, Qu et al. 2021; Preuveneers and Ilie-Zudor 2017; Quadrini, Negri, and Fumagalli 2020; Schiffer, Wiendahl, and Saretz 2019; Schuhmacher, Baumung, and Hummel 2017; Seitz and Nyhuis 2015; Thoben, Wiesner, and Wuest 2017; Tu, Lim, and Yang 2018a, 2018b; Tu et al. 2009; Vachálek et al. 2021; Wang, Zhang, and Zhong 2020; Yan, Zhang, and Fu 2019; Zhang et al. 2018; Zhang, Zhu, and Lv 2018; Zhou et al. 2020
	Data analytics	Bányai 2021; Bányai et al. 2019; Bayhan et al. 2020; Blesing et al. 2017; Boccella et al. 2020; Bonini, Forni, and Mazzolini 2018; Cammardella et al. 2017; Cozmiuc and Petrisor 2018; Culler and Long 2016; Di Pace et al. 2020; Figueiras et al. 2021; Flores-García, Jeong, and Wiktorsson 2021; Glatt et al. 2021; Gonzalez, Zambrano, and Mondragon 2019; Gräßler and Pöhler 2018; Groß, Gerke, and Plapper 2020; D. Guo, Li et al. 2021; D. Guo, Zhong et al. 2021; Z. Guo et al. 2021; Hofmann and Rüsch 2017; Jiang et al. 2020; Jiang et al. 2021; Kalaiarasan et al. 2020; Karabegović, Turmanidze, and Dašić 2020; Li and Huang 2021; Lin et al. 2020; Luo et al. 2017; Müller et al. 2018; Neal et al. 2019; Pan, Wu et al. 2021; Pan, Qu et al. 2021; Schiffer, Wiendahl, and Saretz 2019; Schiffer, Wiendahl, and Saretz 2019; Schuhmacher, Baumung, and Hummel 2017; Thoben, Wiesner, and Wuest 2017; Tu, Lim, and Yang 2018b; Tu et al. 2009; Vachálek et al. 2021; Zhang et al. 2018; Zhang, Zhu, and Lv 2018
	Assistance systems	Blesing et al. 2017; Boccella et al. 2020; Di Pace et al. 2020; Guo et al. 2020; D. Guo, Li et al. 2021; Guo et al. 2022; Huang, Zhang, and Jiang 2008; Jiang et al. 2020; Li and Huang 2021; Lin et al. 2020; Luo et al. 2017; Mark, Rauch, and Matt 2021; Merkel et al. 2018; Müller et al. 2018; Schuhmacher, Baumung, and Hummel 2017; Seitz and Nyhuis 2015; Thoben, Wiesner, and Wuest 2017; Zhou et al. 2020

3.2 A framework to map managerial and digital levers related to the synchronization

As discussed in Section 2, the reviewed literature presents different possible configurations for each lever, which were identified and recorded in a database during the literature review process. The configurations differ among each other for one or more features and, ultimately, for their effects on the synchronization of material flows. Therefore, each configuration was associated to an implementation level of the corresponding lever, ranging from 0 to 3, where a higher implementation level indicates a better ability of the lever to support the synchronization. The results are summarized in the framework shown in Figure 3, while the following subsections provide a literature-based description of the levers and of their configurations.

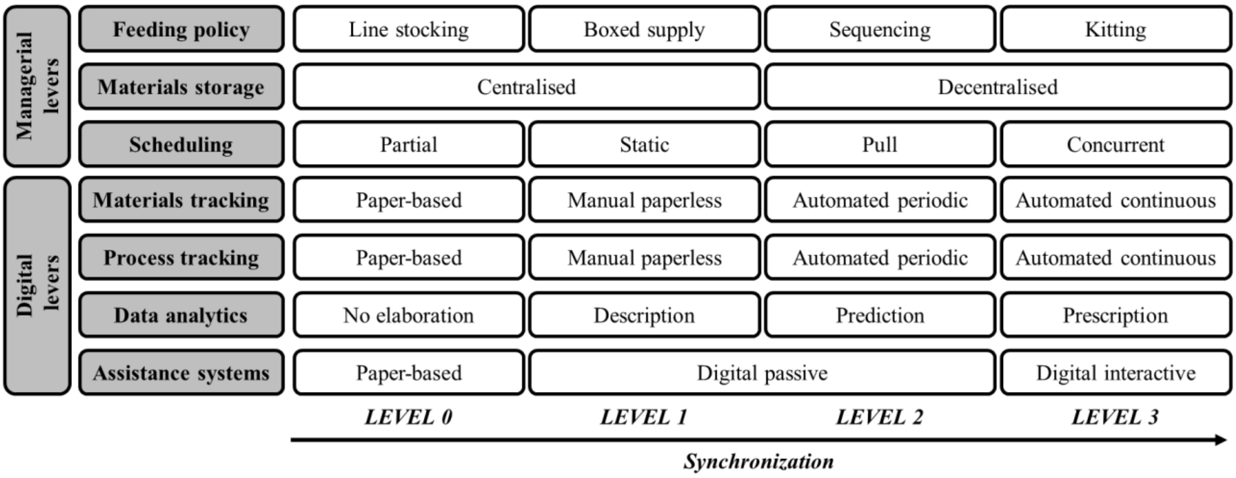

Figure 3. Implementation levels of the managerial and digital levers

3.2.1 Feeding policy

A feeding policy is the set of rules regulating the preparation and transportation of materials to the workstations (e.g., Kilic and Durmusoglu 2015). It significantly affects the amount of materials stored at the border of the workstations and waiting to be processed (e.g., Sali and Sahin 2016; Adenipekun, Limère, and Schmid 2022), which, as discussed in the introductory part of this Section 3, is one of the indicators measuring the synchronization of material flows. In this sense, the selection of a suitable feeding policy is a lever related to the synchronization. Four types of feeding policies exist, with a different impact on the amount of inventory at the border of the workstations (e.g., Schmid and Limère 2019), and thus categorized in this study as four implementation levels:

- *Line stocking.* This level is based on supplying to the workstations big unit loads, like pallets or trailers, containing one material type each (e.g., Boysen et al. 2015). The use of line stocking usually entails a relatively low material handling effort, since the supplied unit are usually the ones received from suppliers or upstream production stages (e.g., Boysen and Emde 2014; Baller et al. 2020). However, this policy also results in large quantities of inventories stored on the shop floor, especially in mass-customised systems where a wide variety of materials are needed for the production of finished goods (e.g., Adenipekun, Limère, and Schmid 2022).

- *Boxed supply.* In this level, big unit loads are broken down into smaller ones, such as bins or boxes, before being transported to the stations: although unit loads still contain one material type only, the average waiting time of materials before being processed is reduced thanks to the smaller size of unit loads (e.g., Schmid and Limère 2019).

- *Sequencing.* In this level, the inventory levels at the border of the workstations are further reduced since mixed unit loads, containing different types of materials, are prepared (e.g., Sali and Sahin 2016): each unit load is filled with different variants of materials belonging to the same family, differing for physical characteristics, like size and colour, or technical functionalities (e.g., Adenipekun, Limère, and Schmid 2022). Processing times are reduced as well, since materials are arranged inside the unit loads according to the production sequence, thus decreasing the time wasted by production operators searching for the right materials (e.g., Cedillo-Campos et al. 2017; Baller et al. 2020).

- *Kitting.* In this level, the waiting time of materials stored on the shop floor is kept to a minimum thanks to the use of a smaller number of mixed unit loads, containing all the materials which are needed to perform a set of production tasks (e.g., Sali and Sahin 2016; Schmid and Limère 2019).

3.2.2 Storage of materials

This lever refers to the number and location of warehouses inside the factory, which are two factors strongly related to the synchronization of material flows. In fact, locating the storage areas closer to the workstations enables a shorter delivery lead time of the needed materials, thus allowing, in turn, to reduce the average inventory at the border of the workstations and/or the waiting time of workstations that are idle due to lack of materials (e.g., Matt 2009; Boysen et al. 2015). Two configurations for the storage of materials in the factory are possible, corresponding to two different implementation levels:

- *Centralised*. In this first level, materials are kept in one or few centralised storage areas, where unit loads are picked and/or prepared before being transported to workstations (e.g., Baller et al. 2020). The centralised storage area is a central warehouse, usually located in one of the factory buildings (e.g., Kilic and Durmusoglu 2015; Luo et al. 2017; Pan, Wu et al. 2021) or in an external site, possibly managed by a logistics service provider (e.g., Cedillo-Campos et al. 2017; Schmid and Limère 2019). The use of centralised areas entails relatively long delivery times and thus poor flexibility and responsiveness of the production logistics system, especially in case of unexpected events or changes in the production schedule (e.g., Battini et al. 2009; Boysen et al. 2015; D. Guo, Zhong et al. 2021).

- *Decentralised.* In this level, waiting times are reduced because the supply of materials to the workstations originates from decentralised storage areas, located on the shop floor, which, in turn, are replenished from the central warehouse (Adenipekun, Limère, and Schmid 2022). Decentralised storage areas are often called supermarkets (e.g., Matt 2009; Boysen and Emde 2014) or preparation areas, to highlight their function of temporary storage of materials and preparation of unit loads like bins or kits (e.g., Ruiz Zúñiga et al. 2021; Adenipekun, Limère, and Schmid 2022). In some cases, line-integrated supermarkets are used, where each supermarket is dedicated to one or very few workstations (e.g., Boysen and Emde 2014; Schmid and Limère 2019).

3.2.3 Scheduling

The scheduling of manufacturing and production logistics activities is a lever related to the synchronization. It involves the allocation of tasks to manufacturing and production logistics resources, and thus it determines the flows of materials within the factory. Four implementation levels can be distinguished for this lever:

- *Partial.* This level corresponds to the case in which only manufacturing activities are scheduled, while no scheduling or routing is performed for production logistics activities. Consequently, capacity constraints of production logistics resources are neglected (e.g., Schmid and Limère 2019) and production logistics workers travel around the factory looking for unit loads which are waiting to be handled, thus resulting in low efficiency of material handling and in long waiting times for both materials and workstations (Luo et al. 2017).

- *Static*. In this level, a static scheduling process is performed: schedules are developed before the start of operations, based on known information and average or forecasted data, and are not dynamically updated (e.g., Dai et al. 2012; Müller et al. 2018). Very often, the manufacturing activities schedule is determined first, and production logistics activities are scheduled accordingly at a later step (e.g., Groß, Gerke, and Plapper 2020). This type of scheduling may still lead to stockouts, large amounts of WIP inventories, and long waiting times for materials arrival, stemming from the lack of coordination between manufacturing and production logistics activities and from the deviations of the actual conditions from the average and expected ones (e.g., Dai et al. 2012; Boysen and Emde 2014).

- *Pull*. In this level, waiting times are reduced since manufacturing and production logistics are dynamically coordinated while running operations, by using systems and tools such as kanban cards and milk-run tours for materials transportation to the workstations (e.g., Boysen et al.

2015; Bayhan et al. 2020). Unlike static systems, pull ones allow getting periodic feedback from the shop floor and adjusting the schedule accordingly, thus improving the capability to detect unexpected events and ultimately reducing inventories at the border of workstations (e.g., Hofmann and Rüsch 2017). However, the production logistics schedule is still developed after the manufacturing activities one, and only once the demand for materials has occurred, leading to possible waiting times especially in environments characterised by high uncertainty (e.g., Tu et al. 2009; Boysen et al. 2015; Schmid and Limère 2019).

- *Concurrent.* In this last implementation level, a joint scheduling of manufacturing and production logistics activities is performed. Several approaches are available for this purpose, including optimisation models, heuristic-based procedures, and cluster analyses (e.g., Aguirre, Méndez, and Castro 2014; Luo et al. 2017; Li and Huang 2021). Moreover, different update frequencies of the schedule are possible, depending on data availability (see Sections 4.1, 4.2). This implementation level supports more effectively the synchronization of material flows compared to the previous ones, since it takes into account both manufacturing and production logistics objectives and constraints when developing the schedule, thus allowing to reduce the overall throughput time by eliminating all the waiting times due to lack of coordination between the two activities (e.g., Aguirre, Mendez, and Castro 2014; Groß, Gerke, and Plapper 2020).

3.2.4 Materials tracking

Materials tracking refers to the possibility to monitor the type, quantity, and location of the materials stored or handled in the factory (e.g., Blesing et al. 2017; Yan, Zhang, and Fu 2019). The tracked materials encompass raw materials, components, finished products, and tools (Bányai et al. 2019; Guo et al. 2022). As synchronization entails that the right materials are delivered to the right workstations at the right moment in time, the possibility to effectively track materials represents an essential condition to achieve the synchronization of material flows. Materials tracking systems are categorized into four alternative implementation levels:

- *Paper-based.* This first level entails that materials tracking information are recorded on paper documents, like packing lists attached to the unit loads (e.g., Dai et al. 2012), thus entailing poor visibility of this information and potentially long propagation times of relevant information within the factory (e.g., Merkel et al. 2018).

- *Manual paperless.* In this level, production and logistics operators manually record tracking data on IT systems. This can be done either by inputting data from terminals (e.g., Schuhmacher, Baumung, and Hummel 2017) or by scanning barcodes or QR codes when an event occurs, e.g., whenever an item is picked or a critical part is used (Tu, Lim, and Yang, 2018b; Müller et al. 2018). Paperless tracking results in improved visibility, thanks to the possibility to collect all the information in IT systems and access them remotely (e.g., Merkel et al. 2018), thus reducing the delay of information propagation within the factory. However, manual paperless tracking systems still entail some inefficiencies, ultimately resulting in waiting times and thus in a poor synchronization of material flows. More in detail, processing times are affected by the time wasted by operators to manually input data or print barcodes and read them (Schuhmacher, Baumung, and Hummel 2017; Tu, Lim, and Yang 2018b). Moreover, a certain delay in information sharing is still present, since information are recorded only periodically, and the manual input might be subject to human errors, possibly causing additional waiting times due to reworks (Luo et al. 2017; Merkel et al. 2018; Müller et al. 2018).

- *Automated periodic.* In this level, data are recorded in IT systems in an automatic way, i.e., without the involvement of operators (e.g., Dai et al. 2012), thus eliminating some of the aforementioned waiting times. These systems are based on the automated reading of barcodes or on RFID tags and readers, which eliminate the need for a direct line of sight for reading data (e.g., Vachálek et al. 2021). The only waiting time left in this case is due to delays in information sharing. Indeed, in automated periodic tracking systems, data is recorded only at fixed time intervals or only when specific events occur. For instance, this kind of system is often adopted when RFID readers are placed onboard forklift trucks; in this case, data need to be acquired only when the truck is in specific positions to ensure a relatively low energy consumption (Frankò, Vida, and Varga 2020).

- *Automated continuous.* In this final level, different types of IoT devices are used to track the status of materials continuously over time (Hofmann and Rüsch 2017; Zhang et al. 2018), thus achieving the real-time alignment between material flows and information flows (Seitz and Nyhuis 2015; Tu, Lim, and Yang 2018b) and eliminating waiting times.

3.2.5 Process tracking

Process tracking refers to the monitoring of the progress of manufacturing and production logistics processes, as well as of possible unexpected events affecting these processes. This is achieved through the tracking of the resources employed in the processes, including manual or automated workstations and material handling equipment (e.g., Jiang et al. 2021; Müller et al. 2018). The gathered data encompasses resources statuses (e.g., working, idle, or failure states, as well as position data and battery level in case of material handling vehicles) and information about the WIP products being processed by each resource (e.g., Blesing et al. 2017; Gräßler and Pöhler 2018 Quadrini, Negri, and Fumagalli 2020). As already discussed for materials tracking (Section 3.2.4), the possibility to track processes is another necessary condition for a timely delivery of the right materials to the workstations where they are needed, and is therefore related to the synchronization of material flows. The identified implementation levels for this lever, as well as their impact on the synchronization of material flows, are the same as the ones described for materials tracking (Section 3.2.4) and are briefly presented below, focusing on the peculiar features of process tracking:

- *Paper-based.* In this implementation level, only average, static information about the processes are available (e.g., Müller et al. 2018).

- *Manual paperless.* In this second level, operators record in the IT system data concerning the progress of manufacturing and production logistics activities (e.g., Schuhmacher, Baumung, and Hummel 2017). For instance, this happens when a barcode is associated to every step of the assembly process and barcode scanning terminals are used by workers to record the completion of each step (Merkel et al. 2018).

- *Automated periodic.* This level relies on IoT devices which automatically gather data concerning the processes. Tracking data are recorded periodically, i.e., whenever an event occurs or certain conditions are verified. For instance, the progress of production activities is monitored through one or few sensors, placed at the end of a production line, thus updating process tracking only when all the needed operations on a product have been completed (Vachálek et al. 2021).
- *Automated continuous.* Also in this last level, process tracking data are automatically gathered through IoT devices. However, data are recorded continuously over time (e.g., the production process is tracked through multiple sensors, placed at each station in the line). For this reason, tracking systems enable the creation of shop floor digital twins, which reflect the processes status in real time (e.g., Wang, Zhang, and Zhong 2020; Figueiras et al. 2021) and ensure that any updates or unexpected events are spotted in a timely way, thus reducing waiting times especially in systems characterised by high uncertainty (e.g., Z. Guo et al. 2021). On the downside, this level entails higher implementation costs, technical complexity, and amount of transmitted data (e.g., Vachálek et al. 2021) compared with an automated periodic tracking, and therefore the choice between the last two implementation levels results from trade-off decisions.

3.2.6 Data analytics

Data analytics refers to the combination and elaboration of tracking data to obtain meaningful information to support decisions such as the scheduling, routing, and resource allocation to manufacturing and production logistics resources (e.g., Bayhan et al. 2020; Kalaiarasan et al. 2020; Guo et al. 2022), on which the timely delivery of materials to the right workstations relies. Therefore, data analytics is a lever related to the synchronization of material flows. Four implementation levels can be distinguished for this lever. While the first level does not exploit the potential of data elaboration, the remaining three entail data-driven decisions with different degrees of data analytics:

- *No elaboration.* This level corresponds to decisions based on average or expected data, known before the start of operations, often relying on the experience of planners and managers (e.g., Luo et al. 2017; Müller et al. 2018) or on pull systems in which the input coming from the shop floor is not further elaborated (e.g., Boysen et al. 2015).

- *Description*. In this level, the data gathered on the shop floor is centralised in digital environments and processed to obtain KPI dashboards which summarise the status of processes and material flows, as well as changes in customers demand (e.g., Dias and Toscano 2018; Tu, Lim, and Yang, 2018b; Wang, Zhang, and Zhong 2020). Lower processing times and smaller space required for materials storage are among the benefits which can be achieved by upgrading data analytics to this level, in which, unlike the previous one, decisions are driven by real-time data, adapting to the actual availability of resources and to possible unplanned events (Cammardella et al. 2017; Gräßler and Pöhler 2018; Bayhan et al. 2020).

- *Prediction.* In this level, decisions are based not only on the current system status but also on forecasts concerning future performance (e.g., Wang, Zhang, and Zhong 2020), thus allowing a further reduction in waiting times. This implementation level is often based on the application of big data analytics such as machine learning techniques, allowing to extract patterns from historical data (e.g., Figueiras et al. 2021).

- *Prescription.* This last implementation level also entails the application of big data analytics techniques, but it additionally implies that the predicted trends lead to the prescription of actions or countermeasures. This often leads to the exploitation of the digital twin of the physical system, on which simulations can be performed to assess alternative future scenarios (e.g., Bányai 2021; Jiang et al. 2021). Simulations allow testing the impact of different decisions before implementing them in the real system, hence choosing the one expected to lead to the best performance (e.g., Figueiras et al. 2021; Vachálek et al. 2021). The *Prescription* level could also allow decentralised decision making, which can either be automated or supported by assistance systems (see Section 3.2.7).

3.2.7 Assistance systems

Manufacturing and production logistics processes encompass both automated and manual operations, and, in the case of manual operations, the delivery of the right materials to the right workstations at the right moment in time relies on the exchange of timely and correct information with workers. For this reason, assistance systems, defined as systems which support workers in the execution of their tasks (Mark, Rauch, and Matt 2021), are related to the synchronization of material flows. Different types of assistance systems exist, categorised into three implementation levels:

- *Paper-based.* In this level, information about orders and operating instructions are printed on paper documents, often attached to unit loads or to WIP products (e.g., Merkel et al. 2018). These systems result in low accuracy of information and in long waiting times, also due to potential errors or to the damage or loss of paper sheets (e.g., Huang, Zhang, and Jiang 2008).

- *Digital passive.* This level leverages mobile devices, like tablets, displays, and projection systems, to communicate information to workers (e.g., Jiang et al. 2020; Mark, Rauch, and Matt 2021). For instance, pick-by-light systems can be placed on the storage racks to give visual information to workers about the correct materials to be picked, either in warehouses or at assembly stations (Shuhmacher, Baumung, and Hummel 2017). Compared to a paper-based system, a digital passive system has the capability of providing workers with up-to-date data, thus allowing to dynamically adapt workers' actions to the current system status (e.g., Merkel et al. 2018; Müller et al. 2018).

- *Digital interactive*. In this implementation level, workers can not only timely receive information but also record data concerning the tasks they are performing (e.g., Blesing et al. 2017). This type of assistance systems often rely on mobile devices, including smartphones, portable PCs and tablets, or on wearable devices, like wrist computers or smart glasses and helmets, potentially coupled with augmented reality technology (e.g., Di Pace et al. 2020; Guo et al. 2022). The possibility for workers to record information and promptly send feedback to planning systems, machines, or other workers further improves the ability to detect unexpected events and errors (Shuhmacher, Baumung, and Hummel 2017; Guo et al. 2020; Guo et al. 2022), reducing, in turn, waiting times due to delays in information sharing or possible reworks. Moreover, the use of wearable devices helps reducing processing times thanks to hands-free operations (Di Pace et al. 2020).

4. Industrial application

The proposed framework was operationalized in four industrial cases, illustrating its application as tool to map the adoption of the levers related to the synchronization.

As shown in Table 2, the case companies cover a variety of sizes and industries: relevant cases were found in the mechanical, pharmaceutical, and machinery industries. The sample heterogeneity appears also in the companies' business models, namely Business-to-Business (B2B) and Business-to-Consumer (B2C), and demand fulfilment strategies, namely Make-To-Stock (MTS), Assembly-To-Order (ATO), and Make-To-Order (MTO). Regarding the investigated manufacturing processes within the selected companies, fabrication (i.e., machining, tooling, or processing), assembly, and packaging were all included in the scope of the study. Further details about the companies, including their names, cannot be provided due to confidentiality reasons. For each case company, the analysis was focused on those processes or areas within the factory where most of the innovations concerning the investigated levers were found (i.e., where the highest implementation levels for the investigated levers were found).

Table 2. Information about the companies selected for the industrial application

	Company A	Company B	Company C	Company D
Size[1]	Medium-sized enterprise	Small enterprise	Medium-sized enterprise	Large enterprise
Industry	Industrial machinery	Mechanical (wheels)	Mechanical (hydronic solutions)	Pharmaceutical
Business model	B2B	B2B	B2B, B2C	B2C
Demand management strategy	ATO	MTS, ATO	MTS	MTS
Analysed processes	Assembly	Assembly	Fabrication, Assembly	Fabrication, Packaging

The following sections 4.1 to 4.4 presents a brief description of each case, showing its mapping into the developed framework. Then, Section 4.5 outlines the insights drawn from the industrial application of the framework.

4.1 Company A

Company A is a medium-sized enterprise which assembles and sells different types of industrial machines. The company has started a profound transformation process of its assembly system, in order to face the increased demand while improving efficiency and delivery dates estimates provided to customers. Focusing on woodworking machines, which represent the main product line in terms of volumes and possibility of customisation, Company A has recently shifted from fixed position assembly to mixed-model assembly lines. Since then, the company has progressively introduced innovations in its manufacturing and production logistics systems. These innovations can be described as changes in the configuration of some of the levers described in Section 3.

The current mapping of Company A into the developed framework is shown in Figure 4. First, the *Line stocking* feeding policy has been replaced with other policies, resulting in lower inventories on the shop floor and in significantly reduced handling of big unit loads (which, in the starting configuration, had to be brought back to the warehouse whenever the contained material was not needed anymore). The *Boxed supply* policy is now adopted for the supply of small components, used for the assembly of a high number of products (e.g., screws and bolts): small bins are brought at the

[1] According to the European Commission: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Enterprise_size

border of the stations and replenished whenever they are depleted. The *Sequencing* policy is adopted for bulky components and subassemblies (e.g., control panels), dedicated to a specific product, which are brought to the stations on pallets, sorted according to the assembly sequence. Finally, the *Kitting* policy is used for smaller parts, dedicated to a specific product, which are collected in a roll container that is delivered by production logistics operators to the first station in the line and then advances along the line together with the product being assembled (traveling kit). While small materials, often coming from external suppliers, are still stored in a *Centralised* warehouse, bigger components, received either from suppliers or from pre-assembly stages, have been recently moved to *Decentralised* storage areas, located closer to the line, thus improving the responsiveness of the internal transportation system. The introduction of *Sequencing* and *Kitting* feeding policies has been accompanied by the shift from a *Partial* scheduling system, where production logistics activities were not scheduled and the supply of materials was based on face-to-face communication between assembly and production logistics operators, to a *Static* one: the assembly activities are scheduled before the start of every shift, based on customers' orders and standard assembly times. Subsequently, the production logistics activities are scheduled, aiming to deliver the sequenced unit loads and kits as close as possible to the moment when the corresponding assembly activities are expected to start. These schedules are not updated during the shift, also because no feedback is gathered on the shop floor until the end of assembly operations. The only form of feedback is based on a paper checklist that reports instructions on the assembly operations and is also used by operators to manually record the actual duration of activities as well as technical parameters measured during the testing phases, and is returned to the scheduling office only after the end of the assembly. The *materials tracking* is also performed according to a *Paper-based* system: lists of required items are printed at the beginning of the shift, used during the picking process, and then attached to the unit loads delivered to the line. Any unexpected events, like the presence of wrong or defective materials, are managed through a direct communication between assembly and production logistics operators, and never recorded.

Summarising, Company A has improved the implementation level of some of the levers supporting the synchronization of material flows, achieving significant benefits in terms of overall lead times reduction (between -7% and -36%, depending on the product features) and delivery delays reduction (between -7% and -26%). However, waiting times still emerge in case of deviations from the expected events, and the company is planning to invest into tracking and data analytics technologies, which will enable a dynamic planning of activities based on the actual shop floor status. In particular, the company will continue its transformation journey by improving process tracking with the introduction of a digital checklist, where operators record the completion of activities and the emergence of errors by reading standard barcodes, and materials tracking, through IoT devices to track the location and consumption of key components.

Feeding policy	Line stocking	**Boxed supply** Bins containing small parts, common to several products	**Sequencing** Pallets with bulky materials, sorted according to the assembly sequence	**Kitting** Roll containers with all the small parts dedicated to one product
Materials storage	**Centralised** Central warehouse for relatively small materials		**Decentralised** Storage areas on the shop floor for bulky materials	
Scheduling	Partial	**Static** Schedules developed before the start of the shift	Pull	Concurrent
Materials tracking	**Paper-based** Paper list of the materials contained in a unit load	Manual paperless	Automated periodic	Automated continuous
Process tracking	**Paper-based** Paper checklist where operators record process information	Manual paperless	Automated periodic	Automated continuous
Data analytics	**No elaboration** Data not elaborated to take decisions	Description	Prediction	Prescription
Assistance systems	**Paper-based** Instructions printed on paper	Digital passive		Digital interactive
	LEVEL 0	***LEVEL 1***	***LEVEL 2***	***LEVEL 3***

Figure 4. Company A mapping

4.2 Company B

Company B is a manufacturer of wheels. Its customers, mainly companies in the mechanical and furniture industries which incorporate the wheels into their final products, have been demanding increasing product variety and extremely challenging lead times. To face these challenges, and specifically to reduce the frequent delays in the delivery of products, Company B has deeply reviewed the assembly operations, performed at fixed-position assembly tables.

First, the company has introduced a Manufacturing Execution System (MES), which processes tracking information, gathered on the shop floor, and combines them with information from other sources, received from the Enterprise Resource Planning system. To do this, the company has shifted from *Paper-based* to *Manual paperless* tracking of both materials and processes. Every unit load is labelled with a barcode and every production logistics operator is equipped with a portable scanner: the barcode is scanned both when starting the picking activities, to associate the unit load with the picked materials, and after the internal transportation, to record the delivery of materials at the border of the assembly stations. Barcode scanners have a screen which works as a *Digital passive* assistance system, reporting instructions about the picking missions to be carried out. Moreover, every station is equipped with a PC, where assembly operators record the start and completion of their activities. Tracking data is sent to the MES, which compares them with the delivery dates promised to customers and with the inventory levels in the finished products warehouse, thus dynamically identifying the most urgent assembly orders for which materials need to be picked or assembled. The PCs placed at assembly stations also act as *Digital interactive* assistance systems: they show the list of assembly orders for which the materials are available at the border of the station, and allow the assembly operators to choose the next order they are going to process, starting from the most urgent ones that are highlighted in red.

Company B has also changed its materials feeding policy, shifting from *Line stocking* to *Kitting*: unit loads, containing all the materials needed for an assembly order, are prepared by production logistics operators in several *Decentralised* areas on the shop floor, located close to the manufacturing units where the main components are produced. Assembly and production logistics activities schedules are strictly interdependent: both schedules are dynamically developed based on incoming customers' orders and promised delivery dates. Moreover, picking operations do not start if assembly queues at the corresponding stations exceed a certain length, thus reducing inventory levels, while assembly orders are not released into production until the materials have been picked and delivered.

The mapping of Company B into the framework is shown in Figure 5. Overall, the company was able to reduce the lead time from 20 to 5 days and is currently satisfied with the achieved combination of levers: therefore, it is expecting to keep the same combination in the future.

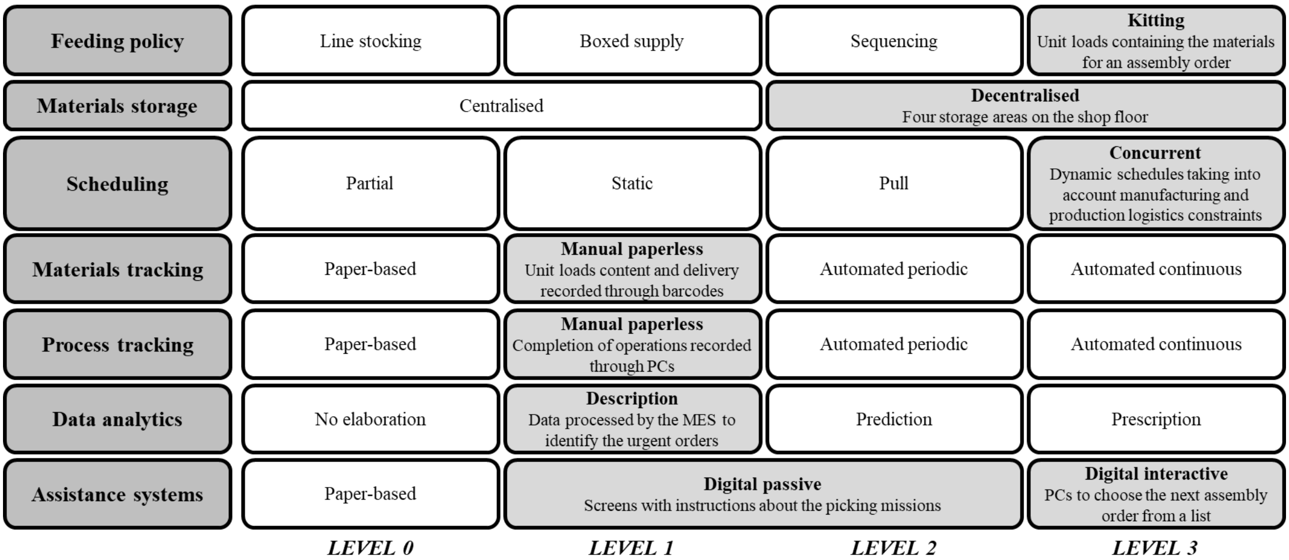

Figure 5. Company B mapping

4.3 Company C

Company C is a producer of mechanical and electronic components for heating, cooling, and energy systems. The company has been reorganising its manufacturing and production logistics systems, with the aim to efficiently face the increase in product variety and the reduction in average quantities ordered by customers.

Considering the components fabrication, carried out in a job shop, and the ensuing assembly process, performed at fixed position assembly stations, the mapping of Company C into the developed framework is shown in Figure 6. Materials tracking is performed according to a *Manual paperless* configuration: barcodes, attached to the unit loads, are scanned both by production logistics operators, whenever a unit load is delivered to a workstation, and by manufacturing operators, whenever a unit load containing WIP or finished products is ready to be picked up. For all the activities performed by human operators, also processes are tracked by manually scanning standard barcodes corresponding to pre-defined process statuses (e.g., damaged tools, lack of materials, tooling in progress). Moreover, manual activities are supported by different types of assistance systems. PCs are *Digital interactive* systems used to access picking lists, visualize instructions about manufacturing activities, and reorder tools. Portable vibration devices are *Digital passive* systems that are picked up by the operators after they reorder any tools and start vibrating as soon as the tools are ready to be collected, thus allowing the operators to perform value-adding activities instead of standing in front of the warehouse and waiting for the tools to be prepared. For the activities performed by automated machines, the process status is continuously tracked through sensors and cameras. In all the cases, tracking data are sent to the MES, which analyses them and sends immediate feedback to the shop floor (e.g., about the materials ready to be picked) and hourly updates to the scheduling department. Based on these updates, the schedule can be modified and sent back to the MES, which immediately communicates it to shop floor resources. While the data analysed by the MES correspond to the *Description* level in data analytics, the *Prescription* level is reached in the decoupling of fabrication and assembly processes: before being sent to the assembly stations, materials from the fabrication process are temporarily stored in a small AS/RS miniload, which is used to decouple the fabrication sequence from the assembly sequence, as well as to change the unit load from metal bins to plastic bins, placed on pallets. The pallets are prepared by an automated machine, located at the output point of the miniload, which, once received the assembly schedule, autonomously communicates with the miniload control system in a decentralised way. Through this communication, the two systems negotiate the palletising sequence that minimises the overall preparation time, taking into account the scheduling constraints, the cycle time of the miniload, and the number of available pallets.

In the future, Company C is planning to invest in more advanced technologies for tracking and data analytics. First, they are going to replace barcodes with RFID tags, so as to avoid human errors and time wasted in the reading activity. Then, they are going to introduce more advanced data analytics tools in order to improve the prediction of future events to be used in the scheduling. The company is also planning to couple the technological innovations with updates in the managerial levers: alternative options are being evaluated for the creation of shop floor supermarkets, replenished from the currently used automated central warehouse, with the aim to reduce the lead time of internal transportation to workstations. Regarding feeding policies, the company has already planned a pilot project, concerning five of its assembly stations, in which the current *Line stocking* policy will be replaced by a *Kitting* one, with kits preparation performed into supermarkets to avoid the creation of a bottleneck at the output of the central warehouse.

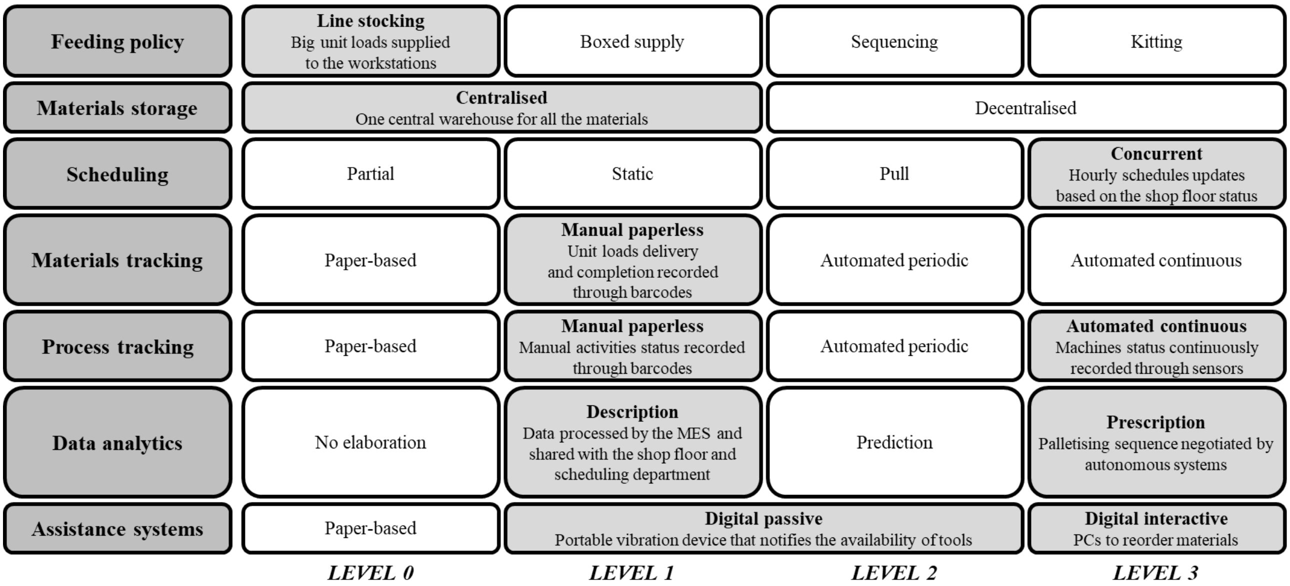

Figure 6. Company C mapping

4.4 Company D

Company D is a leading player in the pharmaceutical industry. The manufacturing process consists of several processing steps, performed by automated machines in a job shop, followed by packaging activities, performed by a semi-automated line. Focusing on a pilot plant, the company has started investing in a redesign of its processes, mainly based on shop floor digitalisation, looking for a model to be extended to all the other plants in the future. The main aim is to improve products' traceability and process control, which are extremely relevant in the pharmaceutical industry, and to increase the overall efficiency.

The mapping of Company D into the developed framework is shown in Figure 7. First, materials and process tracking, which were previously configured in a *Manual paperless* fashion, have been improved. Materials' quantities and locations are tracked in an *Automated continuous* way inside the automated warehouse, through a Warehouse Management System (WMS) software. After being retrieved from the warehouse, unit loads with materials, identified through barcodes, are transported to the workstations, where the barcode is scanned whenever a unit load is loaded onto a machine. The scanning is performed through automated readers placed at the machines input points, thus achieving an *Automated periodic* tracking. Finally, materials are tracked in an *Automated continuous* fashion inside the processing and packaging machines, which automatically record the consumption of materials and the completion of each product. A wide set of sensors is installed in these machines, also allowing to continuously track the progress of activities as well as process data such as temperature, humidity, and air quality. In some cases, the gathered data is analysed by the MES, which also receives real-time information from the WMS. The MES develops KPIs which summarise the shop floor status and the progress of manufacturing activities with different levels of detail (ranging from a single machine and product batch up to the entire process), varying according to the specific user who is accessing the information. For the fabrication process, the MES, integrated with a machine learning software, also analyses the parameters gathered on the machines, aiming to extract patterns and develop predictions which are sent to managers and shop floor supervisors for decision-making. Moreover, data concerning the packaging process are elaborated by processing units installed on the machines, which autonomously compute KPIs and notify the supervisors of any deviations from the target process conditions. This activity is supported by *Digital interactive* assistance systems, in the form of touch screen displays placed at the border of the line.

No changes have been made to the scheduling process, which is configured in a *Static* way: a few hours before the start of each shift, the manufacturing activities schedule is developed by a team of planners and, based on this, all the needed materials are brought to the border of the line. Unit loads, containing one material type each, are retrieved from the *Centralised* warehouse and transported to the shop floor through an automated shuttle, whose throughput capacity is limited. Hence, all the unit loads needed for a shift are brought to the border of the line in advance, to avoid possible production stoppages due to lack of materials. A *Line stocking* policy is used for the supply of materials: unit loads are temporarily stored at the border of the line, where operators need to manually search the required materials, resulting in inefficiencies and potentially long waiting times.

For the future, Company D acknowledges that the available data could be exploited also for a dynamic scheduling system. However, other managerial changes should be made before moving to a *Concurrent* scheduling. For example, the introduction of *Decentralised* storage areas would increase the responsiveness of the production logistics system, thus allowing to supply materials closer to the moment when they are needed. Waiting times could also be reduced by introducing *Sequencing* and *Kitting* feeding policies for the supply of additives and packaging materials, keeping the *Line stocking* only for the supply of the main raw materials.

	LEVEL 0	*LEVEL 1*	*LEVEL 2*	*LEVEL 3*
Feeding policy	**Line stocking** Big unit loads supplied to the workstations	Boxed supply	Sequencing	Kitting
Materials storage	**Centralised** One central warehouse for all the materials		Decentralised	
Scheduling	Partial	**Static** Schedules developed before the start of the shift	Pull	Concurrent
Materials tracking	Paper-based	Manual paperless	**Automated periodic** Unit loads loading on machines recorded through automated barcode readers	**Automated continuous** Real-time materials quantity and location recorded through WMS and machines sensors
Process tracking	Paper-based	Manual paperless	Automated periodic	**Automated continuous** Machines and tools monitored in real-time through sensors
Data analytics	No elaboration	Description	**Prediction** Packaging process data elaborated by machines and notified to supervisors	Prescription
Assistance systems	Paper-based	Digital passive		**Digital interactive** Touch screen displays to monitor and change the process parameters

Figure 7. Company D mapping

4.5 Insights from the industrial application

The application of the framework to the industrial cases allowed to effectively map the managerial and digital levers related to the synchronization in the four companies. For some levers, different implementation levels were found for the same company, as the identified configurations are not necessarily mutually exclusive. For instance, different feeding policies are adopted by

Company A depending on the size of the materials. Similarly, two different types of assistance systems are found in Companies B and C for different processes within the same manufacturing area.

A comparison of the four industrial cases shows that different paths can be followed to improve the synchronization. Some companies start with updating their managerial levers' configurations to achieve an improved organisation of factory activities, and then they introduce digital technologies to support the new organisation and amplify the obtained benefits. As shown in the Company A case, this can be a successful strategy, especially if the starting situation is characterised by high inefficiencies and long waiting times. Other companies begin with the investment in tracking and analytics technologies and then they review their managerial choices afterwards, looking for configurations which allow capturing the benefits made available by the digital levers. This is, for instance, the case of Company D: after updating its digital levers, the company has spotted interesting future opportunities to reduce waiting times by improving its scheduling system and has planned modifications to the other managerial levers accordingly. Finally, other companies work on the joint introduction of managerial and digital levers, dealing with a higher complexity of the change process but also immediately exploiting advantages due to the synergistic interplay between some managerial and digital levers' configurations. For instance, in Company B, the dynamic planning of manufacturing and production logistics activities is made possible by the use of assistance systems that show up-to-date plans to the operators, based on the actual shop floor status which is made available thanks to materials and processes tracking.

5. Conclusions

This study addresses the synchronization of material flows within the factory, presented as a way to enable the effective and efficient implementation of mass customisation. It proposes a novel classification framework of the managerial and digital levers related to the synchronization, developed based on a systematic literature review, and illustrates the operationalization and industrial application of the framework in four cases.

From an academic perspective, this study contributes to advancing the research on synchronization, which is still in the early stages of conceptualisation: as the extant literature is fragmented and focused on specific applications, this study systematizes the existing contributions and provides a comprehensive overview of the managerial and digital levers related to the synchronization, thus consolidating the available knowledge and providing a reference for future research. Moreover, through the industrial application, this study provides insights on how companies concretely work on the identified levers. It shows that companies do not need to develop all the levers at the same time, but they can follow a path, starting from one or few levers and then progressively developing the other ones. It also shows that different companies follow different paths and that different combinations of managerial and digital levers can be used to improve the synchronization in different industrial contexts, also depending on the specific needs and goals.

From a managerial perspective, the study provides a reference for companies that are implementing the mass customisation strategy and are willing to improve the synchronization of material flows within their factories. Indeed, it provides an overview of the key elements to be considered and describes the alternative options which are available to companies. As shown in the industrial application, managers can use the developed framework to map the current configurations of the managerial and digital levers related to the synchronization and to identify improvement areas, thus outlining possible paths towards an improved synchronization.

As a first attempt to systematize the knowledge on the synchronization of material flows, this study presents a few limitations, which may provide opportunities for future research. A first limitation lies in the scope of the research, as it exclusively focuses on internal material flows connecting factory warehouses to workstations. These flows are affected by upstream processes, ending with the receival of materials from previous stages in the supply chain (e.g., Boysen et al. 2015), and have an impact on downstream ones, especially on the shipment of finished products to the following stages (e.g., Chen et al. 2015, Guo et al. 2022). Therefore, future research may build on the findings of this study and enlarge the scope, studying the interplay between different activities and investigating the effect of upstream and downstream activities performance on the synchronization of material flows. Another interesting direction of research lies in the development of performance measurement systems concerning the synchronization of material flows: while in this work general directions and implementation levels were provided, future studies could introduce KPIs to quantitatively assess the level of synchronization, thus providing a tool to measure the performance improvements stemming from different choices or to compare different companies or plants. Finally, the proposed classification framework could be used in industry surveys to investigate the adoption of the synchronization levers in different business sectors. This will allow identifying sector-specific paths towards synchronization, as well as specific barriers and challenges, and potentially facilitating cross-sectorial sharing of best-practices. Moreover, this may support the identification of extant gaps and needs in the industrial domain, thus highlighting the related research opportunities in the academic domain and contributing to aligning practice with theories on the use of advanced technologies for the synchronization of material flows within the factory.

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