The interplay between data-driven decision-making and digitalization: A firm-level survey of the Italian and U.S. automotive industries

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Abstract

With the diffusion of information systems and new technologies for the real-time capturing of data, especially in rapid technological and managerial innovation contexts such as the automotive industry, data-driven decision-making (DDM) has now the potential to generate dramatic improvements in the performance of manufacturing firms. However, there is still a lack of evidence in literature on whether these technologies can actually enhance the effectiveness of data-driven approaches. The aim of this article is to investigate the impact of DDM on operational performance moderated by two main dimensions of digitalization: data integration and the breadth of new digitization technologies. The results of a cross-country survey of 138 Italian and U.S. auto-supplier firms, which was supported by plant visits and interviews, suggest that an interplay between the two dimensions exists. Higher degrees of data integration in information systems increase the positive effect of DDM on the probability of cost reductions. On the other hand, introducing multiple emerging digitization technologies leads to worse DDM results, in terms of cost performance. The conclusion that can be drawn is that the operational employees of auto-supplier firms are now facing difficulties in successfully combining real-time operational data from various sources and in exploiting them for decision-making. Managers and workers need to align their intuition, experience and analytical capabilities to initiate the digitalization process. The challenge, in the medium term, is to limit the difficulties of implementing new digitization technologies and integrating their data, to embrace DDM and fully grasp the potential of data analytics in operations.

Keywords: Data-Driven Decision-Making; Industry 4.0; Digitalization; Digital Technologies; Data Integration; Operational Performance

1. Introduction

Data have been used in operation management for more than a century: since Taylorism and Fordism, managers have been using detailed data on work performance to fine tune their tasks and, ultimately, improve their operational performance. However, in those early days, front-line employees relied only on their senses and experience to gain information about production processes and make operational decisions (Bailey et al., 2012). However, the diffusion of more affordable computers and ICTs then lowered the cost of collecting data and processing information (Bresnahan et al., 2002), thereby increasing the availability of data for managers to help them make tactical and strategic decisions. Data-driven decision-making (DDM), which is also called rational or normative decision-making (Flores-Garcia et al., 2019; Julmi, 2019), is considered the most suitable approach in contexts where data and information flows are increasingly structured (Flores-Garcia et al., 2019; Julmi, 2019). Today, manufacturing is being disrupted by Industry 4.0, a revolutionary technological trend that promises to assign a central role to operational data in decision-making (Kusiak, 2018; Martínez-Caro et al., 2020).

Among the Industry 4.0 technologies that connect the physical world with the digital world, new digitization technologies (DT), such as the Internet of Things or RFID, allow operational data to be automatically captured in digital form at their inception (Pigni et al., 2016). Digitization and digitalization are distinct concepts. Digitization describes the transformation of data from analogic to digital information (Loebbecke and Picot, 2015; Verhoef et al., 2021). Digitalization is instead the transformation of a firm's processes when the firm resorts to the use of enabling technologies and other digital technologies (Verhoef et al., 2021). Integrating these new technologies with more traditional information systems – such as ERP software – represents a digitalization process that transforms operations by enabling a new concept of real-time "data-driven decision-making" (Zhong et al., 2017; Bokrantz et al., 2020b; Dutta and Bose, 2015; Guo et al., 2021; Osterrieder et al., 2020; Parsa et al., 2017).

However, despite the substantial investments that have been made in the new generation of DTs, industrial manufacturing firms are still far from understanding whether, and how, the now obtainable higher quantity of real-time data can generate performance opportunities. The key issue is not the adoption of digital technologies per se, but how such technologies should be used to increase business value by reducing costs and increasing productivity and revenues (Björkdahl, 2020; Martínez-Caro et al., 2020). Some articles have identified a positive impact on narrow operational performance indicators such as scraps or productivity (e.g., El-Khalil, 2015; Rossini et al., 2021; Cette et al., 2022), and others have looked into the benefits of the adoption of numerous standalone digital technologies (e.g., Pfister and Lehmann, 2021). However, it has been hard to observe and quantify the benefits of digitalization at the firm level, e.g., on the overall cost performance, especially for SMEs (Messeni Petruzzelli et al., 2021).

With this article, we want to focus on more integral processes of digitalization, by looking at the increases in the number of technologies used and their level of integration. Therefore, we explore the interplay between manufacturing firms' decision-making processes and their digitalization, as defined by their degree of data integration and the adoption of digitization technologies. The assumptions we have made are that: despite studies stating the contrary (e.g., Brynjolfsson et al., 2011; McAfee and Brynjolfson, 2012), DDM is not necessarily better than its alternative, i.e. intuitive decision-making (Flores-Garcia et al., 2019; Julmi, 2019); non-technological factors could influence the benefits of digitalization (e.g., Cagliano et al., 2019; Tortorella et al., 2020); and that, however, data generated by technology are only relevant if they are used for decision-making (Gandomi and Haider, 2015).

Guided by recent advancements in the organizational information-processing theory, according to which digitalization could represent the information-processing capability to support decision-making processes related to operations management (Li et al., 2020), this article tests the hypothesis that DDM benefits from digitalization to achieve operational excellence, as advanced by Tortorella et al. (2021). Moreover, inspired by the unsolved questions proposed by Abubakar et al. (2019, p. 111) — "Which decision-making style better performs? With what enablers does it deliver optimum result?" — we test three hypotheses using the following closely linked concepts: the relationship between high levels of data integration and the effectiveness of DDM; the relationship between the number of digitization technologies and the effectiveness of DDM; the joint effect of data integration and new digitization technologies on making data-driven approaches effective.

Since Industry 4.0 is a relatively recent topic, empirical evidence is still insufficiently integrated in literature (Bokrantz et al., 2020c). For this reason, this research paper — following a preliminary qualitative step described below — is based on an extensive and unique cross-country survey conducted in 138 firms in Italian and U.S. automotive industries, which we argue is an ideal sector for studying these issues. The automotive component industry in Italy and in the United States is a convenient setting for this study for a number of reasons. First, the automotive industry is of high economic value for both countries, given its large workforce and large share of GDP. The automotive industry has one of the largest and most dynamic manufacturing supply chains, and is highly competitive, more so than most other industries. Automotive suppliers must comply with new product and process requirements, which are subject to strict international standards related to safety, quality, sustainability, and efficiency (Liao et al., 2020). They must continuously innovate to stay ahead of their competitors. Moreover, the industry is appropriate for studying technology-enabled organizational transformations because the firms in this sector tend to be early adopters of new digital technologies (Kamble et al., 2020; PwC, 2018).

The obtained results confirm our hypothesis concerning the interplay between DDM and data integration technologies: it has emerged that among the firms which prefer a DDM approach to manage their operations, those that invested more in fostering data integration through

Enterprise Resource Planning systems were the most likely to witness cost reductions. On the other hand, surprisingly, a greater number of digitization technologies showed a negative interplay with DDM, thus suggesting that approaches based mainly on experience and intuition are more effective in interpreting diverse and unstructured streams of data.

The rest of the article is structured as follows. Section 2 introduces the main concepts used in the paper – DDM and the two dimensions of digitalization – that are used to outline our theoretical framework and the hypotheses developed in Section 3. In Section 4, we describe the data collection and analysis processes. Section 5 presents the descriptive statistics and the outcomes of the quantitative analyses. In Section 6, we discuss the results about the interplay between digitalization and decision-making, supported by qualitative evidence, and suggest a set of recommendations to managers. Finally, Section 7 contains the final considerations about this article, outlining its limitations and opportunities for future research.

2. Literature

The digitalization of operations relies on the adoption of technologies that collect and integrate data for use in operational decision-making with the aim of improving operational performance (e.g., Cifone et al., 2021; Gandomi and Haider, 2015; Osterrieder, 2020). Therefore, in line with the "synchroperation" concept outlined by Guo et al. (2021) and drawing from the organizational information processing theory (IPT), this section summarizes the literatures on DDM, information systems for data integration, and digitization technologies for real-time data collection. The gaps that emerge concerning their intersections are then outlined in Section 3.

2.1 Data-driven decision-making

DDM is loosely defined as "the degree to which decisions are based on data" (Bokrantz et al., 2020a) and as systems that support "all kind of decisions in manufacturing, for instance design, scheduling, process planning and control" (Osterrieder et al., 2020). Key to the concept is that collecting operational data is relevant if the data are used to make decisions (Gandomi and Haider, 2015). An important dimension of DDM, as outlined by Bokrantz et al. (2020a), is "decision augmentation," whereby data are used to assist and complement humans in decision-making, rather than substituting them. Improving the interpretability and transparency of algorithms for DDM can increase a firm's trust in them and influence their adoption and the firm's performance (Bokrantz et al., 2020b). Data, in order to be used, need to be processed to become information, thus generating knowledge which, through sensemaking of what happens in the firm (e.g., at the operational level, on the shop floor) can be subsequently stored and drawn upon to also make decisions at the operational level (Choo, 1996; Comes et al., 2020). According to the organizational IPT, in order to obtain an optimal performance, there must be a fit between the processing needs and capabilities of information (Galbraith, 1973), and organizations should engage in information processing to reduce ambiguity in their information (Weick, 2005; Li et al, 2020). Humans use two primary types of information processing in particular in decision-making: data-driven (DDM) and intuition-driven (IDM) processing (Dane and Pratt, 2007; Flores-Garcia et al., 2019; Julmi, 2019). DDM involves a quantitative assessment, an analytical approach that decomposes and recombines data and information through slow, conscious, and sequential associations. Such a processing is associated with performing an analytical assessment of what is going to occur, the ease of explaining the reasons for certain choices, and the prevalence of explicit knowledge (Fatorachian and Kazemi, 2018; Julmi, 2019). The five main dimensions whereby, according to literature, the two approaches differ are summarized in Table 1.

Table 1
Decision-making dimensions: data-driven (DDM) vs intuition-driven (IDM).

Decision-making dimensions	DDM	IDM
Speed	Slow	Fast
Deliberation	Conscious	Non-conscious
Associations	Sequential (logic-based)	Holistic (pattern-based)
Information processing approaches	Analytical and rational	Experiential and emotional
Forms of knowledge	Explicit	Tacit

It has been advanced that firms which base their strategic or operational decisions on data and analytics, rather than on intuition and experience, should achieve superior performance (e.g., Brynjolfsson et al., 2011; McAfee and Brynjolfson, 2012). On the other hand, recent studies argue that there is no better approach to decision-making. They have found that the best choice instead depends on the "structuredness" of the underlying event that calls for a decision to be made (Flores-Garcia et al., 2019). The structuredness of an event is defined by its analyzability and ambiguity. The more a decision problem or activity benefits from the use of computational, objective rules and procedures, as opposed to personal judgment and experience (Flores-Garcia et al., 2019), the more it is analyzable – i.e., detectable, measurable, and interpretable (Pigni et al., 2016). On the other hand, ambiguity (or equivocality) is the degree to which there are multiple and conflicting interpretations of an event, and it is associated with such problems as confusion and a lack of consensus or understanding. Decisions based on intuition are better for ill-structured events, that is, those with low analyzability and high ambiguity, whereas DDM is a better fit for well-structured events, that is, those that are highly analyzable and unambiguous (Flores-Garcia et al., 2019). However, there is still a gap in this stream of literature concerning the determining of whether new technological factors, such as digitalization, which enable the real-time collection and integration of data, can play a role in improving the structuredness of a firm, thus making DDM a better approach for those firms that have invested in it.

2.2 Data integration and new digitization technologies

> *"From the perspective of IPT [Information Processing Theory], digital technologies represent the firm's information processing capabilities to support decision-making processes related to operations and environmental management."* (Li et al., 2020, p. 3)

Operational decision-making and execution can be enhanced by technologies that collect and integrate data by means of enhanced visibility, precision and speed of execution, feedback, engagement, flexibility in time and space, and prevention (Cifone et al., 2021). According to the definition of Verhoef et al. (2021), we describe digitalization as the transformation that occurs when digitization technologies (as defined by Loebbecke and Picot, 2015; Verhoef et al., 2021) are used together with other enabling technologies. The two main trends in digitalization identified by Culot et al. (2020, p. 6) are "integration between the physical world and the digital one" and "connectivity both locally and with universal direct networking." Thus, Frank et al. (2019) defined two main "base" technological dimensions of digitalization: *data integration,* by means of connectivity provided by network technologies and unified corporate business systems, and the automated digitization of data generated by operational technologies, the "physical world", through new *digitization technologies*.

Data integration is related to the "digital thread" concept, which has been defined as the process of integrating different streams of data into a unified corporate business system (Helu et al., 2017) across a firm (e.g., in manufacturing for production planning, maintenance, quality control, production lines), that connects, for example, the Manufacturing Execution System (MES) with Enterprise Resource Planning (ERP) systems. "Physically centralized" ERP systems support "logically decentralized" decision-making pertaining to inventory control, database management, and the handling of information by suppliers (Almada-Lobo, 2015; Rossit et al., 2019). With ERP systems, operational data are integrated and made available across departments, with an ease of access to a heterogeneous and common pool of data coming from digitized devices and enterprise information systems, including sensory and enterprise data from employees, departments, and business partners (customers, system integrators, suppliers). ERP systems play a knowledge management role in providing access to data, assimilating information, and connecting diverse knowledge (Schniederjans et al., 2020). Although different actors have different goals and viewpoints (Lenz et al., 2018), the accessibility provided by unified corporate business systems can ideally enhance integration (Cui et al., 2020; Fatorachian and Kazemi, 2018) — e.g., between product development and manufacturing, or between maintenance and quality through performance indicators across multiple application domains (Lenz et al., 2018). The synchronization of communication between digitized devices and enterprise information systems (Fatorachian and Kazemi, 2018) ensures that data are always updated in real time in order to optimize a factory's automation systems (Cui et al., 2020; Porter and Heppelmann, 2015). Planning tools can be designed to use integrated data, and the process states of machines can be used for real-time production planning and task scheduling (Lenz et al., 2018). Some analytics applications require real-time data, without any time lag between their capturing from the ERP system and their availability for analytics (Dutta and Bose, 2015). The resulting positive effect on "speed of execution" can reduce time lags and thus enable faster decision-making (Cifone et al., 2021).

A new generation of *digitization technologies* have emerged with the advent of Industry 4.0. These are hardware components that bridge the gap between cyberspace and the physical reality of equipment and semi-finished products (Balsmaier and Woerter, 2019; Culot et al., 2020; Guo et al., 2021). Thanks to their use, computing capabilities are embedded in what used to be non-digital artifacts: physical objects become programmable, addressable, sensable, memorizable, traceable, and associable (Yoo, 2010). These components include sensors, tracking technologies (e.g., RFID, bar codes, smart labels), and machine vision, all of which increase the amount of data generated about a firm's products, processes, and inbound and outbound activities. For example, data can be processed by employees to troubleshoot the root causes of problems or product defects, or to predict quality and equipment problems. As outlined in the Information Processing Theory (IPT), digitization technologies can reduce task uncertainty (Ancarani et al., 2019), thereby resulting in clearer and more analyzable processes that are more suitable for DDM (Flores-Garcia et al., 2019). In addition, cost advantages are associated with a higher technological readiness, in terms of digitalization (Ancarani et al., 2019), as the analysis of big data can enhance data-driven decision-making and lead to better operational performances (Ferraris et al., 2019).

3. Development of the hypotheses

The current literature streams widely discuss both digitalization and DDM. Concepts such as "Industry 4.0" and "smart manufacturing" have been theorized and defined, and research agendas, taxonomies, and roadmaps have been proposed (e.g., Brennan et al., 2015; Culot et al., 2020; Pessl et al., 2017). Moreover, data-driven decision-making is also gaining the increasing interest of researchers. Studies that mention digitalization and decision-making in the abstract, title or keywords are spiking, and they doubled each year between 2018 and 2021. However, the tangible links between data-driven decision-making and digitalization, even when explicitly mentioned, have not been explored (e.g., Kang et al., 2016; Theorin et al., 2016). As a result, the two streams do not yet converge in studies aimed at confirming their interplay on operational performance. Some exceptions can be found in the field of knowledge management. For instance, Abubakar et al. (2019), in their propositions, suggested that decision-making approaches might play a moderating role between knowledge management (of which "IT support" is one of the components) and operational performance, and also suggested the need to study these relationships. This type of study, which is close to our area of investigation, is still at a theoretical level, as it lacks empirical evidence. Firm-level studies that have put together digitalization technologies and managerial approaches, including those of decision-making, with a socio-technical approach are mainly based on qualitative case studies (e.g., Cagliano et al., 2019). Quantitative empirical studies, as mentioned by Bokrantz et al. (2020c), have been scantly integrated in these literature streams. To fill these gaps and to have a firm-level view, we decided to use a mix of qualitative and quantitative data, and to adopt IPT lenses considering digitalization technologies as the capability of a firm to make the use of DDM effective.

The main assumption is that DDM does not necessarily have a positive effect on full industrial cost reduction. This is because there is no best approach to decision-making; instead, the best choice depends on the "structuredness" of the underlying event that calls for a decision to be made. However, a larger amount of operational data, and a greater access to such data can provide front-line events with structuredness, as defined by low ambiguity and high analyzability (Flores-Garcia et al., 2019). On the one hand, the accessibility and synchronization provided by the information systems used for data integration should lower the ambiguity of operational events upon which decisions have to be taken. On the other hand, a wider range of digitization technologies has what is needed to increase analyzability, thanks to the availability of more, varied, and accurate data from multiple sources. Therefore, the presence of these technologies (information systems and new digitization technologies) should show a positive interaction with DDM. Ultimately, this study aims to test the hypothesis through which the two identified dimensions of digitalization benefit from data-driven approaches to decision-making.

The first hypothesis that has to be tested is that the data accessibility and synchronization ensured by *data integration* contribute to making shop floor events well-structured, thus leading to DDM being the best approach to improve cost performance:

H1. A firm that combines a DDM approach with a high level of *data integration* increases its probability of achieving cost reductions.

We chose cost reduction as a dependent variable for three main reasons: our focus on "production decisions" at an operational level (e.g., Bloom et al., 2014); the hypothesis whereby the new digital technologies could drive a cost reduction (e.g., Cifone et al., 2021); and the fact that efficiency-driven investments in digital technologies in manufacturing have cost reductions as the ultimate target (e.g., Kamble et al., 2020; Trantopoulos et al., 2017). Unlike other studies that have used such operational indicators as productivity, inventory levels, or scraps, we decided to use a metric that could be transversal to production, logistics and quality, coherently with the firm-level approach that characterizes this study, with such choices as that of analyzing the digitization technologies pertaining to the three areas (see the next paragraph).

In fact, the second hypothesis that has to be tested regards the technologies that are emerging for the real-time digitization of operational events. Büchi et al. (2020) conceived the concept of "breadth", in terms of the number of Industry 4.0 pillars adopted, which comprises such technologies as cloud computing, augmented reality, and simulation. Here, the focus is narrower, i.e., on the digitization technologies that allow operational data to be generated and automatically collected. Therefore, we have defined a "breadth" subcategory, which we have called "DT breadth" (breadth of "digitization technologies", not "digital technologies" at large). Büchi et al. (2020) were not able to find any statistically significant support to confirm their hypothesized relationship with performance. Using a narrower subcategory, we have tested a similar hypothesis, whereby digitization technologies and their ability to generate real-time data in crucial areas of a firm (production, logistics, and quality) make shop floor events more analyzable, thus making DDM the best approach to achieve operational performance:

H2. A firm that combines a DDM approach with greater *DT breadth* increases its probability of achieving cost reductions.

Finally, data integration and DT breadth are expected to have mutually reinforcing effects on making DDM effective, because operational data made available in real time to all those who have access to ERP systems allow data-driven decisions to be made at all levels:

> **H3.** Simultaneously increasing the levels of *DT breadth* and *data integration* has a greater effect on increasing the probability of cost reductions in DDM firms than increasing only one of the two dimensions.

The three hypotheses are summarized in Figure 1.

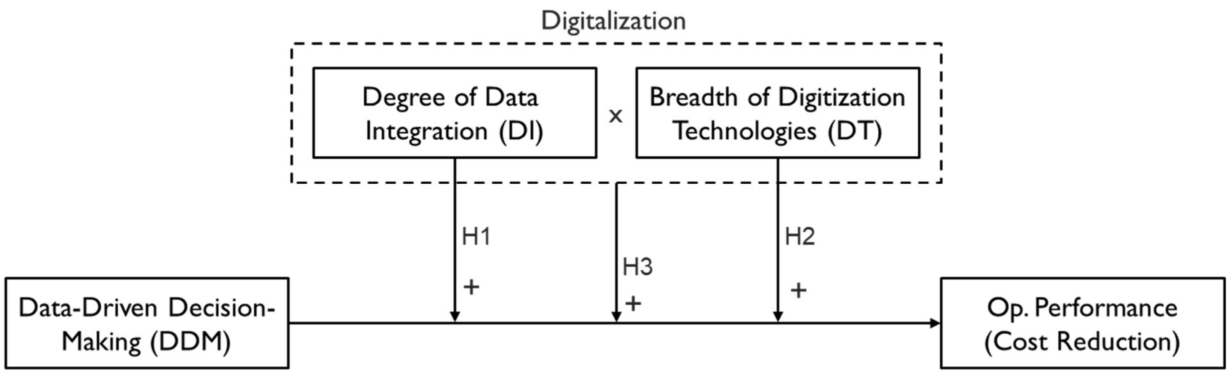

Fig. 1. The theoretical three-way interaction model and the hypotheses

4. Methods

4.1 Data collection

We used a mixed-method approach that combined quantitative and qualitative data. Both phases focused on the adopted technologies, the investment objectives, the use of data in the operations and maintenance, the main approaches to decision-making, and the operational performance of the manufacturing plant.

Prior to conducting the survey used in the quantitative study, we visited sixty manufacturing plants throughout Italy and the USA with the aim of having "hands-on experience" and of better understanding the phenomenon of this study. We conducted semi-structured interviews with

CEOs, production managers and workers to learn about their experience with new technologies, and toured production lines to see the new technologies in action. Apart from supplying specific qualitative insights that would support the quantitative findings, the interviews helped the research group create and conduct the survey itself reducing the risk of biases, as they allowed the members of the group: to understand whether the same concepts existed in both countries and, if so, whether they were relevant to the same extent, to confirm what the main digitization technologies that had to be considered were, to check whether there were any relevant aspects that had not emerged in the generation of the hypotheses, and to understand what variables were the most appropriate to measure the investigated concepts. In this regard, the reduction of the full industrial cost was confirmed by the majority of the participants in the interviews to be the most relevant ultimate target objective and indicator of improved operational performance.

The quantitative stage of the research involved two detailed multi-respondent, comprehensive and fully comparable surveys of Italian and U.S. firms active in the automotive sector as part suppliers in the 2018-2020 period. The survey was carried out with the support of the major industrial automotive associations in both Italy and in the US, and the sampling was made with firms that were part of these associations; among them, the response rate was 15-20% in Italy and 20-25% in the USA. The questionnaires were issued via email after a first phone contact, and they were completed by more than 200 manufacturing plants. Production managers, sales managers, and HR managers – who were identified during the preliminary phase as the ideal respondents to satisfactorily cover the investigated areas – answered the questionnaire separately. Some of the firms were not suitable for the analysis, due to their size (for instance, micro firms with fewer than 10 employees were excluded), or their business and position in the supply chain were not consistent with the scope of the study. In other firms, missing values were found for one or more of the investigated variables. After data cleaning, 138 questionnaires were considered suitable for the data analysis. Among them, 65% are Tier-1 firms that ship directly to the automaker, being the rest mainly Tier-2 suppliers. Consistent with the differences between the two industries, the average number of employees per firm in our sample is 610 for the US firms and 151 for the Italian firms. The next section introduces the measures used in this studies, whose main descriptive statistics can be found in Section 4.3.

4.2 Measures

Cost reduction. This variable was chosen to answer the question: "did your operational performance improve?". In order to avoid social-desirability bias and answers skewed toward "yes", the dependent variable was operationalized using the answers of production plant managers to a multiple-choice question about the exact range of product unit costs in the previous three years: (a) less than –10%; (b) between –10% and –3%; (c) ±3%; (d) between +3% and +10%; (e) more than 10%. With these answers, we were able to compute an unbiased cost reduction dummy variable that equaled 1 if the respondent indicated product unit costs of (a) or (b), or which coded as 0 if the respondent indicated (c), (d) or (e).

Data integration. Plant managers were also asked whether the plants used a corporate business system that integrated and linked sensor data with enterprise information systems (e.g., MES, ERP, SCM, CRM); whether data were shared among other operational departments (that is, once the data had been collected and stored in ERP systems, they did not remain in "silos"). We asked the sales managers whether an ERP was also used in their units, with the aim of adding a degree of integration outside the operational environment. We then summed these three binary responses to create a measure of the degree of data integration. The resulting variable ranged from 0 to 3. As explained in the literature section, such network technologies as cloud services are still immature in manufacturing (Dalenogare et al., 2018; Frank et al., 2019) and their effects are not yet visible; instead, the comprehensive use of a unified corporate business system can be considered a better proxy for data integration and the related accessibility and synchronization properties of vertical integration (Almada-Lobo, 2015; Frank et al., 2019).

DT breadth. We asked the plant managers to indicate whether they adopted or did not adopt specific digitization technologies. The qualitative research allowed us to identify three main types of technologies that cover the main operational areas of the analyzed manufacturing plants, and which are already present in most of them: IoT sensors (production monitoring), material tracking (internal logistics), and machine vision (quality control). We can also find in literature that IoT, RFID, and machine vision are among the most relevant technologies used to enable the real-time monitoring of operations and data-driven decision-making processes (Rossit et al., 2019; Vukićević et al., 2021). Consistent with the concept of "breadth" conceived by Büchi et al. (2020), and with a focus on the variety of data acquired, we summed these three binary responses to create a variable that equally measured the number of different data sources (digitization technologies, "DT") in each plant. The resulting "DT breadth" variable ranged from 0 to 3.

Data-driven decision-making. As seen during the qualitative phase, the DDM and IDM approaches were both found to be present in the firms; however, one always emerged as being prevalent (consistent with literature, see Bokrantz et al., 2020a). We asked the production managers whether operational decisions in their plants were mainly based on data and complemented by human intuition (data-driven) or driven by intuition and experience, with data only being used as a complement (intuition-driven). We then used these responses to create a binary variable to measure the "degree to which decisions are based on data," in line with the "data analysis," "decision making," and "decision augmentation" categories of DDM outlined by Bokrantz et al. (2020a). To avoid any social-desirability bias that could lead to a prevalence of DDM, and therefore increase robustness, a third option – "we do not use data in our operations" – was made available to the respondents. The answers were evenly distributed between the other two options, thus confirming the empirical evidence of variance that had emerged during the interviews.

Control variables. Last, we included a set of control variables to control for factors that could have an impact on cost reductions, such as differences in institutional background (between the U.S. and Italy), and the size and position of the firm in the supply chain (e.g., Tier 1), which could affect the result of managerial practices aimed at reducing operating costs. The operationalization of the theoretical model variables (Figure 1) is summarized in Table 2.

Table 2
Operationalization of the model variables.

Variable type	Variable name	Variable description
DVs	Cost Reduction	Average annual percentage change in the "cost per unit produced" (Kamble et al., 2020) over the previous three years: (a) less than –10%; (b) between –10% and –3%; (c) ±3%; (d) between +3% and +10%; (e) more than 10%. Dummy variable: • [1] if (a) or (b) • [0] if (c) or (d) or (e)
IVs (manag.)	Prevalence of Data-Driven Decision-Making	Degree to which decisions are based on data, with respect to experience and intuition (Bokrantz et al. 2020a) Dummy variable: • [1] if decisions are based on data, and experience and intuition are used only as a support to aid decisions (DDM) • [0] if data are used occasionally, only to support decisions that are mainly driven by intuition and experience (IDM)
IVs (tech.)	Degree of Data Integration	Continuous variable [0–3], a summated scale that measures the degree to which data are vertically integrated (Frank et al, 2019) throughout the production plant: • data are sent automatically to a unified ERP system • data are shared among operational departments • the ERP system extends beyond the manufacturing department (e.g., the sales department)
	Breadth of Digitization Technologies	Continuous variable [0–3], a summated scale that measures the digitization breadth (a subset of the concept inspired by Büchi et al., 2020) i.e., the number of digitization technologies adopted among three main types: • IoT sensors on equipment (production process data) • tracking technologies such as RFID (logistics data) • machine vision (quality data)
CVs	Firm size, Country (Italy or the USA), Supply chain position (Tier 1, 2, 3+)	

4.3 Data analysis

We used a logistic regression to determine the probability of a cost reduction as a function of the interaction between DDM and the technological variables. Since the logistic regression coefficients provide a coefficient γ in logarithms of odds (i.e., the ratio of the probability of success to the probability of failure), we used the following formula to transform the log odds into probabilities (p): $prob_{cost\,reduction} = \frac{\exp(\gamma)}{1+\exp(\gamma)}$). The calculated coefficients represent the estimated probabilities of a cost reduction for an increasing rate of adoption of digital technologies and when a data-driven or an intuition-driven approach is preferred, respectively. The results were then used to perform a margin analysis, using the margin command in the STATA statistical analysis software, which estimated the probability of a cost reduction for increasing degree of DI and DT breadth.

5. Results

5.1 Descriptive statistics

Most of the firms (89% of the sample) had introduced at least one digitization technology and were therefore suitable for our analysis. The difference in the adoption of digitization technologies between the two countries is shown in Figure 2.

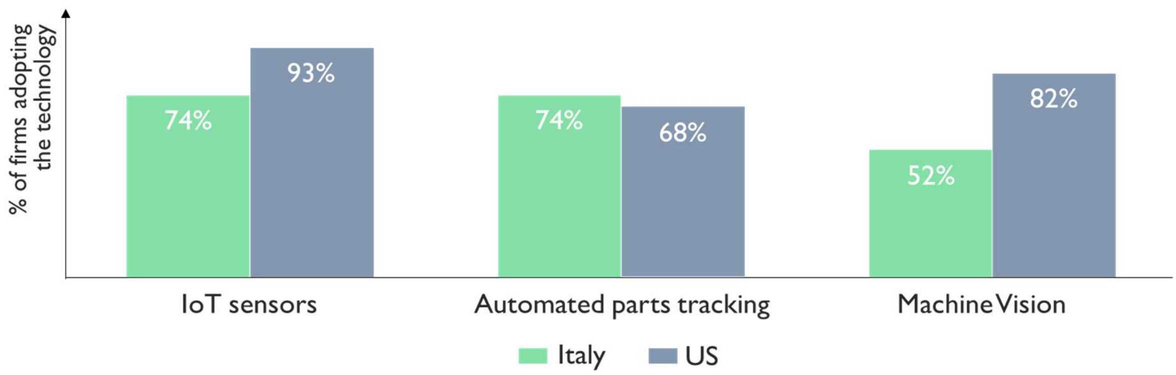

Fig. 2. Adoption rates of the main digitization technologies used in the model

About half of the interviewed firms used data-driven decision-making at the plant level, at a similar adoption rate for the two countries (53.5% in Italy and 65.4% in the U.S.). On average, more data-driven (22.5%) than intuition-driven (19.6%) firms achieved cost reductions over the previous three years.

5.2 Regressions and margin analysis

Table 3 shows the results of the five logistic regression models, of which model 4 is the most complete and significant, because it includes all the interacted and control variables.

Table 3
Outputs of the logistic regression models

DV: Cost Reduction	**(1)**	**(2)**	**(3)**	**(4)**
Size	-0.025	-0.335	-0.411	-0.404
	(0.261)	(0.348)	(0.355)	(0.356)
US	0.374	0.497 *	0.602 *	0.590 *
	(0.262)	(0.294)	(0.305)	(0.307)
Tier-1	-0.058	-0.000	-0.122	-0.117
	(0.259)	(0.269)	(0.289)	(0.292)
Data-driven Decision-Making (DDM)		0.272	0.361	0.438
		(0.267)	(0.290)	(0.330)
Data Integration (DI)		0.106	-0.069	-0.065
		(0.251)	(0.270)	(0.272)
DT breadth (DT)		0.040	0.304	0.383
		(0.281)	(0.334)	(0.372)
DI x DDM			**0.481 ***	**0.489 ***
			(0.292)	**(0.293)**
DT x DDM			**-0.724 ****	**-0.824 ****
			(0.317)	**(0.378)**
DI x DT			0.037	0.093
			(0.269)	(0.280)
DDM x DI x DT				-0.176
				(0.289)
Constant	-1.159	-1.142	-1.111	-1.170
	(0.246)	(0.259)	(0.281)	(0.306)
N	138	138	138	138
Pseudo R^2	0.110	0.160	0.186	0.189

Notes: Coefficients expressed in log-odd ratios, with the standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results confirm that DDM has no direct effect on cost reductions, unless moderated by technological variables (as predicted in H1 and H2). We also computed the effects of the technological variables without considering the DDM variable; this was to function not only as a control for the regression, but also as to confirm that the effects of digitalization become more evident when the managerial variables (in this case, a firm's approach to decision-making) are examined.

On the basis of these results and the conversion from log odds to probabilities, we show, in Table 4, that the prevalence of DDM in firms is associated with: (i) a high probability of a cost reduction (62%) if the degree of data integration is increased, and (ii) a low probability of achieving a cost reduction (30%), as a result of increasing a firm's DT breadth. Therefore, H1 has been confirmed (data integration has a positive moderating effect on the relationship between DDM and cost reduction) and H2 has been refuted (DT breadth has a negative moderating effect on the ability of DDM to drive a cost reduction). However, the opposite effects of the two variables contributed to the impossibility of confirming or refuting H3, since the interaction of the two dimensions of digitalization did not produce a statistically significant effect on moderating the impact of DDM on cost reductions. A more detailed interpretation of these results is provided in the Discussion section.

Table 4
From log odds to probabilities: description of the results.

Hypothesis	Confirmed	Variable	Log odds	Probability
Increasing the degree of data integration is associated with a higher probability of achieving a cost reduction where DDM is prevalent **[H1]**	Yes	DI x DDM	0.489 * (0.595)	62%
Increasing the DT breadth is associated with a higher probability of achieving a cost reduction where DDM is prevalent **[H2]**	No	DT x DDM	-0.824 ** (0.767)	30%
Breadth and data integration have a joint effect in making DDM firms achieve a cost reduction **[H3]**	_ [1]	DT x DI x DDM	-0.176 (0.586)	_ [1]

[1] not statistically significant

The results of the margin analysis performed with the outputs from model 4 in Table 3 are reported in the appendix (Table A1). Figure 3 shows graphically the estimated probabilities of a cost reduction for increasing DT breadth and data integration when a firm prefers a DDM approach. It is possible to appreciate how DDM shows opposite interplays for the two technological subsets under analysis: higher levels of data integration throughout the firm are beneficial in helping data-driven firms achieve a cost reduction; on the other hand, increasing the number of data sources (DT breadth) has a negative moderating effect and – at each level of data integration – the higher the number of DTs is, the lower the probability of a cost reduction. In the appendix, Figure A1 shows the corresponding results for IDM.

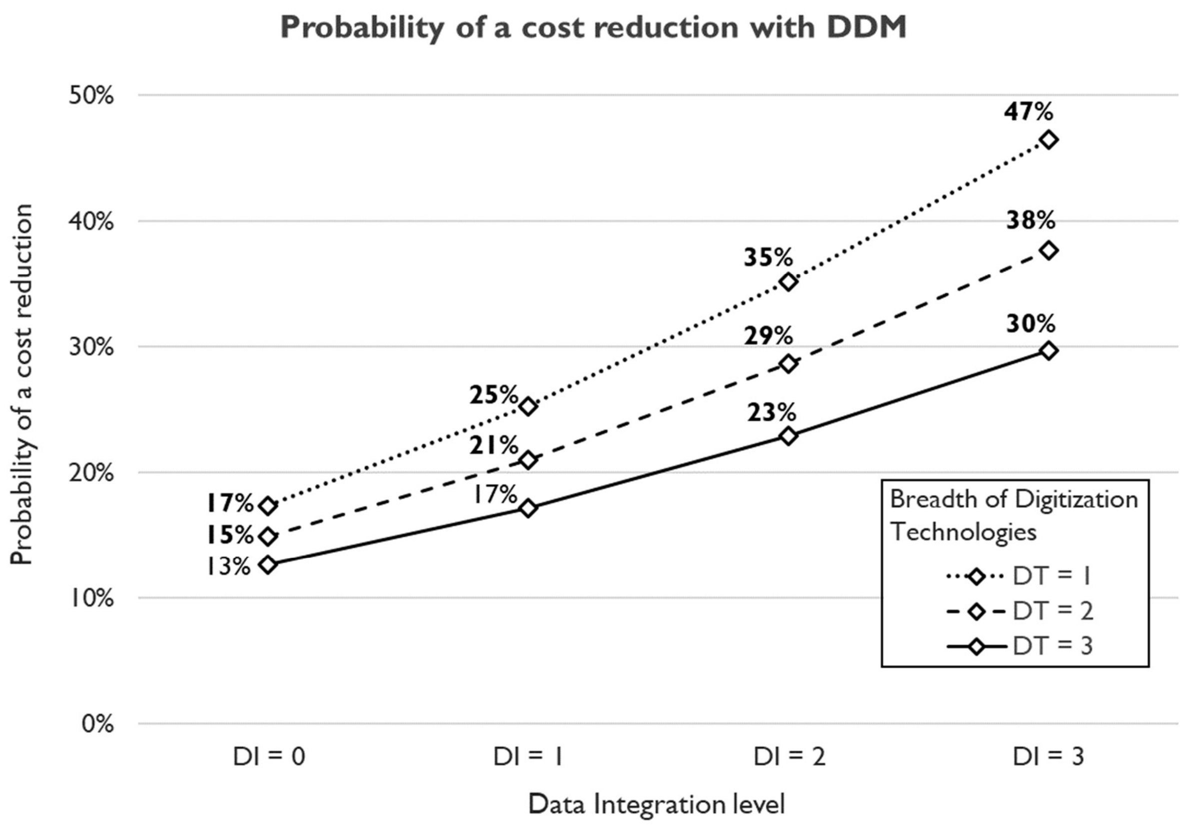

Fig. 3. Probability of a cost reduction for increasing degrees of data integration, by DT Breadth (the statistically significant values are in bold)

6. Discussion

We hypothesized that whether data-driven decision-making leads to a performance improvement depends critically on the moderating effects of technologies that enable the integration of data and their automated collection. In this section, we discuss the partial support of our hypotheses that we have found using novel data on Italian and U.S. manufacturers in the automotive sector. Next, we set out the implications of our findings for managers and policymakers.

6.1 The interplay between digitalization and decision-making

Increasing the level of digitization and data integration affects how DDM drives operational excellence (Tortorella et al., 2021). However, such an effect is not positive, regardless of the type of digital technology adopted, nor is there any interplay between the two dimensions of digitalization. The two dimensions of digitalization (data integration and automated data collection with digitization technologies) showed opposite effects on how DDM drives cost performance because they have different properties.

The *digitization* of operational data, which have been made available by ERP systems for decades, is already well established. These data can be collected either manually, on paper or directly from machines, or automatically, through another set of technologies. Relying on data for decision-making is an approach that works where such information systems as ERPs are well established and used throughout a firm. A higher integration of data makes the data more reliable and usable throughout the firm, and it also allows for more structured operations, routines, and decisions. Confirming both literature and the findings of our interviews, data integration helps reduce ambiguity by making data accessible, by synchronizing data among physical devices and information systems, and by storing all the data and information in one place; this, in turn, provides access to information and sources of knowledge (Schniederjans et al., 2020). With such a "single source of truth," workers have access to the right information in the right place at the right time. Accessibility allows bottom-up knowledge to be created and this knowledge enables DDM to be decentralized. Synchronization produces “a single source of truth” that makes DDM more easily accepted and reliable, even when delegated to the production line. Indeed, the distinctive characteristics of Industry 4.0 are autonomy, real-time information transparency, and process integration (Culot et al., 2020). This supports our findings, for which the adoption of a DDM approach is more likely to lead to cost reductions in manufacturing plants where the degree of data integration is higher.

On the other hand, *digitalization* is about changing processes and organizational structures. Having new technologies available to capture data from their inception means changing the way in which data are collected, as well as the creation of new processes to interpret and analyze them. This also calls for new, more decentralized capabilities. Operational workers, in order to grasp the benefits, should be in charge of monitoring these data and of transforming them into valuable information for data-driven decision-making. However, rather than the expected effect, that is, adopting more digitization technologies (DTs) provides benefits by enabling a more extensive and valuable use of data, a “complexity” dimension seemed to emerge that makes the variety of data difficult to analyze centrally through a data-driven approach. In order to use integrated data to make decisions, it is necessary to collect such data in a reliable and standard way; however, the qualitative part of our research has confirmed that production workers and team leaders are not ready for this. A line manager in one of the Italian firms we visited expressed the same concern as other interviewees when he told us that, despite data collection being automated locally through sensors and other new technologies, their input into an information system is still highly prone to operators’ mistakes.

Heterogeneity of data sources is one of the factors that can affect the link between the adoption of digital technologies and a firm’s performance (Ferraris et al., 2019). Augmenting the number of data sources increases the ambiguity and results in ill-structured events, which is exactly where DDM leads to lower operational results (Flores-Garcia et al., 2019). Despite the role of digitalization in making it possible to recombine different sources of knowledge (Schniederjans et al., 2020), the presence of multiple data sources (e.g., Tortorella et al., 2021) appears to require more intuition, experience, and tacit knowledge for their interpretation. Therefore, DDM is not suitable (or ready) for dealing with such a large variety of data from multiple sources. As a result, the breadth of digitization technologies shows a negative synergy with DDM. Confirming previous studies (e.g., Flores-Garcia et al. 2019; Julmi 2019; Cappa et al., 2021), we have found that DDM seems to work better when the variety of data is smaller (low number of DTs). However, a firm that increases its ability to generate data through a higher number of digital technologies and builds up its internal information architecture is expected to increase its information processing capability (Li et al., 2020). Therefore, the effect found through the regression analysis could be temporary, as the learning curve might be slow, and firms might just need time to acquire the necessary organizational knowledge to exploit multiple sources of data.

Another interesting aspect of the results is that the use of DT, DI, or DDM alone did not have a statistically significant effect on cost reduction. This result confirms previous studies, based on socio-technical theories, and management innovation literature streams (e.g., Damanpour et al., 2014; Cagliano et al., 2019), according to which, in order to discuss operational performance, technological and managerial aspects should be considered as a whole. Moreover, the interaction between DT, DI and DDM was not statistically significant, due to the opposite effects of DI and DT when interacting with DDM.

The findings we have presented here confirm the proposition of Flores-Garcia et al. (2019), who stated that DDM is more suitable for “well-structured” events. Increasing the level of data integration, especially in “simpler” environments with a lower DT breadth and therefore fewer data sources, makes events more analyzable and less ambiguous, and a data-driven approach has shown a higher probability of achieving a cost reduction. These findings reinforce previous studies on IPT (e.g., Li et al., 2020), thus confirming that information processing capabilities (DDM) and high information quality (provided by accessible and synchronized data) can contribute to the performance of a firm. Contextualizing the concept of "data-driven decision-making" within information system theories can also be highly promising for the knowledge management literature that analyzes the role of big data in providing information and creating knowledge (e.g., Jennex, 2017; Tortorella et al., 2020) and the relationships among digital technologies, information processing systems, and the accumulation and deployment of knowledge for decision-making in manufacturing (in a similar way to the approach proposed by Schniederjans et al., 2020, for supply chain management). DDM cannot (yet) be considered a better or worse approach to achieve operational performance, in particular due to the current transition phase toward the digitalization of firms. However, its interplay with both data integration and DT breadth, and the role of such an interplay in achieving structuredness, is essential to explain how a cost reduction is achieved.

6.2 Managerial implications

In our qualitative investigation, we have witnessed that operational workers and line managers still have to become used to the new increased availability of real-time data. First, there are technical issues. RFID and other technologies for logistics automatically feed ERPs with inventory data which, at times, are not consistent with the actual physical inventory levels. In an Italian Tier-1 firm we visited, an operator had to carry out a physical inventory of the whole warehouse and production line every morning, and manually update the ERP to fix the data according to his count. Such discrepancies make it difficult to fully rely on data for decision-making. Similar issues arise for production and quality data when collected automatically through IoT sensors and other technologies. Since these data also contribute toward feeding inventory data, the error propagates. A manager in a highly automated US firm described how it still relies heavily on intuition because of issues in data collection from sensors: “Sometimes the sensors go bad – about once a week a sensor will tell us the product is defective when it really isn’t. Then we have to check things out manually.” This is consistent with our quantitative results: the more the automated-data-collection technologies are, the less DDM can have a positive effect on improving a firm’s operational performance.

Second, there are also human mistakes, issues in inputting data, and interpreting them without a well-established structure. From a socio-technical perspective of the phenomenon, this “social system” component is just as relevant as the technical one. Our qualitative investigation shows that, as also demonstrated in previous literature, managers face “a cultural resistance to change with respect to decision-making practices” from workers who feel threatened by algorithms (Bokrantz et al., 2020b). An Italian firm’s plant manager told us: “We have recently bought machines that ‘speak,’ but we do not listen.” If the ability to interpret data and algorithms increases, trust in them will positively influence their adoption and the operational performance achievable through DDM (Bokrantz et al., 2020b). However, the lack of digital skills in under-qualified employees is still a key barrier to realizing Industry 4.0 (Raj et al., 2020). Therefore, investing in their upskilling will be of key importance, as they need increased capabilities to interpret big data and make effective operational decisions at the shop floor level (e.g., Helper, 2009; Colombari and Neirotti, 2021).

However, we believe that both of these effects might be temporary: as technology improves and line operators and managers learn to leverage on it, automatically collected data will become more and more reliable, and therefore more suitable for DDM. We witnessed this pattern in some of the firms that had a longer trajectory in the adoption and use of new digitization technologies. However, especially in this first phase of the introduction of new technologies, intuition seems to play an important role in combining different data, and to be a key to learning how to use them in decision making. Our results show that intuition and experience are more effective when different operational areas automate their data collections. This might support the need for developing organizational capability to leverage on both DDM and IDM, as both, depending on the technological moderating conditions, are currently associated with a cost reduction. According to the IPT, the needs and capabilities of information processing should match to obtain an optimal performance, and decision-making can be improved by organizational practices that either reduce the need to process information or increase the information-processing capacity (Galbraith, 1973; Li et al., 2020). Therefore, in order for employees to be able to satisfy the evolving information-processing needs of a firm, we suggest that both systems have to be activatable, in line with the "dual process" concept (Evans, 2003; Dane and Pratt, 2007). Front-line employees have traditionally adopted more of a "System 1" approach, i.e., the type that refers to innate intuition and domain-specific knowledge (Evans, 2003). However, with digitalization, they are now in possession of real-time data at the operational level (Veile et al., 2020) that enable "System 2" approaches, i.e., of the type that allows fast abstract reasoning and hypothetical thinking (Evans, 2003). In the medium term, once these new processes have become well established, managers will be called upon to understand what decision-making approach is best in each situation. Even where using intuition and experience might appear to be the best approach, the bases to operate by means of DDM should be set throughout the firm; shop floor workers need to be made aware of the benefits of data-driven decisional processes, and the importance of participating in them, to generate information from everyday operational data and create operational knowledge that is actionable for decision-making. Although intuition and experience are already present in all firms, a "data-driven culture", which is fundamental to exploit the recent increase in real-time big data (Ferraris et al., 2019), still needs to be diffused widely. Therefore, front-line managers and employees should be advised to complement their experience and domain knowledge with data analytics skills, in order to exploit both approaches and be prepared to fully leverage on DDM to improve their firms' operational performance.

7. Conclusions

In this study, we have investigated under what conditions Data-driven Decision-Making (DDM) can lead to improvements in operational performance. We used digitalization as a moderating variable and defined it through two main enabling technologies: information systems for data integration, and digitization technologies for real-time automated data collection. Instead of finding a joint effect of the two dimensions, we found two opposite interplays. On the one hand, well-established information systems, such as ERPs, that make data available and synchronized throughout a firm, represent the information-processing organization capability that is key to achieving operational performance through DDM. On the other hand, a wide range of diverse operational data, captured in real-time through new technologies, is not – yet – showing positive results with DDM approaches. This raises a new question: will the adoption of several "Industry 4.0" digitization technologies become solid enough to leverage on them for DDM? We expect such a result to only be a matter of time and a question of organizational learning; in a few years, a new wave of surveys could show an inverse trend for which a higher number of digitization technologies are associated with a better performance of DDM. This expectation opens opportunities for future research.

This study presents some limitations and inspiration for future research. First, it was intended to simplify the phenomenon through a strong contraposition between DDM and IDM, with the aim of understanding their high-level interplay with the two different dimensions of digitalization. Therefore, as both approaches can be found at the same time and both can lead to improved performance, the authors would like to stimulate other researchers to carry out further research using more shaded and granular scales of DDM. Moreover, the digitalization scales were purposely simplified to ensure a high replicability of the study; however, future research could operationalize more technologies into the digitization scale to make it more granular. The other main feature of this article is that it has focused on firm-level outcomes and, even though country specific institutions have been controlled for in regressions, there may be important differences across Italy and the U.S.A. that need to be explored (e.g., Ancarani et al., 2019; Raj et al., 2020). Other qualitative studies could be aimed at understanding decision-making mechanisms at a lower level of analysis, for example, that of individual workers' routines. This would in turn contribute to guiding innovation in education and training for front-line employees, who are currently experiencing a whole new set of needs in the era of digitalization. Finally, other industries could be taken into consideration to generalize these findings; indeed, the automotive industry is just one of the increasingly competitive and capital-intensive traditional manufacturing industries facing disruptions brought about by digital technologies, and more empirical evidence is needed to validate these findings as a general pattern for digitalization.

Considering all these limitations, this study is intended to inspire further empirical research aimed at confirming – or refuting – the identified interplay between data-driven decision-making, well-established and new technologies for digitalization, and operational performance.

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Appendix

Table A1
Results of the margin analysis based on the results of Table 3 (model 4)

Degree of:		Probability of a Cost Reduction in the case of:	
DT Breadth	Data Integration	Intuition-driven Decision-making (DDM = 0)	Data-Driven Decision Making (DDM =1)
1	0	0.182 (0.135)	0.174 (0.139)
2	0	0.314* (0.181)	0.149* (0.087)
3	0	0.464 (0.349)	0.127 (0.104)
1	1	0.062 (0.048)	0.253*** (0.096)
2	1	0.166** (0.072)	0.210*** (0.062)
3	1	0.362** (0.174)	0.172** (0.078)
1	2	0.019 (0.029)	0.352*** (0.110)
2	2	0.079 (0.057)	0.287*** (0.063)
3	2	0.271** (0.124)	0.229*** (0.072)
1	3	0.005* (0.013)	0.465** (0.229)
2	3	0.035 (0.045)	0.377*** (0.134)
3	3	0.189 (0.189)	0.297** (0.143)

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients expressed as probabilities.

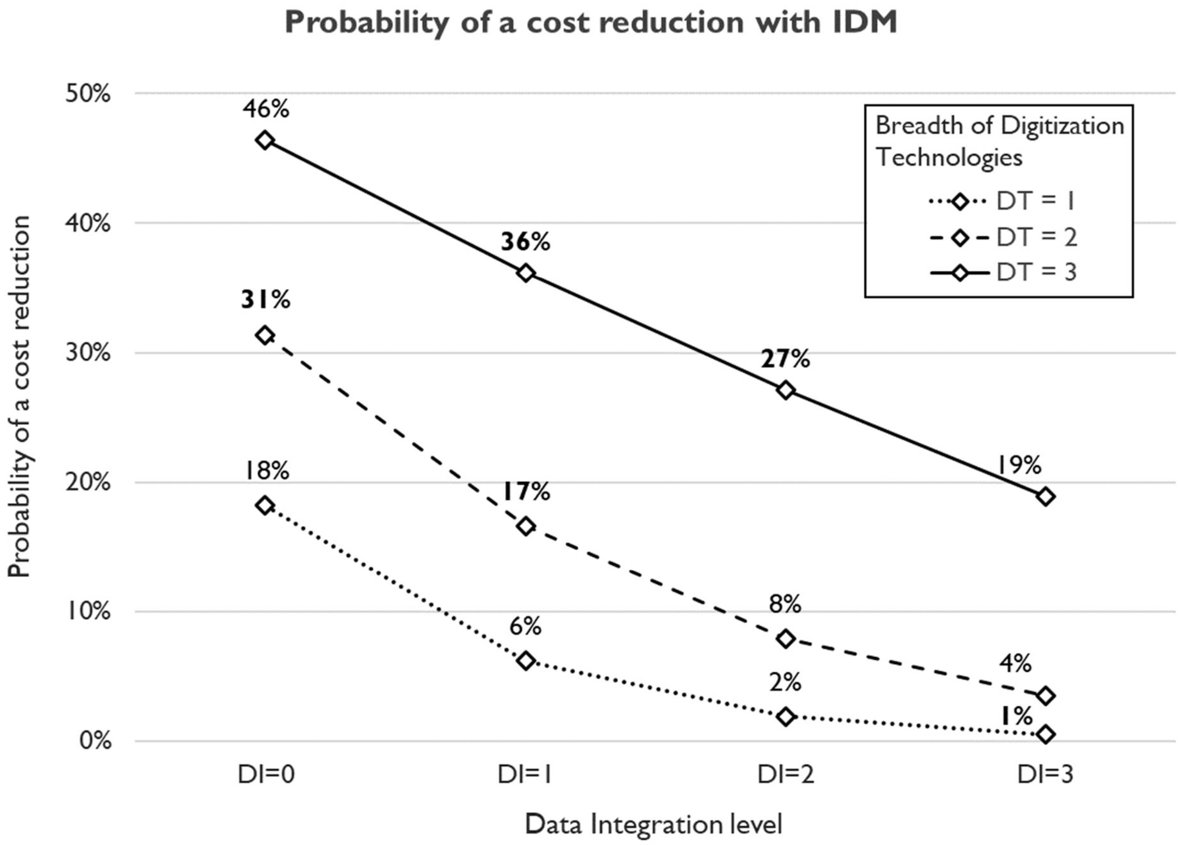

Fig. A1. Output of the margin analysis – Intuition-driven Decision-Making (DDM=0).