Impact of COVID-19 on Digital Transformation: An Empirical Analysis of Manufacturing Companies[1]

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Abstract

Purpose of the paper: *This study explores whether and how the restrictions resulting from COVID-19 crisis have affected digital transformation (DT) measured by the adoption of data-driven decision-making (DDD) and structured management (SM) practices.*

Methodology*: On the basis of an original survey of 102 manufacturing firms located in Lombardy, we explore the DDD and SM practices before and during the lockdown, which began on 8 March 2020. The factors explaining heterogeneous responses to the crisis, namely, institutional logic, firm size, technological sectors, and family business, are also considered.*

Findings*: We find that during the lockdown, firms suffered a setback in the use of DDD and SM. However, there is a significant heterogeneity in the response across firms. The factors considered in our study poorly explain this heterogeneity in DDD. Meanwhile, all factors, except institutional logic, effectively explain the differences in SM.*

Research limits: *This study provides a preliminary and descriptive analysis. Further analysis is needed to better identify causality and co-factors.*

Practical implications*: DT could be particularly sensitive to crisis, and crisis response varies across different dimensions of DT (i.e. DDD and SM) and types of firms. This implies that a variety of firms may benefit from DT but that DT requires specific managerial attention.*

Originality of the study: *This study employs an original dataset that sheds new light on how the pandemic has affected DT. It focuses on one of the largest European manufacturing regions which was severely hit by the first wave of the pandemic.*

Key words: data-driven decision making; management practices; digital transformation; institutional logics; COVID-19.

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1. Introduction

The widespread adoption and application of digital technologies calls for a significant transformation in the way organisations conduct their activities, undertake decisions, and craft and execute strategies. Scholars refer to this phenomenon as digital transformation (DT), an 'organizational change triggered and shaped by the widespread diffusion of digital technology' (Hanelt *et al.* 2021, p. 1187) or 'a change in how a firm employs digital technologies, to develop a new digital business model that helps to create and appropriate more value for the firm' (Verhoef *et al.* 2021, p. 889). Scholars have also discussed the impact of DT on performance and the difficulties faced by firms in attaining the potential efficiency gains promised by DT due to the lack of analytical culture and established management practices (Davenport *et al.* 2010).

The extensive and diverse literature on DT lacks a general agreement on what exactly DT is and what it encompasses (Hanelt *et al.* 2021). However, as Hanelt *et al.* (2021) noted, DT is about organisational change for several reasons. Firstly, DT entails a significant increase in the availability and effective use of data, which is enabled by sophisticated tools for data collection and analysis, such as big data analytics, machine learning, social media, mobile technology, and cloud computing. This wide pool of digital technologies allows firms in different industries to change the way decisions are undertaken. DT leads managers to change management practices and the way they make decisions from traditional methods based on intuition and experience to a data-driven decision-making (DDD) approach, which consists of accessing and using data in real time to manage and test alternative hypotheses and measure performance (Davenport *et al.* 2010; Brynjolfsson and McElheran 2016a, 2016b). Secondly, when firms adopt digital technologies, they interact with management practices (Hanelt *et al.* 2021). Some structured management (SM) practices, such as monitoring (i.e. how firms react to production problems) and performance-based compensation and promotion, may not be directly related to data but are associated with DDD (Brynjolfsson and McElheran 2016a, 2016b). Moreover, SM practices, such as performance-based compensation, positively impact firm performance (Trevor *et al.* 2012; Bloom *et al.* 2013) and innovation (Ederer and Manso 2013). Their association with DDD and their impact on innovation make SM practices a key dimension of DT.

However, several factors may affect the adoption and effective implementation of DT and thereby impact the potential performance gains that firms can capture (Aral *et al.* 2012; Brynjolfsson and McAfee 2012; McElheran 2015). Although the potential benefits of DT in ordinary times are widely known, in the face of shocks and crises, firms may find it difficult to incorporate and benefit from new DDD processes and SM practices. Indeed, crises may have an impact on firms' willingness to invest in innovation and their ability to do so effectively (Archibugi *et al.* 2013a, 2013b; Brem *et al.* 2020). Hence, a crisis may bring about challenges for firms attempting to embrace DT.

The recent accounts about the effects of COVID-19 on the diffusion of digital technologies suggest that this shock has accelerated the adoption of digital collaboration platforms and remote working (McKinsey 2020; Ferrigno and Cucino 2021). Although the use of such digital tools and working practices has channelled many firms into a digitalisation path, it is still unclear whether this shock on digitalisation has urged firms to embrace DT and as to what extent it has spurred a change in DDD and SM. Factors that influence DT during the pandemic, such as firm characteristics, are still not well understood. Therefore, the objectives of this study are as follows: 1) to understand how the restrictions resulting from the COVID-19 crisis have impacted two key dimensions of DT, namely, DDD and SM; 2) to understand whether this impact has been heterogeneous across different firms; and 3) to identify firms' characteristics based on such heterogeneity.

This study aims to address these objectives by analysing a sample of manufacturing firms in the Lombardy region.

2. Theoretical grounding

In the last decades, DT has been at the forefront of firms' innovation efforts, representing an imperative for executives and top management teams engaged in extracting value from (and transforming their business with) new technologies and digital solutions (Fitzgerald *et al.* 2014).

The potential gains triggered by the rise of digital tools have prompted firms to revolutionise their usual way of doing business, urging them to develop novel capabilities and embrace innovative business models to increase value creation and appropriation (Reis *et al.* 2018; Nambisan *et al.* 2019) and investing in high-skill workers accordingly (Balsmeier and Woerter 2019).

These technologies have some distinctive features relative to previous information technologies (IT) as they are more pervasive and transformative (Bharadwaj *et al.* 2013; Verhoef *et al.* 2021). This implies deeper organisational change (Hanelt *et al.* 2021). As observed by several scholars, many difficulties in navigating DT are related to the organisational and managerial changes required to leverage the opportunities of digital technologies. To better understand the implications of DT for strategy and organisational change, Hanelt *et al.* (2021) suggested a multidimensional framework. They mapped the literature on DT into *contextual conditions, mechanisms,* and *outcomes*. The two dimensions of DT introduced previously, namely, DDD and SM, fall under *contextual conditions* and *outcomes*.

Firstly, DDD and SM are related to the contextual conditions that trigger DT. DDD refers to material conditions (i.e. data availability and use) whilst SM pertains to organisational determinants (i.e. organisational strategy and legacy). DDD and SM are strictly intertwined. As explained by Hanelt *et al.* (2021, p. 1166), 'when digital technologies enter organizations, they interact with organizational antecedents, particularly organizational and managerial characteristics'. This is especially challenging when firms introduce new technologies that imply significant organisational investments, such as those in the form of the time and cost involved in workforce training (Davenport 1998; Devadoss and Pan 2007; Kudyba *et al.* 2020). For example, the adoption of a new enterprise system that combines all application software in a single system imposes a change in a company's strategy, organisation, and culture. Because of its integrating nature, a new enterprise system requires the standardisation of data across functions so that employees are trained in the use of software and understand the logic of the system (Devadoss and Pan 2007). The change required to introduce a new technology rests on the current and past history of an organisation (Devadoss and Pan 2007); hence, firms may face different challenges in implementing DT based on their organisational and managerial characteristics. Managerial practices, such as the adoption of measures to prevent productivity problems, are a crucial means to navigate change. Although not necessarily linked to data, these practices have proven to be positively correlated with DDD (Brynjolfson and McElheran 2016a, 2016b) and firm performance (Bloom *et al.* 2013). Thus, besides DDD, SM preconditions, such as monitoring and people incentives, put firms in a favourable position to embark on DT.

Secondly, DDD also refers to the *outcomes* of DT and, in particular, to a change in the organisational setup (i.e. data-driven processes). In addition, SM can be considered an organisational outcome of DT. Although Hanelt *et al.* (2021) mostly focused on organisational outcomes directly triggered by digital technologies (e.g. more agile structures, data-driven management), SM is not directly related to digital technology. However, the use of digital technologies is associated with the codification of business processes and more structured management (Brynjolfsson and McElheran 2016a, 2016b). Although the direction of this association is difficult to establish, digital technologies can stimulate the adoption of more advanced SM. For example, AI can be used to assess people's performance more accurately (Kretschmer and Khashabi 2020), thereby making the adoption of performance-based compensation and promotion more appealing.

Although DT has unfolded along a linear trajectory for several years, resulting in heavy worldwide investment in digital solutions by firms and in the increasing adoption of a DDD approach and SM, the recent COVID-19 crisis may have significantly challenged firms' efforts to navigate DT. Scholars have investigated the impact of economic crises on firms' innovation initiatives (i.e. 2008-2009 economic and financial crisis, see Archibugi *et al.* 2013a). However, the effects of the COVID-19 pandemic on DT may provide new insights to the management and innovation literature for two reasons. Firstly, COVID-19's pervasive effects have urged firms to act rapidly on information and communications technology (ICT) and distance work. In addition, COVID-19 is different from previous crises; rather than being a recessive crisis triggering a general decrease in demand, it has spurred different effects across the economy, with some sectors being hit by the crisis (e.g. tourism, food service) and with others actually benefitting from it (e.g. e-commerce, pharmaceuticals) (Craven *et al.* 2020).

Secondly, to fully reap the potential benefits of DT, firms must invest in different complementary dimensions, such as DDD, SM, and skills. As earlier studies suggest, investing in multiple complementary dimensions requires significant amounts of resources and time, which may prove challenging for firms (e.g. Brynjolfsson and Hitt 2000; Giuri *et al.* 2008). Hence, COVID-19 provides us with a natural experiment setting to explore the effects of the challenges in several dimensions of DT on firms.

Extant innovation studies on the impact of crises on firms' willingness and ability to innovate (Archibugi *et al.* 2013a, 2013b; Brem *et al.* 2020) have proposed two contrasting views on the effects of crises on firms' innovation investments. Building on the Schumpeterian idea of 'creative destruction' (Schumpeter 1939), the first view depicts firms' innovation investments following a countercyclical path, increasing during periods of recession. In these periods, a low level of demand leads firms to allocate their resources to research and development (R&D) productivity-enhancing activities rather than to production activities (D'Agostino and Moreno 2018). This argument is based on the assumption that R&D and production activities compete to allocate limited resources (Barlevy 2004).

The second view maintains that innovation investments run in the same direction as business cycles and thus decrease, rather than grow, during periods of recession because of two reasons. Firstly, during recessions, firms experience significant financial constraints; thus, even if more resources can be allocated to R&D than to production activities, the absolute level of resources available for investment in innovation is limited (Aghion *et al.* 2012). Secondly, because of a low level of demand during recessions, firms may not be able to take advantage of their innovation investments in the short term (Fabrizio and Tsolmon 2014). Thus, firms have limited incentives to invest in innovation because the time window to reap the benefits of innovation investments is limited and, in the long run, competitors may challenge the appropriability of innovation (McGahan and Porter 2003; D'Agostino and Moreno 2018).

These considerations lead to the following research question: *To what extent have firms undertaken DT in response to the COVID-19 crisis?*

Firms differ in their resources and capabilities and in the beliefs and values they may pursue (i.e. in the institutional logics they incorporate). Thus, firm heterogeneity should be considered to fully understand innovation ability and crisis response. The strategic management literature has theorised and found persistent within-industry differences across firms in terms of profitability and competitive advantage, which reflect a significant asymmetry in resource and capability endowments (Barney 1991; Rumelt 1991; Teece *et al.* 1997). In addition to resources and capabilities, differences in performance and productivity depend on organisational design and management practices (Englmaier *et al.* 2018). For example, Bloom and Van Reenen (2010) studied the effects of managerial practices (i.e. monitoring, outcomes and goals, incentives, and rewards) on performance and productivity and how they explain a significant portion of the variance between firms. More recently, Brynjolfsson and McElheran (2016a, 2016b) examined the heterogeneity in SM, ICT investment, and DDD across firms.

These differences in resources, capabilities, and managerial practices will likely yield different responses to crises in terms of firms' innovation efforts. Some firms may decrease their innovation efforts in view of the resource constraints triggered by crises and the inability to promptly reallocate the resources needed to navigate crisis-related challenges. Other firms may be endowed with specific capabilities and resources to run in a countercyclical direction and embrace innovative efforts.

This potential heterogeneity spurs us to explore the following research question: *Which types of firms have undertaken DT in response to the COVID-19 crisis?*

As discussed above, investing contemporaneously in all dimensions of DT may prove to be particularly harsh for some firms and less detrimental to others, thus reflecting the importance of firm-specific characteristics. Aside from the specific endowment of resources and capabilities, such heterogeneity in the effects triggered by the COVID-19 crisis on the different dimensions of DT may be determined by the set of firms' institutional logics, that is, 'the socially constructed, historical patterns of material practices, assumptions, beliefs and rules by which individuals produce and reproduce their material subsistence' (Thornton and Ocasio 2008, p. 101).

Studies have shown that shocks or crises may impact the logics that firms incorporate and the ways these logics come to be instantiated within organisations (e.g. as dominant or peripheral) (Ramus *et al.* 2017). In addition, radical organisational changes, such as those implied by DT, often entail incorporating different logics, some of which may ease DDD and SM dynamics or actually hinder their development. In particular, scientific logic, characterised by the willingness to share knowledge, freedom, and orientation to innovation (Sauermann and Stephan 2013), may be more in line with some DT dimensions and encourage firms to adopt DDD and SM in comparison with market logic, which is centred around hierarchical control and customer focus as means to capture economic returns.

Indeed, firms whose logic is predominantly scientific and only peripherally market-oriented are more likely to maintain or increase their investment in DT notwithstanding a crisis. This is because as shown in the definition provided above, by incorporating scientifically dominant logic, firms' practices, beliefs, and values become centred on innovative and scientific principles, which likely make them more eager to adopt DDD and SM.

This argument motivates us to explore the following research question: *How do institutional logics affect the response to the COVID-19 crisis in terms of DT?*

3. Data and sample

Our study is based on an online survey of a sample of 102 manufacturing firms in the Lombardy region of Italy. The survey was conducted in collaboration with the local trade association Assolombarda between April and May 2021.

Most questions required answers in two different periods - before and during the lockdown, which started on the date of the first urgent restriction act by the Italian government (DPCM 8 March 2020). Table 1 provides an overview of the firms' size and technological sectors in our sample.

Tab. 1: Firms in the sample by sectors and size class

	up to 49 employees	50-249 employees	>250 employees	Total	
High-tech	3	1	4	8	**8%**
Medium-high tech	12	14	15	41	40%
Medium-low tech	12	14	4	30	29%
Low tech	11	12	0	23	23%
Total	38	41	23	102	100%
	37%	40%	23%	100%	

Note: sectors are based on NACE Rev. 2 classification at 2-digits, Eurostat (2018)
Source: Authors' elaboration

The appendix shows the questions used to construct the two main indicators of DT, as discussed in next Section.

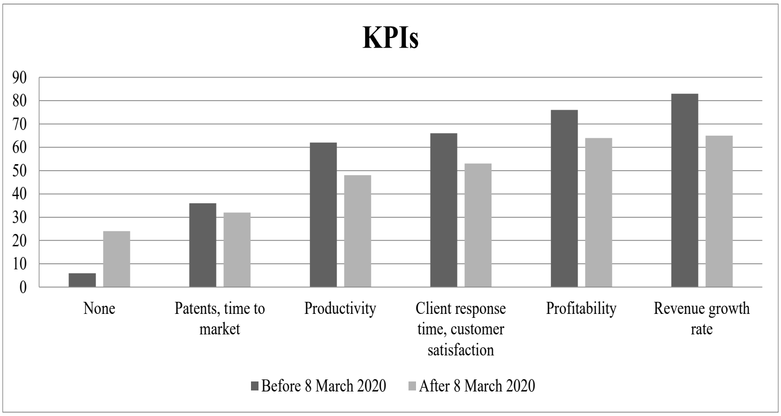
The average share of ICT investments in revenue was 2.28% in 2017-2019, and the forecast for the period of 2020-2022 was 3%. These firms adopted a range of IT applications before the lockdown, and after 8 March 2020, the use of video conference systems increased remarkably and not surprisingly.

4. DT and the pandemic

4.1 Data-Driven Decision Making

We distinguished four pillars of DDD: 1) the use of key performance indicators (KPIs), 2) availability of data, 3) use of data, and 4) short- and long-term targets. The first pillar is the extent to which firms monitor their processes using quantitative measures. A higher number of KPIs suggest a more sophisticated approach to management practices centred on data collection and analysis (Brynjolfsson and McElheran 2016a, 2016b). On average, the sample firms monitored 3.2 KPIs before the lockdown; during the lockdown, the average number dropped to 2.6, with 24 firms selecting none of the KPIs. Fig. 1 shows the number of firms that monitored each KPI before and during the lockdown. Firm growth was the KPI used by most firms before and during the lockdown (i.e. 83 and 65 of the sample firms, respectively); however, it was also the KPI that was most frequently abandoned afterwards: 18 respondents failed to consider growth as a relevant KPI during the lockdown. KPIs related to product innovation (such as the annual number of patents and time to market), chosen by 36 firms in the first period and 32 firms in the second period, were the KPIs that lost the least during the lockdown probably because they are long-term indicators.

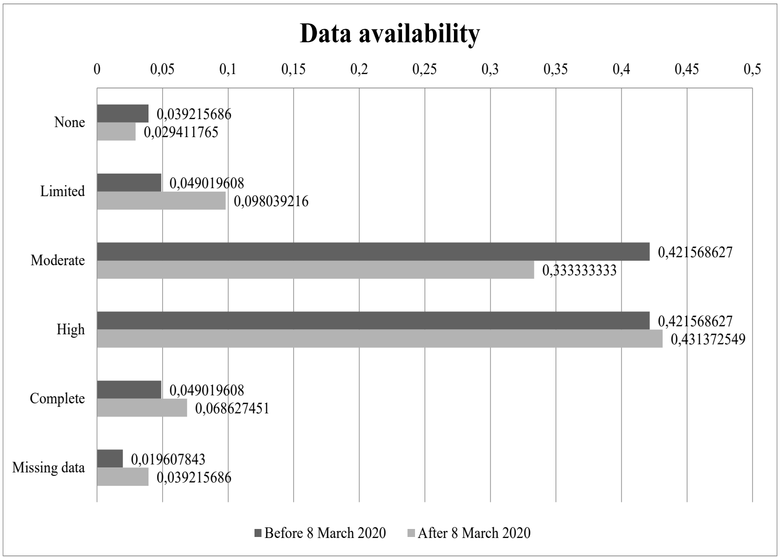
Fig. 1: KPIs monitored by firms



Source: Authors' elaboration

The second pillar of DDD is the availability of data (from none = 1 to complete availability = 5). As Fig. 2 shows, most firms (84%) had moderate or high availability of data in the first period. During the lockdown, this percentage dropped to 76% whilst one of the lowest categories (limited) and the highest category (complete) increased their percentages. Therefore, the lockdown appeared to have reduced the responses at the bottom of the data availability distribution (the sum of moderate, limited, and non-use dropped from 51% to 46%) and increased the responses at the top of the data availability distribution (the sum of high and complete increased from 47% to 50%).

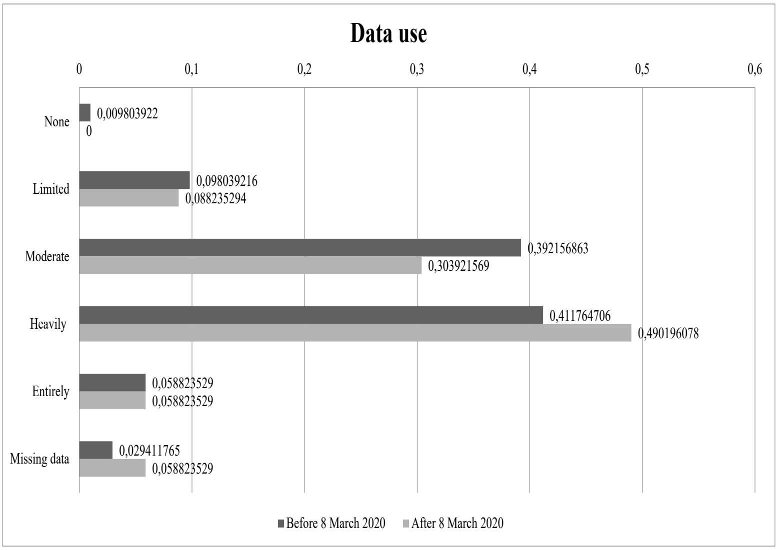
Fig. 2: Availability of data



Source: Authors' elaboration

The third pillar is the use of data (from not used = 1 to highly used = 5). Most firms (80%) reported moderate or heavy use of data for decision making before the lockdown. During the lockdown, this percentage remained stable (79%); there were 6 missing observations, and no firm declared that they had not used data for decision making. Fig. 3 shows that in the second period, a larger proportion of firms used data heavily or entirely (from 47% to 55%) whilst a smaller proportion of firms reported the non-, limited, or moderate use of data (from 50% to 39%)[2]. Therefore, the intensity of data use during the pandemic appeared to have increased in general.

Fig. 3: Use of data



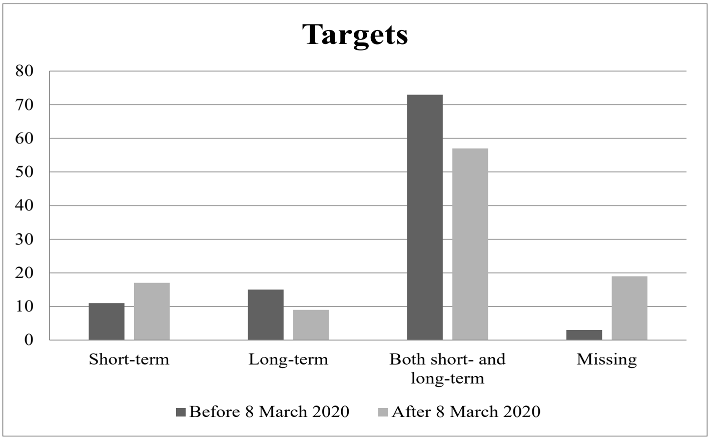
Source: Authors' elaboration

The fourth pillar of DDD is the use of short- and long-term targets (Drucker 1954; Gibson and Tesone 2001; Hertel *et al.* 2005). Targets help managers assess the performance of organisational processes, identify the sources of problems, and take appropriate actions (Brynjolfsson and McElheran 2016b). We measured the importance of management by objectives in a DDD setting by examining the use of short-term, long-term, or a combination of short-term and long-term targets.

Fig. 4 shows that most firms used a combination of short- and long-term targets in both periods. However, fewer firms used long-term and combined targets during the second period. It is interesting to note the increased numbers of short-term targets and missing answers (mostly from firms that used a combined approach before the lockdown), which reflect the difficulty in setting clear, long-term goals under conditions of high uncertainty and tight financial constraints.

[2] It is worth noting that the use of data refers to available data. For example, it is possible that a firm makes a heavy use of moderately available data.

Fig. 4: Type of targets



Source: Authors' elaboration

We used the four pillars discussed above to build an indicator for DDD. Table 2 shows the number of firms that reached the relevant thresholds for each of the four pillars. Building on Brynjolfsson and McElheran (2016a, 2016b), we selected the top categories of each pillar that signal a strong firm commitment to the DDD approach: (a) at least four out of five KPIs monitored, (b) high or complete data availability, (c) heavy or complete use of available data, and (d) a combination of short- and long-term targets. Whilst the availability and use of data increased during the lockdown, the number of KPIs and combined use of targets decreased. The bottom row in Table 2 shows the number of firms that are at the forefront of DDD and satisfy the four conditions above. Thus, DDD is a binary variable that takes the value of 1 if a firm selects at least four KPIs, the top categories for availability and use of data, and combined targets.

In the first period, 19 firms were heavily committed to DDD (18.6% of the sample); this number dropped to 10 in the second period (9.8%). This declining trend is driven by the KPIs and combined targets.

Tab. 2: Indicator of data-driven decision making (DDD)

Data-related management practices	Before 8 March 2020		After 8 March 2020		Diff.
	# (missing)	%[a]	# (missing)	% [a]	#
At least 4 KPIs monitored	48 (6)	47.1%	39 (24)	38.2%	-9
Top 2 categories for "availability of data"	48 (2)	47.1%	51 (4)	50.0%	3
Top 2 categories for "use of data"	48 (3)	47.1%	56 (8)	54.9%	8
Short-term and long-term targets (combined)	73 (3)	71.6%	57 (19)	55.9%	-16
Data-driven decision making (DDD)	19	18.6%	10	9.8%	-9

[a] Shares are computed on whole sample

Source: Authors' elaboration

4.2 Structured management practices

In addition to the DDD approach, other management practices that are unrelated to the use of data comprise DT, and one such practice is SM. In this study, we considered how firms deal with productivity problems and the criteria for assigning performance bonuses and promotions.

To analyse the approach to problem solving, we asked how each firm typically addresses productivity problems, such as late or inadequate responses to customer requirements. The answers ranged from 1 (no action is taken) to 4 (actions are taken to prevent the problem from happening again, and a process to anticipate similar problems is activated)[3]. The average answer was similar in the two periods: 3.6 and 3.7. However, 24 firms failed to respond in the second period. Moreover, 70% of the firms in the first period adopted the most advanced approach; however, in the second period, 18 of these firms left the box blank. This suggests that the lockdown prevented firms from dedicating enough resources to maintain a sophisticated approach to solving productivity problems.

We also considered performance bonuses and promotion criteria for top managers, middle managers, and employees. Approximately two-thirds of the firms declared that they assign performance bonuses. In the first period, company-level performance bonuses were the most frequently used incentive (40%), followed by individual-level bonuses (33%). Bonuses at the team (16%) or office/department (10%) level were less frequent. The frequency of individual- and company-level bonuses declined during the lockdown whilst the frequency of team and office/department bonuses did not change between the two periods.

The individual-, company-, team- and office/department-level promotion criteria provided a less clear picture because of many missing values (i.e. 32% and 10% of responses, respectively) before the lockdown; the missing values further increased in the second period (40% and 21%, respectively). This result reflects the difficulty of focusing on promotion policies during the crisis. Performance and ability were the most frequently used criteria in our sample for the top managers (52%) and other employees (68%) before and after the lockdown (46% and 59%, respectively)[4].

Table 3 shows the frequency of use of the most advanced approach to solving productivity problems, bonuses based on individual or team performance, and promotion criteria based mainly on individual performance and ability. The bottom row shows the composite indicator of SM. SM is a binary variable equal to 1 if all three conditions in the rows above apply. We found that 30 companies fell into this category before the lockdown and that only 21 firms met the three conditions during the lockdown. This result confirms that SM was losing ground during the pandemic.

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3 Category 2 is 'The problem is fixed, but the firm does not take further action', and category 3 is 'The problem is fixed, and we took actions to make sure that it did not happen again'.

4 The residual categories are 'Performance and ability along with other factors such as tenure' and 'Mainly other factors such as tenure'.

Tab. 3: Indicator of structured management practices (SM)

Structured management practices	Before 8 March 2020		After 8 March 2020	
	# (missing)	%[a]	# (missing)	%[a]
Top category for the solution of productivity problems (4)	72 (1)	70.6	58 (24)	56.9
Performance bonuses at the individual or team level	50 (28)	49	44 (28)	43.1
Promotion criteria based on performance and ability only	74 (8)	72.5	65 (18)	63.7
Structured management practices (SM) indicator	30	29.4	21	20.6

[a] Shares are computed on whole sample

Source: Authors' elaboration

5. Differences in DT related to firm- and sector-specific factors

In general, the pandemic has forced firms to reduce their commitment to more advanced management practices related to DT. At the same time, we observe significant heterogeneity in the response to lockdown across firms, which may reflect firm- and sector-specific characteristics. In this section, we correlate these characteristics with DT.

We compare the frequencies of DDD and SM firms with firm-specific (*institutional logic, firm size,* and *family business*) and sector-specific characteristics (*technological intensity*).

We identify the predominant *institutional logic* on the basis of the founding values self-identified by firms, namely, knowledge sharing, orientation to innovation, freedom, hierarchical coordination, customer orientation, and pragmatism. Scholars have acknowledged how knowledge sharing, freedom, and orientation to innovation represent values that characterise firms primarily pursuing scientific logic (Sauermann and Stephan 2013) and how bureaucratic and hierarchical control and customer focus as means to capture economic returns and pragmatic decision making to improve efficiency are associated with commercial, market-oriented logic (Murray 2010). The literature has also posited that although firms may incorporate multiple logics (Greenwood *et al.* 2011), they may be instantiated differently, with one logic being central and predominant to organisational functioning and with other logics being less core (i.e. peripheral) to organisational functioning (Besharov and Smith 2014). Building on this distinction, we claim that if a firm has selected more values associated with scientific logic (i.e. the first three), it has a predominantly central *scientific-oriented* logic*;* if a firm has selected more values associated with market logic (i.e. the latter three), it has a predominantly central *market-oriented* logic. The residual cases are categorised as *others* because they incorporate multiple logics that are equally dominant, that is, the number of scientifically related values selected is equal to the number of market-related values (i.e. three, two, or one value for both logics).

With regard to size, we distinguish between small and medium-sized enterprises (SMEs) (less than 250 employees) and large firms. We aggregate *technological sectors* into high- and medium-high tech sectors and medium-low and low tech sectors. *Family business* is identified by a binary indicator that takes the value of 1 if at least 50% of the capital is owned by a family.

Tables 4 to 7 report the contingency tables of DDD and SM firms by *institutional logic, size, technological sectors*, and *family business* in the two periods (before and after 8 March 2020). They also show the results of Fisher's exact test of correlation, which reveal whether the differences in the adoption of DT practices are associated with firm- and technology-specific factors.

In terms of *institutional logic* (Table 4), we observe that before the pandemic, more market-oriented firms or other firms used DDD and SM than scientifically oriented firms. At the same time, 8 out of 31 (i.e. 26%) firms with scientifically related logic adopted DDD whilst 11 of 71 (i.e. 15%) market-oriented or other firms adopted DDD; in terms of SM, the pattern is similar but with higher shares (42% and 24%, respectively). After 8 March 2020, fewer firms with both types of logic adopted DDD and SM, although there seems to be a higher persistence of firms with scientifically related logic in DDD and SM in the second period. However, despite the differences in the frequencies pre- and post-COVID, we fail to reject the hypothesis of independence between *institutional logic* and each of the two managerial practices (the p-values are larger than 0.05). This suggests that having a specific logic does not constitute a relevant factor in explaining the systematic differences in DDD or SM.

Tab. 4: DT by institutional logic

Before 8 March 2020					After 8 March 2020			
	Market or other	Scientific	Total			Market or other	Scientific	Total
DDD=0	60	23	83		DDD=0	67	25	92
DDD=1	11	8	19		DDD=1	4	6	10
Total	71	31	102		Total	71	31	102
Fisher's exact test: p-value = 0.271					Fisher's exact test: p-value = 0.063			
SM=0	54	18	72		SM=0	60	21	81
SM=1	17	13	30		SM=1	11	10	21
Total	71	31	102		Total	71	3	1
Fisher's exact test: p-value = 0.097					Fisher's exact test: p-value = 0.066			

Source: Authors' elaboration

With respect to *size* (Table 5), more large firms used DDD and SM before 8 March 2020 in comparison with SMEs. Specifically, 8 out of 23 (34%) large firms adopted DDD whilst 13 out of 23 (56%) used SM; by contrast, 11 out of 79 (14%) SMEs used DDD whilst 17 out of 79 (21%) used SM. These differences are statistically significant in Fisher's test of correlation ($p < 0.05$). Moreover, these differences persist in the results pertaining to DDD during the pandemic, although they are not statistically significant. Meanwhile, a smaller number of SMEs adopted advanced SM in comparison with large firms, and these differences in both periods are statistically significant. Thus, size appears to be a relevant factor for DDD only in the first period and for SM in both periods. The differences between SMEs and large firms for the period after 8 March 2020 remain, although they are smoother. Our results confirm the difficulties of SMEs in undertaking DT because of limited resources and capabilities (Li *et al.* 2018; Bettiol *et al.* 2021).

Tab. 5: DT by size

Before 8 March 2020					After 8 March 2020			
	Large firms	SMEs	Total			Large firms	SMEs	Total
DDD=0	15	68	83		DDD=0	20	72	92
DDD=1	8	11	19		DDD=1	3	7	10
Total	23	79	102		Total	23	73	102
Fisher's exact test: p-value = 0.034					Fisher's exact test: p-value = 0.69			
SM=0	10	62	72		SM=0	12	69	81
SM=1	13	17	30		SM=1	11	10	21
Total	23	79	102		Total	23	79	102
Fisher's exact test: p-value = 0.003					Fisher's exact test: p-value = 0.001			

Source: Authors' elaboration

The differences between firms in the higher and lower technology sectors are not straightforward (Table 6). Not surprisingly, the share of firms with heavy commitments to DDD and SM in the first period is larger in the medium-to-high tech sectors. However, we note a remarkable drop in the number of firms on the frontier of DDD and SM practices in the second period. Moreover, the differences between sectors in terms of DDD in either period are not statistically significant possibly because of a high variance across firms within sectors in the first period and a substantial drop in the number of heavy DDD adopters in the higher technology sectors in the second period. The lack of a significant difference in DDD adoption between higher and lower tech firms may be explained by the characteristics of our sample, which includes the most productive firms in Lombardy; therefore, even firms in lower tech sectors are likely to use data (e.g. to better manage the value chain or monitor their costs).

The differences in SM between the two sectors in both periods are statistically significant ($p < 0.05$), with higher tech firms being more heavily committed to SM before 8 March 2020. Although the crisis put a strain on their managerial practices in the second period, a larger share of firms in sectors with higher technological intensity maintained a high commitment to well-defined management practices, such as individual performance bonuses. This result is in line with the fact that firms in higher tech sectors typically invest more in R&D, IT, and skills.

Tab. 6: DT by technological sectors

Before 8 March 2020					After 8 March 2020			
	Low/ Medium-low tech	Medium-high/High tech	Total			Low/ Medium-low tech	Medium-high/High tech	Total
DDD=0	46	37	83		DDD=0	47	45	92
DDD=1	7	12	19		DDD=1	6	4	10
Total	53	49	102		Total	53	49	102
Fisher's exact test: p-value = 0.203					Fisher's exact test: p-value = 0.74			
SM=0	43	29	72		SM=0	47	34	81
SM=1	10	20	30		SM=1	6	15	21
Total	53	49	102		Total	53	49	102
Fisher's exact test: p-value = 0.018					Fisher's exact test: p-value = 0.026			

Source: Authors' elaboration

A higher share of *non-family* firms were heavily committed to DDD in both periods (Table 7). In the first period, 11 out of 78 (14%) and 8 out of 24 (33%) *family* and *non-family* firms engaged in DDD, respectively. However, these differences are not statistically significant. Meanwhile, a much larger share of *non-family* firms used SM in both periods (16 of 24 or 66% and 12 out of 24 or 50%), and the differences with family firms in both periods are statistically significant ($p < 0.05$). Therefore, although ownership does not explain the differences in the adoption of DDD, it explains the more frequent adoption of SM by non-family businesses. Family firms are indeed very heterogeneous, but they are inherently different from other firms because they are typically oriented towards the preservation of their socio-emotional wealth, which refers to nonfinancial aspects or social and affective endowments (Berrone *et al.* 2012), such as maintaining influence on the firm and passing the business to the next generation. In particular, family firms may invest less in talent management (Basco *et al.* 2021), although they offer a loyal, stable, and long-term relationship with employees (Rondi *et al.* 2021). Therefore, our results confirm the use of less SM in favour of other means, such as social capital and family influence.

Tab. 7: DT by family business

Before 8 March 2020					After 8 March 2020			
	Non-family	Family	Total			Non-family	Family	Total
DDD=0	16	67	83		DDD=0	21	71	92
DDD=1	8	11	19		DDD=1	3	7	10
Total	24	78	102		Total	24	78	102
Fisher's exact test: p-value = 0.068					Fisher's exact test: p-value = 0.69			
SM=0	8	16	72		SM=0	12	69	81
SM=1	16	14	30		SM=1	12	9	21
Total	24	78	102		Total	24	78	102
Fisher's exact test: p-value = 0.000					Fisher's exact test: p-value = 0.000			

Source: Authors' elaboration

6. Discussion and conclusion

In this study, we focus on two complementary dimensions of DT before and during the pandemic: DDD and SM. The challenges faced by firms engaged in DT are substantial during normal times and have become even more demanding during the pandemic.

To answer the first research question, we explored each dimension and its components. For DDD, whilst the availability and use of data increased during the pandemic, the number of KPIs and combined targets decreased. By considering the different dimensions of DDD together, we find that the number of firms with a high commitment to DDD declined between the two periods. A much larger share of the sample firms adopted SM practices, such as individual and team bonuses and promotion mechanisms based on performance and ability rather than tenure. However, the share of firms that adopted SM declined during the pandemic. Hence, both indicators suggest that the commitment to DT has slowed down during the pandemic, signalling that on average, the sample firms had to concentrate their efforts on solutions for more basic problems, such as the organisation of distant work and bottlenecks in the supply chain. In all probability, the financial constraints due to the slowdown of operations have contributed to the reduced investments in DDD and SM. Therefore, our response to the first research question is that firms have slowed their DT as a response to the COVID-19 crisis.

To address the second research question about the types of firms that undertake DT in response to the COVID-19 crisis, we correlate the changes in DT during the pandemic with various factors. Differences in the two DT dimensions are only partially explained by *institutional logic* (scientifically oriented values vs market-oriented values), firm *size, technological sectors,* and firm ownership (*family business vs non-family business*). In particular, as far as DDD is concerned, we find a correlation only with *firm size* before the pandemic. As far as SM is concerned, we find that all factors, except *institutional logic*, explain firm heterogeneity. Hence, to answer our third research question, we observe the limited relevance of institutional logics as a discriminant factor in the adoption of DDD, which is probably because the effective use of data would equally benefit scientifically oriented firms and firms that are more oriented towards customers' demand and market values. We find that the importance of firm size as a discriminant factor for DDD is probably due to economies of scale in data management and previous higher investments related to ICT and skills. Larger firms show a higher level of commitment to SM than SMEs, and this commitment persists over time probably because their greater organisational complexity makes the adoption of SM practices more compelling.

It is important to note that the differences in SM practices between groups (e.g. SMEs vs large firms, high tech and low tech sectors, and family business vs non-family business) persisted during the pandemic despite the generalised decline in SM frequency. Meanwhile, the differences between groups in terms of DDD practices in both periods were less significant and tended to disappear during the pandemic period. This suggests that SM is more deeply rooted in the organisation and is thus less affected by the turbulence of the external environment. Conversely, DDD practices are more vulnerable to crises because they may be less embedded in the organisation and have been adopted only recently by firms. Another reason could be that they are inherently more complex to pursue in fast-changing and uncertain scenarios, such as a pandemic; for example, extracting relevant information from data during the pandemic could be more challenging than assigning bonuses (whose criteria have probably been established long before the beginning of the pandemic).

Our analysis contributes to the literature on DT in various ways. Firstly, we highlight two important dimensions of DT (i.e. DDD and SM) which have been analysed in a few earlier studies and deserve further in-depth analysis. Secondly, we provide a preliminary and exploratory overview of how the COVID crisis has affected DT. Our findings highlight the importance of firm- and industry-specific factors that affect DT before and after the pandemic. Therefore, these factors contribute to a better understanding of firm heterogeneity in DT under different economic conditions.

This study has valuable implications for business practice. Firstly, the results show that despite the fact that COVID-19 may have accelerated digital investments, the management of DT is particularly challenging for organisations, especially during turbulent times. Technologies and data may open up new business opportunities, but organisations must adapt accordingly. This calls for managerial focus on how to navigate the DT, possibly with a strong attention to leadership skills, such as awareness of data availability and technologies, fast execution and experimentation to facilitate organisational learning whilst reducing the risk associated with ex-ante planning, and the integration of digital processes within the existing organisation by facilitating the communication and interplay between 'digital' business units and people and their 'physical' counterparts and fostering the widespread acceptance of a new digital culture at various organisational layers (Hanelt *et al.*, 2021). Secondly, although the small sample size limits the significance of the results, we find evidence of differences in the rate of DT adoption between large firms and SMEs and between family-owned firms and other firms. This finding may yield substantial long-term implications for the capacity of smaller family-owned firms to adapt to DT and maintain their competitive advantage. Entrepreneurs and top managers of these firms must be aware of the importance of DT even during crises. Thirdly, organisations with predominantly scientific institutional logic appear to adopt DT roughly at the same rate as organisations with market logic. This suggests that the managers of these firms should not take for granted the fact that scientific institutional logic puts their organisation in a favourable position in successfully adapting to DT. It is likely that the managerial challenges in integrating digital tools within scientifically oriented organisations may be as strong as those in organisations with more market-oriented approaches.

This study has various limitations, but it also raises interesting and relevant points for future research. Firstly, although this is a descriptive and exploratory analysis, the findings provide a useful basis for future research that will dig deeper into the causal links between firms' characteristics and

DT and how this relationship varies as a consequence of a shock like a pandemic. Secondly, although our study is centred on one of the largest manufacturing regions in Europe, future research is needed to extend the analysis to other locations to determine the level of generalisation of our results.

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Appendix

A) DDD

1. *KPI*
   D2 Which ones of the following key performance indicators (KPI) was monitored by your firm in the first and the second period (mark all that apply)?

	Before DPCM 8 March 2020	After DPCM 8 March 2020
Measures of customer satisfaction (e.g. retention rate and rebuy rate)	☐	☐
Client response time (e.g. pre- and post-sale assistance)	☐	☐
Profitability (ROS, return on sales)	☐	☐
Productivity (added value/employees)	☐	☐
Time to market (time between the idea about a new product/service and its market introduction)	☐	☐
Growth rate of revenues	☐	☐
Number of patents per year	☐	☐

2. *Availability of data*
   E1 Which of the following conditions best described the availability of data to support decision making in your company in the first and the second period?

	Before DPCM 8 March 2020	After DPCM 8 March 2020
None	☐	☐
Limited	☐	☐
Moderate	☐	☐
High	☐	☐
Complete	☐	☐

3. *Use of data*
   E2 To what extent is the decision-making process in the company based on the use of data to support decisions in the first and second period?

	Before DPCM 8 March 2020	After DPCM 8 March 2020
None	☐	☐
Limited	☐	☐
Moderate	☐	☐
Heavily	☐	☐
Entirely	☐	☐

4. *Short- and long-term targets*
   D3 What best describes the time frame of targets in your company, in the first and second period?

	Before DPCM 8 March 2020	After DPCM 8 March 2020
Main focus was on less than one year (short-term)	☐	☐
Main focus was on more than one year (long-term)	☐	☐
Combination of short-term and long-term targets	☐	☐
No targets	☐	☐

B) SM

1. *Productivity problems*
   D1 What best describes what happened at a typical establishment of your firm when a productivity problem arose (e.g. long response time to requests by other units, or unsatisfactory solution of problems indicated by external clients)?

	Before DPCM 8 March 2020	After DPCM 8 March 2020
No action is taken	☐	☐
The problem is fixed but the firm does not take further action	☐	☐
The problem is fixed, and we took actions to make sure that it did not happen again	☐	☐
The problem is fixed, actions are taken to prevent that the problem will happen again, and a process to anticipate similar problems is activated	☐	☐

2. Performance bonuses

D6 What were performance bonuses of managers and employees usually based on at this establishment in the first and second period (mark all that apply)?

	Before DPCM 8 March 2020		After DPCM 8 March 2020	
	Top managers	Middle managers and employees	Top managers	Middle managers and employees
Their own performance as measured by targets	☐	☐	☐	☐
Their team performance as measured by targets	☐	☐	☐	☐
Their office or department performance as measured by targets	☐	☐	☐	☐
Their company's performance as measured by targets	☐	☐	☐	☐
No performance bonuses assigned	☐	☐	☐	☐

3. Promotion criteria

D7 What was the primary way managers and employees were promoted at this establishment?

	Before DPCM 8 March 2020		After DPCM 8 March 2020	
	Top managers	Middle managers and employees	Top managers	Middle managers and employees
Promotions were based solely on performance and ability	☐	☐	☐	☐
Promotions were based partly on performance and ability, and partly on other factors (for example, tenure)	☐	☐	☐	☐
Promotions were based mainly on factors other than performance and ability (for example, tenure)	☐	☐	☐	☐

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