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Leveraging Frontline Employees' Knowledge for Operational Data-Driven Decision-Making: A Multilevel Perspective

Ruggero Colombari and Paolo Neirotti

***Abstract*—With the digitalization of manufacturing, firms can now increasingly access and analyze data in real-time, enabling data-driven decision-making (DDM) also at the operational level. Using a multilevel perspective and a mixed-methods research, this article aims to test whether production workers' involvement (organizational level) and frontline managers' competency (individual level) are associated with the use of operational DDM. The results of the regression models based on a survey of Italian auto suppliers show that high-involvement lean production practices are associated with a higher probability of DDM adoption when controlling for Team Leaders' and Supervisors' competency level, which have a positive moderation effect. Triangulated with qualitative interview data, these findings suggest that firms with skilled frontline managers are more likely to adopt DDM as they can leverage their production workers' context-dependent knowledge for sense-making, information processing, and knowledge creation. Also, the moderation effect is stronger for Team Leaders, suggesting a central role for them in firms' digitalization. This study contributes to literature with a socio-technical model that describes operational DDM by integrating organizational and individual dimensions into the data-information-knowledge-decision-making cycle. Organizational and individual implications of this skill-biased technological and organizational change are discussed, and recommendations are offered to managers and education policymakers.**

***Index Terms*—Data-driven decision-making, industry 4.0, knowledge management, lean manufacturing, operations management.**

I. Introduction

INDUSTRY 4.0 represents an unprecedented opportunity for the evolution of manufacturing firms and the organizing principles of their operational activities. Digitization technologies for real-time data generation (such as sensors for production lines management, radio-frequency identification (RFID) for internal logistics, or machine vision for quality management) and integration (higher connectivity, data lakes, ERP and Manufacturing Execution Systems) are enabling the digitalization of shop-floor operations, generating high expectations about the impact of data-driven decision-making (DDM) on organizational performance [1]. According to recent literature, firms that derive their strategic or operational decisions on Big Data and analytics can improve their business process outputs and achieve superior operational and financial performance [2], [3], [4]. It is worth mentioning that data have long been used to manage operations. However, the current technological wave marks a difference, as the increasing volume and quality of operational data—captured in digital form at their inception and available in real time—is now enabling a new and game-changing concept of "real-time data-driven decision-making" [5], [6].

This new paradigm shifts the focus toward frontline production managers, who monitor operational KPIs and use manufacturing real-time data on a daily basis for operational decisions related to the continuous improvement of efficiency in production and internal logistics, and of process and product quality. These decisions become crucial with the operational complexity faced by firms today, where shorter product life cycles lead to reduced learning times and increased product variety. Also, the diffusion of IT technologies calls for more empowerment and decentralization of the operational line [7]. With their interpersonal, informational, and decisional roles, frontline managers are in the position to play a key role for creating value in the age of digitalization, where the use of digital technologies on the shop floor generates opportunities for a bottom-up knowledge creation and decentralized decision-making [8], [9]. They also play a key role in the involvement of production workers—who are in even more direct contact with operations—in the continuous improvement of production processes, and are in the position to leverage on their context-dependent knowledge [10].

However, despite their importance for firm performance, frontline managers have been neglected in studies dealing with team effectiveness and operational performance [11], [12]. Then, organizational literature has focused on the complementarity of production workers with new information technologies, but not on the role of their involvement and participation in decision-making and its effect on operational outcomes, about which empirical studies are lacking in literature [13], [14]. Also, despite wide evidences that a socio-technical approach

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is needed to capture the complex implications brought by the digitalization of manufacturing, its impact is often analyzed under a pure technological perspective, disregarding organizational and managerial perspectives [15], [16]. As a result, little is known about possible organizational and individual factors which could enable DDM at the operational level. Therefore, this article adopts a multilevel approach focused on the role of the social system at the meso level (organizational structure) and micro level (people's individual capabilities) [17], [18]. The unit of analysis of this firm-level study is the manufacturing shop floor. In particular, the objective is to study high-involvement organizational practices as enablers of operational DDM, and test the hypothesis for which the competency levels of frontline managers—Production Supervisors and Team Leaders—play a moderation role. Regression models based on quantitative survey issued in the Italian auto supplier industry were supported by semi-structured interviews to improve the constructs and support the discussion of the results. The complementarity between high-involvement practices and individual frontline managers' skills is interpreted using a Knowledge Management (KM) perspective on DDM as a result of data sense-making, information processing and knowledge creation.

The rest of the article is structured as follows. Section II outlines the theoretical background and the conceptual multilevel framework. In Section III, the research setting and the processes of data collection and analysis are explained. The descriptive statistics and the results of the regressions are presented in Section IV, and discussed in Section V from theory and practice standpoints. Section VI concludes the article and outlines the opportunities for future research.

II. Theoretical and Conceptual Framework

The complex changes induced by digitalization in firms go beyond technology; to understand them, organizational and managerial aspects need to be considered [15]. With this aim, a comprehensive and rigorous theoretical framework can be provided by the socio-technical systems theory, according to which firms are described by the interplay among components of their *technical systems* (*technologies* and *tasks/processes*) and *social systems* (*organizational structures* and *people*) [19]. Within this study, DDM is the decision-making *task/process* driven by operational data obtained through digitization *technologies*; therefore, Section II-A is focused on the *technical system*, using KM theories and models to conceptualize DDM as driven by cycles of data-information-knowledge. In Section II-B, organizational literature helps introduce the two elements of the *social system* hereby tested as factors associated to the adoption of operational DDM: at the meso level, the shop-floor *organizational structure* and management through formal practices for production workers' involvement; at the micro level, the *people* component, i.e., frontline production managers' competencies for their managerial roles.

A. Data-Driven Decision-Making: A Knowledge Management Perspective

Data-driven decision-making (DDM) is defined as "the degree to which decisions are based on data"—collected and analyzed to

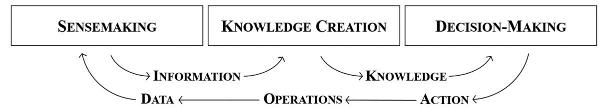

Fig. 1. D-I-K-DM cycle (own elaboration from [28], [31], and other authors).

augment and automate human decision-making—over intuition [20], [21]. Informed and timely decision-making depends on the availability and quality of data, and refining low-level data into real-time useful information can enhance a firm's competitiveness and lead to data-driven optimization [5], [22], [23]. Since the knowledge "mined" has a huge potential for decision-making, but "the quality of decision-making algorithms depends on the quality of the knowledge extracted from data sets", the challenge is data management and transformation into information and knowledge to drive—and eventually automatize—decisions [22], [24], [25].

In order to associate the concept of DDM to the agents in charge of it, it is necessary to disentangle the process that leads from data to decision-making. Leveraging organizational theories of information processing, knowledge creation and sense-making, prior KM literature has theorized data-information-knowledge models [9], [26], [27], [28], [29], [30]. The latter have been often conceptualized in pyramidal form due to their sequential selection process: there is more data than information, and more information than knowledge [30], [31], [32], [33]. In his "knowing cycle" Choo analyzed how each step precedes the other; however, since prior information and knowledge intervene in the observation and selection of the signals to transform into data, the sequence as "more like a circle than a hierarchy" [34]. In all these models, KM is a mean to "provide intelligence to the organization for use in decision making," corroborating the view for which the ultimate goal of transforming data into information and then knowledge is decision-making [33]. Fig. 1 synthesizes the cited KM models and Choo's organizational knowing cycle: through sense-making, data are interpreted and become information; combined with tacit knowledge, information (also identified as "explicit knowledge" [32]) contributes to the creation of new knowledge, used in turn for decision-making; the latter implies action on operations (e.g., process improvement), from which new data will be generated and enter the "D-I-K-DM cycle" again.

Concerning the other component of the technical system, "technology," a "revised knowledge pyramid" was proposed to consider Big Data and mechanical data-capturing sensors such as the Internet of Things (IoT) [33]. KM leverages different information systems in the Data-Information-Knowledge-Decision-Making (D-I-K-DM) process: data are used in transaction processing systems, information in management information systems, knowledge in decision support systems [32]. Similarly, different operational roles have different degrees of involvement at each stage of the process.

B. Agents of Operational Decisions: Frontline Workers and Managers

The cycle outlined in Fig. 1 disentangles the *task/process* component of the technical system through which decision-making

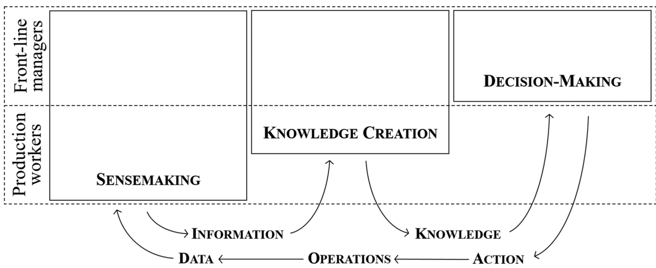

Fig. 2. D-I-K-DM cycle from a socio-technical perspective—meso level.

is driven by data. This section introduces the social system in charge of this process—i.e., the main literature gap identified—at two levels: the organizational meso level (the *structure*) and the individual micro level (*people* and their competencies).

1) Meso Level: Organizing the Shop Floor to Leverage Workers' Knowledge: At the shop-floor level, frontline managers are in charge of handling production data and take operational decisions, whereas production workers possess the tacit knowledge that is required to process big and "small data," i.e., those collected through their direct interactions and relationships with the object of their operations [13], [35]. Then, sense-making from information is a collective process (in the case of production shop floors, between frontline managers and workers) [36]. Seeing the D-I-K-DM cycle from a socio-technical perspective allows to add the *structure* dimension and point out the joint role of frontline managers and workers in the sense-making and knowledge creation that lead to operational decision-making. Fig. 2 synthesizes the concept for which production workers are those who are closer to the place where data are generated, and are fundamental in their sense-making, other than contributing to knowledge creation through their tacit knowledge about the process.

When knowledge has to be created from Big Data, their veracity has a positive impact [37], making it fundamental having them input properly by production workers in charge of documenting defects, breakdowns, and line slowdowns. Involving them could increase veracity of data and thus the propensity to use them to create explicit knowledge for operational decision-making. This view is shared by lean production, or lean manufacturing, a high-involvement management system that gives a central role to the involvement of production workers for knowledge creation [38], [39], [40]. Lean manufacturing envisages a bottom-up collection of qualitative and quantitative data for continuous improvement, i.e., root-cause analyses carried out by frontline managers are based on quality circles, kaizen weeks and formal programs for workers' suggestions, collectively analyzed with production workers for a better sense-making of operational problems [41]. The described joint decision-making among production workers and their supervisors is defined as "participation in decision making" [42], [43]. In lean manufacturing, "teamwork and group problem solving allow decision-making to be decentralized and therefore variance and uncertainty is managed more easily" [10]. Lower uncertainty is associated to "structuredness" that, boosted by technologies for data integration and analytics, make DDM a better approach to achieve higher performance [1], [21], [44]. Lean manufacturing was associated to operational DDM also by Veile et al. [45], who suggested it as a proper management method to achieve faster and decentralized effective decision-making, and claimed that firms should "revise their organizational structure to lay down an adequate foundation for Industry 4.0". To resume, involved production workers ("soft" lean, see [46]) input better data, contribute to better sense-making of small data thanks to experience and contextual knowledge, and give invaluable insights for the recombination of tacit and explicit knowledge by participating in kaizen events, quality circles and suggestion programs. Their involvement brings tacit knowledge into the knowledge cycle. In addition to this, lean practices force the use of analytical tools for problem solving and continuous improvement ("hard" lean) that can bring analyzability to uncertain situations and make DDM a more trustable approach, such as Kanban, statistical process control, Pareto diagrams, A3 problem solving, and KPI dashboards placed throughout the shop floor.

Hence, the first hypothesis of this article is that all these elements contribute to make DDM more reliable as an approach in the shop floor, making the formal involvement of production workers through lean manufacturing practices a factor that is associated with a higher probability of adopting and trusting operational decisions driven by data.

H1. A greater involvement of production workers through lean manufacturing practices is associated with a higher probability of using DDM in operations.

2) Micro Level: The Individual Role of Frontline Managers: As anticipated in the previous section, those in charge of involving production workers are frontline managers, who also have a liaison role with data analysts that process the Big Data coming from new digitization technologies [10], [47]. With an increasing volume, variety, and velocity of data, frontline managers and workers need increasingly higher competencies to make sense of them and understand which operational problems should be addressed to improve quality, increase capacity utilization, reduce downtimes, optimize production processes and maintenance cycles [48]. Indeed, employees that interact with digital technologies need adequate competencies to embrace data-driven approaches, and lean manufacturing literature showed that team leaders' skill gaps can lead to worse performance [49], [50].

However, frontline production management has more than one layer, and it is necessary to distinguish between two key figures: Supervisors (SVs) and Team Leaders (TLs). In lean manufacturing practices, for every five or six production workers there is a *hancho* (TL) leading the *han* (team), and for every two or three *hans* there is a *kumicho* (SV) [12]. Both of them are "lower-level managers responsible for operational control, maintaining day-to-day interaction with blue collar workers" [12]. Having to deal with operational control and monitoring, materials handling, and decision-making, many frontline individual roles contain both managerial and supervisory elements [51]. Especially with lean production, many functions (e.g., maintenance, problem solving) have moved to the line. *Supervisors* are in charge of training workers for discipline,

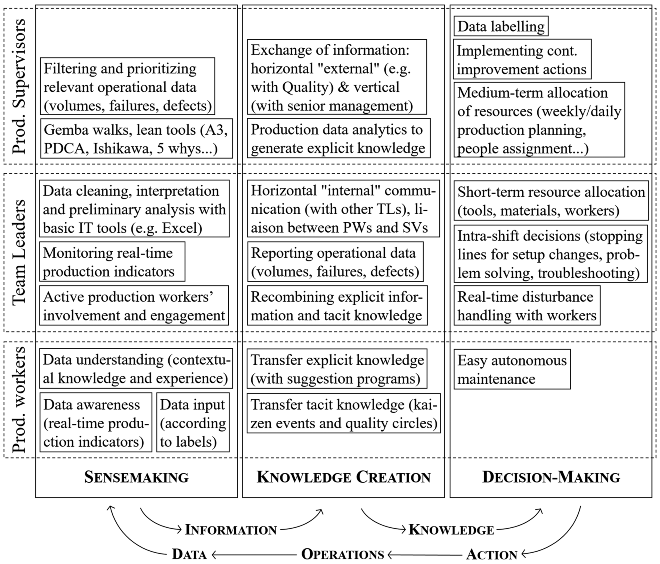

Fig. 3. D-I-K-DM cycle from a socio-technical perspective—micro level.

multiskilling and continuous improvement [12], and of performing managerial ("control and schedule" [52]) activities without working on the line: they manage workers' vacancies, prepare statistical process control charts, revise standard operating procedures, acquire information about failures and give instructions to act accordingly (from the "group leader" job description of [11]). Also, they are in charge of creating a climate that encourages continuous improvement [10]. *Team Leaders*, on the other hand, are in charge of the micromanagement of the line by responding to malfunctions, keeping the production flowing and facilitating kaizen activities; moreover, when a vacancy occurs, they substitute the production worker and join the line [11], a peculiarity for which they need to know the standard operating procedures as they were production workers. As a result, TLs develop the necessary context-dependent knowledge to carry out a proper sense making and, potentially, preliminary data analysis.

TLs have "primary responsibility of process improvement," they set the work pace and the training activities [52], [53]. TLs also perform a "transformational leadership" role of facilitating team members' creativity leveraging on their capabilities and team knowledge [50]. At the micro level, TLs' competency is fundamental as they directly involve and motivate production workers, with whom they exchange information [42] to share their knowledge [9], [12]. Also, they are in charge of preliminary data analysis for operational decision-making (e.g., shop-floor problem solving). Leveraging on previous literature on operations management and on-field interviews, it was possible to identify which sense-making, knowledge-creating and decision-making activities are carried out by each organizational component of the frontline "operating core": Production Workers, TLs, and SVs [54]. Their roles in the operational D-I-K-DM processes are systematized in Fig. 3, which expands on Figs. 1 and 2 by adding the social-system dimensions (organizational structure and people) to the model.

The overarching hypothesis is that the ability of frontline managers in performing their managerial roles (competency level) enhances the engagement in lean activities and further increase the probability to use DDM approaches. Consistently with the previous section, the aim is to investigate the complementarity of frontline managers' roles and their organizational context, rather than separating the meso and micro levels of analysis. Therefore, the second hypothesis tests their competency level as a moderator in the relationship between Production Workers' involvement and DDM adoption:

H2. The competency level of frontline managers has a positive moderation effect on the relationship between Production Workers' Involvement and the probability of using DDM in operations.

However, the present section shows, with the support of Fig. 3, that SVs' and TLs' organizational roles in information processing, knowledge creation and operational decision-making are different. As a result, different outcomes should be expected, and the moderating role of frontline managers' competency level might vary between SVs or TLs. Taking into consideration the differences between the two, H2 will be tested separately for each category1 and rephrased as: *"The competency levels of production Team Leaders (H2.1) and Supervisors (H2.2) have a positive moderating effect on the relationship between Production Workers' Involvement and the probability of using DDM in operations."*

III. Methods

To address the research hypotheses, this article relies on survey data collected in the Italian automotive suppliers' industry, supported by semi-structured interviews for a more accurate interpretation of the quantitative results. A mixed-method approach allows to integrate multiple sources of data to provide a more complete understanding of complex research questions, increase the validity and rigor of findings by overcoming a method's limitations, and provide stronger conclusions through convergence (triangulation) of findings. [55], [56], [57].

A. Empirical Setting and Data Collection

The automotive industry's international competition generates strong pressure on efficiency, which is passed on to the supply chain. Suppliers are pressured by car makers to use and share data to improve collaboration and shorten time-to-market, leading to increased efficiency, transparency, and traceability of production. Furthermore, car makers transfer knowledge of organizational practices such as lean production to suppliers, who heavily rely on shop-floor manufacturing operations. Thus, auto suppliers are an insightful setting to study the joint involvement of first-line managers and workers in operational DDM, given their reliance on data and lean practices on shop-floor manufacturing operations, unit of analysis of this study.

A multirespondent and comprehensive survey—investigating the digitalization from a socio-technical perspective—was issued to HR managers, plant managers, and sales managers of Italian auto supplier firms between March 2019 and February

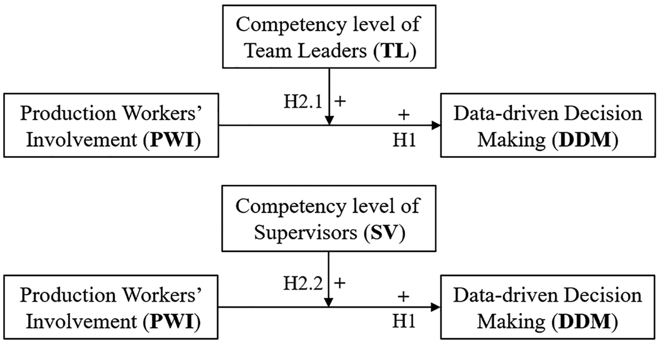

Fig. 4. Research hypotheses and the two theoretical moderation models.

2020. The survey was issued to the entirety of firms making part of national automotive trade associations, a sampling that allowed to avoid selection bias. Throughout the process, firms that did not answer were recontacted prioritizing them based on plant sizes, geographical regions, and supply chain positions that were under-represented in the sample, with the aim of obtaining a sample representative of the population. Finally, a total of 101 auto suppliers participated in the survey, with response rates of 7% over the population and 20% over the sampling frame.

The quantitative analysis was complemented by a set of 27 semi-structured interviews conducted with operational figures such as production managers, lean manufacturing engineers, and frontline managers of Italian auto supplier firms meeting criteria relevant to the hypotheses while also representing a diverse range of characteristics. The qualitative evidences served two purposes in a recursive and complementary *qual-quan* process [57]. First, they allowed to understand the setting and complement the literature on the activities outlined in Fig. 3 prior to developing the hypotheses, as well as establish the construct validity and reliability of the production workers' involvement and competency level measures. Second, they were used to interpret the quantitative findings, and expressed by means of quotations in the discussion section, to contextualize it and make it more insightful for the reader.

B. Model and Measures

Logistic regressions were used to determine the probability of using DDM in production plants using production workers' involvement (PWI) and the competency levels of TL and SV as continuous predictors. Fig. 4 shows the moderation models chosen to test the hypotheses: the effect of PWI on adopting DDM (H1) and the moderating effects of TL (H2.1) and SV (H2.2), tested separately by means of their interaction with PWI. A predictive margins analysis was computed with the STATA software, and its results were drawn in two interaction plots to allow for a clearer discussion upon the results.

The dependent variable is *data-driven decision-making* (DDM), operationalized, as in previous literature [1], as a dummy variable indicating whether the use of intuition and experience (0) or data (1) is predominant in the operational decision-making process. This variable is meant to be purely managerial, assessing the inclination toward a data-driven mindset rather than the presence of Big Data analytics technologies. However, to further validate its capability to represent the actual use of data in operations, a pairwise correlation of this measure with the number of employees using data analytics software was performed ($r = 0.4$, $p = 0.0001$).

TABLE I
OPERATIONALIZATION OF PRODUCTION WORKERS' INVOLVEMENT

Scale items	**Operationalization**
Formal program to collect lean suggestions from production workers [52]	• 0 (if no) • 1 (if yes)
Formal lean production programs for the involvement of production workers in formal meetings (quality circles and kaizen weeks, see [52], [58])	• 0 (if no) • 1 (if yes)
% of production workers who took part in the mentioned formal-lean meetings in the past six months	• 0 (if 0%) • 1 (if >0%)
% of production workers who carried out formal training activities on lean production methodologies and/or continuous improvement [52]	• 0 (if 0%) • 1 (if >0%)
"Performance is continuously tracked and communicated, both formally and informally, to all staff (including production workers) using a range of visual management tools" (adapted from [59], and [52]: "work teams receive detailed information about quality, performance and accidents").	• 0 (if 1 or 2 or 3) • 1 (if 4 or 5)

The two independent variables are organizational and individual. At the meso level, *Production Workers' Involvement* (variable *PWI*) was obtained with a Principal Components Analysis of five variables related to the involvement of production workers in the management of shop-floor operations, reduced to one component that was validated for internal consistency (Cronbach's Alpha $= 0.82$, interitem correlation $= 0.47$). The five items (see detail in Table I) were computed as binary variables with diverse rationales. Given its objectivity, the existence of formal programs (items 1 and 2) was asked directly through a binary variable. Concerning the other items, to avoid "social desirability bias," the respondents were asked to provide the percentages of workers involved in formal meetings and trainings. Since the objective was not to identify any variance, but rather to confirm actual involvement, and due to the low reliability of such "gut" percentages provided, the answers were meant to be used as proxy to discriminate between 0 (0%) and 1 (>0%). The same control for social desirability bias was conducted for the transparency in data diffusion at the shop-floor level, measuring the participation of workers in monitoring operational data through a 1–5 scale incorporated as binary in the construct.

At the micro level, two measures of *competency* were computed for production Team Leaders (variable *TL*) and production Supervisors (variable *SV*) using Likert scales through which HR managers assessed how adequate these employees are to perform the specific tasks referred to their professions. The

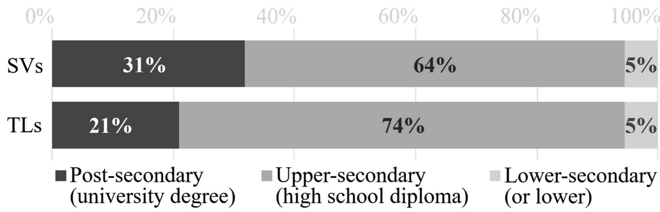

Fig. 5. Average educational attainment of TLs and SVs in the sample.

scale was tested using a single item to increase its reliability by making it as transversal as possible across firms. Extensive literature comments how single-item measures can be as valid as multiple-item measures [60], [61], [62], if not even superior to them when the concept to measure is straightforward [63]. In particular, Gardner et al. [63] and Lance et al. [64] back the use of single-item measures for raters to estimate how well ratees "perform their job in general."

Last, a set of control variables was added. *Firm Size* (number of employees) isolates the effect of bigger manufacturing plants having access to more digitization technologies and data. *Tier-1* (1 if tier-1, 0 if tier $\geq$2) measures whether a firm ships directly to the car maker, since the latter may require suppliers to use and share their data to meet quality standards. *Employees Average Age* controls for long-standing workforce's biases in preferring experience rather than data. *DT breadth* (breadth of digitization technologies) was included to measure the use of shop-floor data independently from the level of digitalization, which might induce a bias in the DDM measure; the measure was computed following [1], i.e., a summated scale of technologies used to collect data related to production, logistics and quality: sensors on equipment (IoT), tracking technologies (RFID), and machine vision for quality control. Last, the regressions are controlled in terms of *Educational level* (both of TLs and SVs) being 3 = postsecondary degree, 2 = high school diploma, 1 = any lower degree; this ensures that the competency variable is related to capability to carry out frontline managers' tasks, rather than their educational attainment.

IV. Results

A. Descriptive Statistics

In the sample used for the regressions, 38.6% of firms ship directly to car makers (Tier-1). The average firm size is 156 employees, with an average age of 43.2. DDM is the prevalent approach in 55.2% of the cases, and frontline managers are predominantly schooled, with secondary or postsecondary education attainments (see Fig. 5).

However, skill gaps are widely diffused: low competency levels (values $\leq$ 2 out of 5) are frequent for both TLs (34.2% of firms) and SVs (31.6%). Table II shows the descriptive statistics concerning the rest of the measures used in the regressions (note: the values have been normalized to facilitate comparison; prenormalized ranges are shown in the fifth column).

TABLE II
Descriptive Statistics of the Variables Used in the Regressions (Normalized Values)

Variable	Mean	Std. Dev.	Range	Range (pre-norm.)
DT breadth	.627	.351	[0;1]	[0;3]
Educational level of Team Leaders	.575	.250	[0;1]	[1;3]
Educational level of Supervisors	.634	.269	[0;1]	[1;3]
Production Workers' Involvement	.584	.385	[0;1]	[−1.4;1.2]
Competency level of Team Leaders (TL)	.496	.299	[0;1]	[1;5]
Competency level of Supervisors (SV)	.511	.309	[0;1]	[1;5]

TABLE III
Output of the Logistic Regression Models

Dependent Variable: DDM	(H1)	(H2.1)	(H2.2)
Tier-1	.1719 (.3462)	.1104 (.4073)	.0013 (.3917)
Firm Size	1.242 *** (.4009)	1.499 *** (.5265)	1.362 *** (.4639)
Average Age of employees	−.0468 (.3210)	−.2201 (.4531)	−.1294 (.4928)
DT breadth	.1136 (.3721)	.0527 (.3852)	.1352 (.3642)
Education Level of Team Leaders	.0040 (.3339)	−.1121 (.3272)	−.1100 (.3261)
Education Level of Supervisors	.0551 (.3824)	.1605 (.3455)	.1345 (.3605)
Production Workers' Involvement (PWI)	(.5452 (.3562)	.7598 ** (.3808)	.7546 ** (.3827)
Competency level of Team Leaders (TL)		−.6320 (.3847)	
PWI x TL		1.119 *** (.4313)	
Competency level of Supervisors (SV)			−.5844 (.3963)
PWI x SV			.7917 ** (.3820)
Constant	−.0097 (.3086)	−.1345 (.3477)	−.0459 (.3446)
N	68	68	68
Pseudo R^2	.2960	.3923	.3766

Note: Coefficients expressed in log-odds; standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B. Regressions

Table III shows the results of the three logistic regression models: H1 (PWI), H2.1 (PWIxTL), and H2.2 (PWIxSV). Variance inflation factors were computed to test for multicollinearity, absent in the three models (mean VIF 1.40, 1.35, and 1.35;

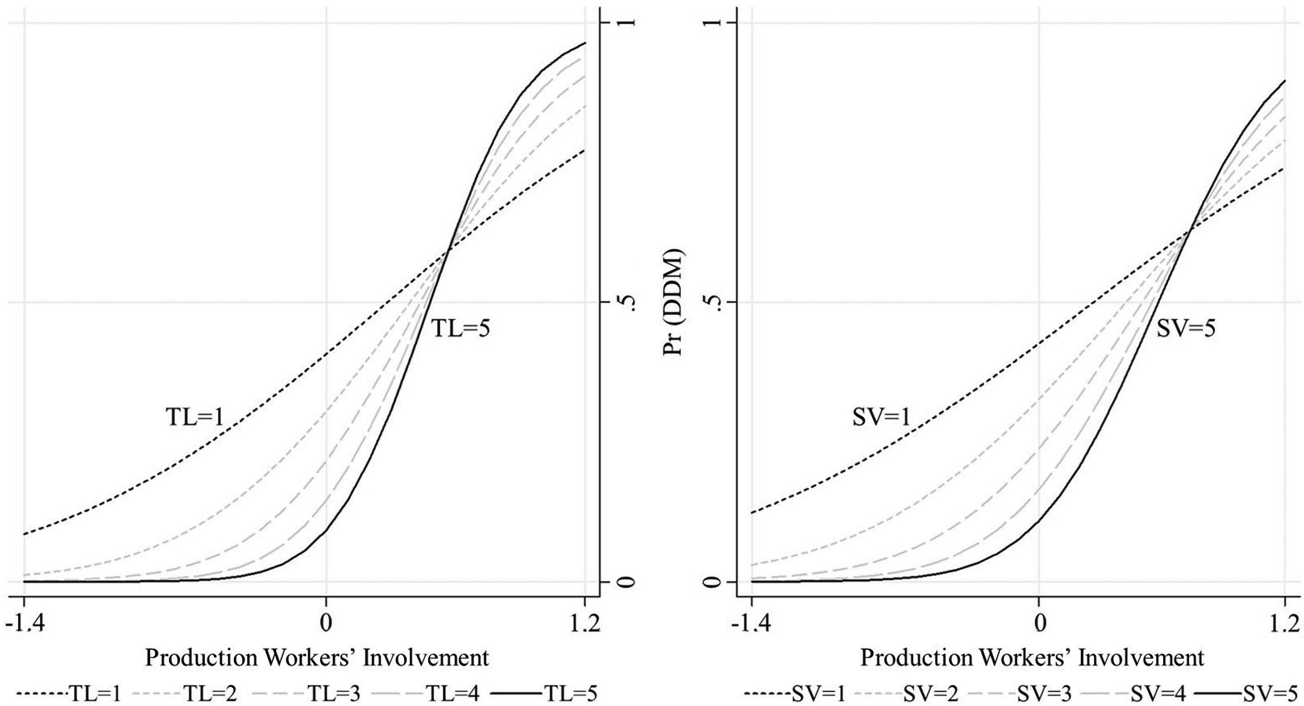

Fig. 6. H2's predictive margins: PWI vs DDM probability, at different levels of TL and SV.

highest value 2.02, 2.07, 2.04). Note that all the variables were standardized to allow for comparability of coefficient values.

The results show that the effect of PWI on DDM is not statistically significant unless controlled for TL and SV; therefore, H1 is confirmed only partially. On the other hand, both H2.1 and H2.2 have been confirmed; the acquisition of significance by PWI strengthens the argument of complementarity between PWI and, respectively, TL and SV. The third observed result is that PWIxTL has a much higher point estimate and relevance than PWIxSV, suggesting a stronger effect of the role of TL than the one of SV. In Model H2.2, the effect of the interaction is lower, and supported by a weak statistical significance. As a result, the effect is attenuated, resulting in less steep curves in the interaction plot based on the margins analysis (see Fig. 6).

V. Discussion

The results of the regression models are discussed at the meso (H1) and micro (H2) levels in Section V-A, supported by qualitative evidence. Section V-B provides the contributions to theory and the implications for practice at the organizational and individual level.

A. Discussion of the Results

The first section provides a two-step discussion of the results: first, an overall discussion of the moderation effect of frontline managers' competency level; second, the rationales for which such an effect is stronger for TLs than SVs, with a focus on the central role of TLs.

1) High Involvement and DDM: The Moderating Role of Frontline Managers: At the meso level of analysis, the lack of statistical significance when testing H1 suggests that introducing high-involvement practices cannot be automatically associated with a higher probability of using data-driven approaches to operational decision-making. However, H1 was partially confirmed, since the effect of PWI on DDM becomes statistically significant when TL and SV are considered in the regressions (the two versions of model H1 with TL and SV as control variables not interacted with PWI were not included in Table III, as they were not representative of the hypotheses; however, in both cases PWI acquired statistical significance). This result is highly relevant, as it confirms that, in line with the objective of the multilevel analysis, the effects of organizational and individual factors on the adoption of DDM need to be analyzed together. The interplay between PWI and DDM is evident in Fig. 6: the probability of having data-driven operations increases at increasing degrees of production workers' involvement. The involvement of production workers in lean practices can increase the probability of trusting data and therefore contributing to DDM approaches in operations. This not only corroborates previous literature (e.g., [15], [65]), but also contributes to the body of knowledge on the interplay between lean manufacturing and digitalization, explaining how the former can enable practices (DDM) that motivate firms' investments in the latter.

At the micro level of analysis, H2 has been confirmed: higher competency levels of frontline managers are associated with higher marginal effects of PWI on the probability to adopt of DDM. This finding is highly insightful, as it unveils a complementarity between organizational and individual social-system factors linked to DDM. In presence of highly skilled frontline production managers (see curves TL = 5 and SV = 5), operations tend to be driven by data only when there is a high level of PW involvement. Competent frontline managers leverage involved production workers' tacit knowledge to process shop-floor data [13], and are able to recombine it with explicit knowledge (or information) to create operational knowledge to feed decision-making. On the other hand, low levels of involvement are associated to a lower veracity of data that enters the cycle, leading competent frontline managers to a lower propensity toward using them in decision-making. As a result, high competency levels of TLs and SVs are associated to a zero probability of adopting DDM in correspondence with low levels of PWI. These results suggest that if a firm has not put in place formal programs to involve production workers, skilled frontline managers prefer to rely on their intuition, rather than on ill-informed D-I-K-DM cycles. Unskilled frontline managers, on the other hand, seem to be less sensitive to the importance of involved production workers in the sense-making of data and knowledge creation from information; as a result, the probability of having data-driven decisions is less dependent on the variation of PWI levels.

Information-processing and decision-making happen by horizontal communication among frontline employees, who possess the relevant domain knowledge and need support from intelligent knowledge management systems to enhance their skills and competencies [66]. Production workers' involvement in operational decision-making is empowered by increasing the exchange of information with TLs and SVs [42]. Frontline managers, in turn, can facilitate continuous process improvement by fostering an organizational climate where workers feel safe and "obliged" to contribute their knowledge and suggestions [12]. Doing so, they can extract value from production workers and create knowledge by combining "strategic, macro, universal information and hands-on, micro, specific information" [9]. A great deal of interview data supports this finding, well summarized by the following excerpt:

> *Surely, having as much data as possible on the plant allows the machine operator to be able to make decisions also on the quality of the material. [...] The more information we give them, the more they can become autonomous in their own area of work [...] he is authorized to make a decision both in terms of quality and maintenance and above all to manage it (Production Supervisor of a Tier-1 supplier)*

Such a collaborative process (involvement of production workers and their tacit knowledge) is moderated by the competency of frontline managers who combine it with data to create and use operational explicit knowledge for DDM. These results can support the view for which production workers' tacit knowledge and experience are fundamental in the sense making of shop-floor data [13], and that involving them could increase the propensity toward DDM.

2) Team Leaders and Supervisors, Two Different Roles in the D-I-K-DM Cycle: At the micro level, another relevant finding is that H2.1 was found to be backed by a higher statistical significance than H2.2. The difference between the two interaction plots (see Fig. 6) is particularly evident at high levels of PWI, where the difference in probability of DDM adoption between competent and unskilled managers is higher for TLs than it is for SVs. Firms with very competent TLs are those who are most likely to use data in their operations, suggesting that involving production workers for a "bottom-up" DDM might depend more on TLs than on SVs.

Even though both TL and SV show managerial and supervisory elements [51], their roles are different [11], [12], [50], [52]. TLs are more engaged in interpersonal and decisional roles of disturbance handling and short-term resource allocation (real-time changes to planned setups and reallocation of workers). On the other hand, SVs' managerial roles are mostly informational and mainly focused on medium-term resource allocation (e.g., shift-based production planning and people assignment). Regarding lean manufacturing, SVs' focus is on the "hard" part of continuous improvement actions, rather than the "soft" component of involvement [12]; for instance, their personnel management duties include training and multiskilling, rather than motivation and engagement. Also, SVs have a greater span of control over the production process as a whole, and perform their activities without working on the line. On the other hand, TLs are closer to production workers, and horizontal communication flows more naturally, human relationships are stronger, sensemaking about shop-floor events is more aligned. TLs directly encourage participation of frontline workers in continuous improvement and exchange information with them to share their knowledge. A better understanding of these concepts is provided by a continuous improvement engineer of a medium Tier-1 firm:

> *Team leaders' main role is that of collaborating in the working group to bring, let's say, the problems that come right from the field, because perhaps he, knowing that there is a focus on that line, spends time near the machine when he has time [...] They need to be able to use the Pareto analysis to say what is the major cause of loss on that machine to then go on to think about what to do [...] The fact of having to analyze more data has also forced him to take a growth step towards the analysis of numbers, for instance about cycle times and OEE.*

TLs know which operators are more skilled and experienced and that human and machine are two different types of resources [67], and take this into account when assigning them tasks related, for instance, to data collection and labelling. As emerged in several interviews, the same machine could provide the same data, but different operators may be differently experienced or motivated in making sense of them, labelling, interpreting and even reporting them, generating variable degrees of propensity to trust them in DDM at higher managerial levels:

> *It is not enough to focus on the data, you need to have a clinical eye and an ability to use them with significant experience about the process. This is very important. I can't take a figure by itself and say something about it [...] I have to understand why, I need to be able to analyze it, to have a clinical eye because sometimes data can be fake. We still enter them by hand. One must understand almost immediately if that is an error or a process drift. If I have entered them incorrectly, there has been a change or they are not up-to-date, we can throw away our Industry 4.0 data.* (operations manager at a Tier-1 car key manufacturer)

Being directly involved in leveraging frontline workers' involvement, TLs have a more prominent role in the integration of operational data and domain knowledge for D-I-K-DM. Supporting previous studies according to which Team Leaders' skill gaps can lead to worse operational performance [50], and assuming that DDM can increase firm performance [2], [3], [4], we conclude that, in manufacturing sectors where high-involvement lean practices are increasingly diffused, firms with competent TLs are those that are closer to fully capitalize on the potential benefits offered by digitalization.

B. Contributions to Theory and Implications for Practice

By providing empirical evidence about organizational and individual factors related to DDM, this study contributes to theoretical aspects of knowledge creation and management literature, and offers valuable recommendations to practitioners including production managers, HR managers, and educational policymakers.

1) Socio-Technical View of the "Bottom-Up D-I-K-DM Cycle": Both organizational and individual factors were found to be associated to the probability of adopting DDM approaches. From a socio-technical perspective, the results suggest that the propensity toward operational DDM depends on social variables, confirming the interplay between social and technical systems. The importance of involving production workers in a collaborative DDM process is explained with organizational and ecological KM perspectives, focused on organizational design and individuals' interaction to facilitate knowledge creation processes. Also, empirical evidence is provided to enrich the knowledge-based theory of the firm, which interprets knowledge creation for decision-making as a collaborative process integrating information coming from interpretation of data and context-dependent knowledge.

This article's main contribution to theory is the development of the "three-dimensional" D-I-K-DM model introduced in Section II, where socio-technical theory's concepts have been integrated into KM literature by adding a social system dimension. We adapted the "organizational knowing cycle" [28] model of KM to operational decision-making and disentangled the roles of different organizational levels (production workers and frontline managers) in sense making of, and knowledge creation from, the analysis of operational data. Answering the question "who creates and exploits operational knowledge?" allows for a shift from generic dynamics to focused perspectives on specific operative and managerial profiles. This study also contributes to overcome genericity limitations of the information-processing theory by specifying—or, better, prioritizing—which categories of managers must urgently acquire the competencies to create knowledge from Big Data and context-dependent knowledge.

Ultimately, this article's findings contribute to reconcile organizational, operations management and information system literatures (as advised by Cagliano et al. [15]) through the use of theories on sensemaking, information processing and knowledge creation. In 1988, Nonaka [68] advanced the idea of a "middle-up-down management," highlighting the importance of middle managers in resolving the contradictions between visionary top managers and experience-driven shop-floor employees. The findings of this article suggest that, with DDM enabled also at the operational level by digitalization, the organizational performance of firms will rely on their capacity to leverage production workers' knowledge creation with skilled frontline managers, often disregarded by similar literature streams in favor of a focus on middle and top managers [69]. The result is a shift from the middle line to the front line, re-vamping the importance of bottom-up (and decentralized, [7]) knowledge creation.

2) Implications for Practice: Lean Programs and Team Leaders' Upskilling: Even in small and Tier-2 firms that are not explicitly required to adopt them, formal lean programs can be crucial to exploit the benefits of digitalization, whose ultimate goal is not collecting data per se, but to inform better decisions. In this vein, a main recommendation is that of introducing formal lean practices to foster a culture where frontline employees' knowledge can be leveraged for operational DDM. Insisting on the importance of production workers' active contribution to operational DDM, typical of lean production, this work contributes to the literature stream that explores the interplay between digitalization and lean practices (e.g., [65], [70], [71]). Another aspect that unites lean practices and digitalization is decentralization, which is in turn associated with more autonomy and delegation of decision-making. Our findings suggest that these synergies are more likely to happen in firms with competent frontline managers. The shift from intuitive to data-driven decision-making is a "skill-biased technological and organizational change" [72]:

> *The organization of the workplace has changed a lot, so we did training, because before the operator didn't even know how to read the drawings, while now there is the totem, the drawing, the core defects, as envisaged by Lean; there is all the information the operator must have in order to make the most of the product in terms of quality, organization, management.* (Owner at a medium Tier-1 supplier)

According to the information-processing theory, these new information-processing needs have to be matched by the capabilities to do so, and the results of this article suggest to focus on TLs. The latter not only need a new set of analytical skills to carry out their decisional roles and participate purposefully in information processing and knowledge creation (informational roles) for medium-term operational and strategic decisions made at higher levels. They also need to stress on their interpersonal roles to involve production workers and have their "loyalty" in correct data input, participation through suggestions, information exchange and knowledge sharing [9], [12], [42], a concept well exemplified by the plant manager of a Tier-1 firm:

> *The datum that they have to provide is what starts everything and therefore has great importance; this must be told to them, and they must be very responsible for this datum [...] So we ask them not only "tell me when the car stops or breaks down", but also "tell me what you would do to improve it, and what you would do to improve safety". So the data we ask for, the flow of data, we also ask for suggestions, improvements, things that are wrong. And this makes the data credible.*

A formal upskilling of production TLs is needed to exploit the benefits of digitalization through DDM. In our sample, the TL role is carried out with an upper-secondary education level in 74% of the firms (see Fig. 5), and 89.8% of the firms envisage additional training after their hiring, i.e., the canonical definition of "middle-skill jobs" [73], [74]. For these jobs, the digital transformation is generating a demand for digital and interaction skills that is not being met, inducing a so-called "middle-skills gap" also in skilled blue collars and frontline production managers threatening productivity and competitiveness of advanced countries' manufacturing industries [75], [74], [76]. Therefore, our findings show to HR managers the importance for operational roles to acquire, develop and retain the competencies required to create knowledge from Big Data and context-dependent knowledge. Job rotation and knowledge sharing can increase competencies related to DDM [77]; notwithstanding, specific and soft-skill training courses are offered by a low number of firms. When posed with the question of whether their TLs received training to manage data, a lean production engineer in a Tier-1 firm answered:

> *Yes, a little something, in a slightly lighter way than their supervisors. They have taken general courses about people management and also a bit of problem-solving. Their problem-solving approach is to understand what is the cause, like the classic "5 whys", then try to go a little more specific and understand if there have been any deviations in the process [...] they are currently trained on this sort of analyses; we're not yet at the level of having them prepared for a more quantitative approach.*

The recurrence of such responses during the interviews emphasizes the imperative need for prompt action. Policymakers, universities, and secondary education systems need to be aligned and cooperate among themselves and with firms, and engage in the co-creation, for instance, of ad-hoc educational curricula and training programs [76], [78]. Industrial learning and challenge-based innovation programs can contribute to develop the needed competences in living labs, learning factories, or even online to optimize firms' resources [79], [80]. In this vein, this work contributes to literature by providing evidence on how digital transformation influences the processes of new knowledge search by firms and the need for new competencies, an area that recent literature suggested to investigate [81]. Since "an organization processes information to make sense of its environment, to create new knowledge, and to make decisions" [28], investing in frontline DDM capabilities is an increasingly fundamental priority.

C. Limitations and Future Developments

This study presents limitations that must be taken into account. One such limitation relates to its generalizability, which may be affected by the relatively small sample size and the fact that only one industry in a single country was considered. However, to enhance the internal validity of the quantitative findings, several control variables were utilized to mitigate the influence of confounding factors. For instance, the impact of production workers' involvement was isolated from the statistically significant effect of firm size on DDM adoption, which can be explained by the fact that larger firms typically have greater production volumes, increased availability of data, and more standardized operations. Another limitation of this study is that it was not possible to establish causality in the quantitative analysis, as a unidirectional effect of PWI leading to DDM could not be determined. It is possible that a reverse effect cannot be ruled out, leading to an additional interpretation of the results for which a data-driven environment can, in turn, motivate and increase the development of formal programs to involve production workers. Nonetheless, this would not affect the conclusions drawn regarding the moderating role of team leaders and supervisors in the interplay between PWI and DDM, which is the most significant and insightful finding of this article.

The results of this study, along with its limitations, have highlighted areas that require further investigation. Specifically, this study presents an opportunity for future qualitative research that aims to characterize the specific skill gaps in sensemaking, knowledge creation, and decision-making in Big Data contexts, while exploring ways to address the upskilling needs of TLs. Also, the question of how educational systems can respond to the emerging need for upskilled TLs remains unresolved and is an important avenue for future research. Further considerations on employees' training practices will be required to develop a more comprehensive theoretical and empirical understanding of the challenges and benefits associated with the adoption of new digital technologies for data-driven decision-making.

VI. Conclusion

With more data available to production lines, information-processing tasks will be increasingly decentralized, making it relevant to study what factors are associated to DDM at the shop-floor level. This article found a complementarity between production workers' involvement and frontline managers' competency level in the adoption of operational DDM. The interpretation of the results through KM models, with the limitations outlined in Section V-C, suggest that competent team leaders can leverage the experience and tacit knowledge of production workers—as long as the latter are involved in the process—in the sensemaking of data, processing of information, and knowledge creation that precede operational decision-making. These results offer two main recommendations to managers interested in capitalizing on their investments in digitalization and improve their firms' operational performance. First, as Team Leaders are acquiring a central role through operational DDM, firms are advised to prioritize their upskilling over that of other frontline employees such as production workers or supervisors. Second, organizations are called to embrace lean production with its high-involvement management principles and bottom-up approach to knowledge creation. Finally, this article enriches well-known KM models by accounting for the organizational structures and the individuals involved in DDM's constituent steps of data-to-information-to-knowledge. Such a socio-technical approach reconciles KM models, organizational theories and literature streams on digitalization, thus providing a solid basis for future theoretical and empirical studies on operational data-driven decision-making.

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