Algorithms for operational decision-making:

An absorptive capacity perspective on the process of converting data into relevant knowledge.

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Abstract

The organisational mechanisms through which algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making have not yet been fully investigated from an absorptive capacity perspective. Previous studies underlined a rise in new digital specialised roles, but they said little about how the organisational knowledge and structures should be redesigned to take advantage of these data-rich operational environments.

In this article, we present the findings of a case study on the way algorithms can be exploited in the electrical sector to shed light on these issues. We then develop a framework to theorise how the organisational mechanisms associated with absorptive capacity influence the way algorithms can be exploited to convert data into relevant knowledge for operational decision-making.

Our emerging framework reveals that to convert data into relevant knowledge for operational decision-making, the involvement of line employees and liaison roles are required to introduce system-level knowledge that algorithms are able to capture less effectively. Additionally, more formalisation is needed in operational work to ensure the quality of the data that feed such algorithms. Finally, socialisation tactics facilitate the convergence between the knowledge produced from algorithms and the experiential knowledge of line employees.

Keywords: Data-driven decision-making, digital transformation, algorithms, absorptive capacity, knowledge creation, organisational mechanisms.

Paper type: Research paper

1. Introduction

"I thought it was all about technology. I thought if we hired a couple thousand technology people, if we upgraded our software, things like that, that was it. I was wrong. Product managers have to be different; salespeople have to be different; on-site support has to be different."

Jeff Immelt, former CEO of General Electric

Organisations are facing a change in their management practices, due to the increasing amount of data produced by smart connected products and Internet of Things (IoT) architectures, which offer new managing operation possibilities to identify quality problems and cost inefficiencies (Philip, 2018; Agrawal et al., 2018). In this context, organisations are relying more and more on their operational decision-making processes to analyse large volumes of data. They can do this in two main ways: through big data analytics (i.e., a process of inspecting, cleaning, transforming and modelling data to visualise information and statistically support decision-making – Davenport, 2013) or through machine learning and artificial intelligence algorithms (i.e., a systematic procedure that takes available data and uses it to generate information that is not available, such as the answer to a question or the solution to a problem – Agrawal et al., 2018). Following Agrawal et al. (2018), in this paper, we refer to algorithms as a set of predictive technologies (data analytics, artificial intelligence and machine learning) that receive a large amount of data as input and provide a result as output which can influence the operational decision-making processes of a firm through "*better, faster, and cheaper predictions than humans can*" (Agrawal et al., 2018; p. 104).

An increasing body of studies have shown that companies that make strategic or operational decisions based on algorithms, rather than on the experience, "gut-feeling" or judgement of their managers, achieve superior performance (Blazquez and Domenech, 2018; Brynjolfsson, Hitt, and Kim, 2011; McAfee, Brynjolfsson, Davenport, Patil and Barton 2012, Sheng Amankwah-Amoah and Wang, 2019). From such a perspective, several studies have pointed out a rise in new, highly-skilled and specialised roles, such as that of data scientists and data engineers (e.g., Davenport and Patil, 2012; Troilo et al., 2017), but they have said little about how the organisational knowledge-creating processes and structures (Nonaka, 1994) should be redesigned to take advantage of this more data-rich operational environment (Chalvatzis et al., 2019). This issue becomes particularly relevant in contexts in which the flows of data, information and knowledge do not come from outside a firm's boundaries (e.g., from other actors who are part of the firm's ecosystem), but are generated within the company (Brynjolfsson and McElheran, 2016). On the other hand, the literature on absorptive capacity is well-established and has identified that the common features of combinative capabilities (see Kogut & Zander, 1992) involve organisational mechanisms that influence absorptive capacity in specific ways (e.g., Henderson & Cockburn, 1994; Van den Bosch et al., 1999; Jansen et al., 2005). However, no insights have been gained into how organisational mechanisms, associated with combinative capabilities, influence the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making.

In this article, we present the findings of a case study on the way algorithms can be exploited in the electrical sector in order to shed light on such issues. Our case design has allowed us to capture how common features of combinative capabilities affect the dimensions of absorptive capacity when the source of knowledge is not external, but instead consists of data generated by sensors installed and connected to a firm's production assets. The electrical sector is characterised by a broad use of big data to improve activities related to the installation, maintenance, repairs and monitoring of electrical grids and power generation assets (Chalvatzis et al., 2019), as well as to knowledge-intensive activities, such as demand and supply management (i.e., dispatching), and can therefore be considered a "revelatory context", that is, one in which a phenomenon of interest can be "transparently observed" (Yin, 1994: 40).

On the basis of our observations, we have developed a framework which theorises the links between the organisational mechanisms associated with combinative capabilities and the absorptive capacity dimensions associated with the process of converting data into relevant knowledge for operational decision-making. Our emerging framework reveals that the involvement and liaison roles of line employees are required to introduce the system-level knowledge that algorithms are able to capture less effectively. Additionally, more formalisation is needed in operational work to ensure the quality of the data that feed such algorithms. Finally, socialisation tactics ensure that the knowledge produced from algorithms can converge with the operational work of line employees, thus helping to spread a data-driven culture.

Our study improves the more general understanding of scholars on when and how organisations build an absorptive capacity that is specifically aimed at generating knowledge from a multitude of internal data generated in operational processes by plants and machinery. Drawing on our observations and building on the organisational mechanisms that organisations create to build their absorptive capacity (Jansen et al., 2005), we contribute to the literature in two ways. First, we contribute to research regarding the link between combinative capabilities and absorptive capacity (Kogut & Zander, 1992; Van den Bosch et al., 1999; Jansen et al., 2005). We empirically examine how the common features of combinative capabilities affect the absorptive capacity dimensions in a data-driven context when the knowledge is generated internally – and not externally, as examined in previous studies (cf. Jansen et al., 2005). Hence, this study reveals how organisational antecedents matter, and examines the linkage between specific organisational mechanisms, such as the common features of combinative capabilities and the dimensions of absorptive capacity in a data-driven context - when the source of knowledge is not external, but consists of data generated by sensors installed and connected to a firm's production assets. Second, we contribute to the literature on process innovation in the digital competences of the workforce area (e.g., Bala and Venkatesh, 2017; Chalvatzis et al., 2019; El-Kassar and Singh, 2019; Lam et al., 2017; Murawski and Bick, 2017) by investigating the organisational configurations and roles required to integrate the knowledge generated from data with the operational decision-making processes. Our emerging framework may offer a baseline to continue the investigation on the process improvements and organisational configurations of firms in data-driven operational environments.

2. Theoretical background

2.1 The value of algorithms for operational decision-making.

Faced with an ever-growing volume of data, firms today are increasingly turning to algorithms to obtain useful insights, patterns and correlations that might facilitate - or even automate - efficient operational decision-making processes (Božič and Dimovski, 2019; Kellogg et al., 2020). In this sense, algorithms refer to a variety of techniques, technologies, systems and applications aimed at helping an organisation analyse big data in a way that enhances its ability to make business decisions (Shrestha et al., 2019).

Specifically, by synthesising robust patterns from large data sets, algorithms enable the creation of new information and predictions from big data that can inform and guide operational decision-making processes (e.g., predictive maintenance on machinery based on the prediction of future breakdowns). Furthermore, algorithms can affect the operational procedures and routines of line operators in their day-today tasks to optimise and automate processes and support the monitoring and control of machinery (Porter and Heppelmann, 2014). Using real-time data, algorithms can alert operators about changes in the condition and operation of machinery, and about the external operating environment through sensors and external data sources. Such connected machinery can be controlled through remote commands or artificial intelligence algorithms that reside in the cloud. This rich flow of monitoring data, coupled with the capacity to remotely control product operations, allows companies to optimise processes in new and efficient ways, many of which had not been previously possible. For example, Porter and Heppelmann (2014) highlighted how a local microcontroller in wind turbines can adjust each blade on every revolution to capture the maximum wind energy, thereby maximising the performance of a single turbine and minimising its impact on the efficiency of those nearby. In this vein, real-time monitoring data enable firms to optimise processes by performing preventive maintenance and accomplishing repairs remotely. Moreover, even when the on-site intervention of line employees is required, real-time data about what had happened and how to resolve the issue reduces costs and optimises operations.

Taken together, real-time monitoring data and algorithms allow previously unattainable levels of autonomy in organisational knowledge-creating processes and operational decision-making structures to be informed and guided. However, although the challenges of designing organisational knowledge-creating processes and operational decision-making structures involving human actors have been clearly investigated in the absorptive capacity literature (Fosfuri and Tribò, 2008), the rise in big data and algorithms introduces a new set of challenges to this stream of literature. Recent studies have shown that the application of algorithms to facilitate improved decision-making may introduce and amplify hidden challenges and biases in the way organisational knowledge is created and shared (Shrestha et al., 2019; Kellogg et al., 2020; Lanzolla, Santoni, Tucci, 2021). Simply acquiring new information and knowledge does not necessarily lead to improved operational decision-making processes (Lane et al., 2006). Firms should instead be able to acquire, assimilate, transform and exploit this new knowledge to promote new and/or improved operational decision-making mechanisms (Chen et al., 2009). Thus, understanding how the organisational antecedents of absorptive capacity have an effect on how algorithms and AI can improve operational decision-making and minimise biases in such processes remains a still underexplored issue. In order to investigate this issue, we refer to the role of combinative capability as a precondition to synthesise and apply prior and acquired knowledge (Kogut and Zander, 1992). Kogut and Zander (1992) defined combinative capabilities as “the intersection of the capability of the firm to exploit its knowledge and the unexplored potential of the technology, or what Scherer (1965) originally called the degree of ‘technological opportunity’.” (Kogut and Zander, 1992; p. 391).

In this article, we ground such a concept by developing a framework that addresses the theoretical (and practically relevant) question: *How do the organisational mechanisms associated with combinative capabilities influence the way algorithms can be exploited in the process of converting data into relevant knowledge that guides operational decision-making?*

2.2 Absorptive capacity at work in a data-driven context.

In the absorptive capacity literature, the context and the processes in which knowledge is created and shared essentially correspond to four distinct components of the absorptive capacity constructs: acquisition, assimilation, transformation and exploitation (Zahra and George, 2002). These four constructs can be grouped into two higher-level constructs, namely potential and realised absorptive capacity.

In a data-driven context – by readapting the distinctions between the potential and realised absorptive capacity developed by Zahra and George (2002) – Lam et al. (2017) distinguished between acquisition, assimilation, transformation and application capacities.[1] Acquisition capacity refers to the routines used to identify and acquire data considered critical for organisational operations. In a data-driven context, such a capacity requires roles with business acumen to formulate research questions that are critical for business performance (as Picasso remarked, since computers at the moment just provide answers, humans need to have the ability and the curiosity to identify relevant questions). In the same way, the acquisition capacity also needs roles specialised in designing the architecture of a database (i.e., a data architect and a data engineer), the data structures and the processing methodologies that drive algorithms (De Mauro et al., 2018). Assimilation capacity refers to those routines and processes that allow an organisation to analyse, process, interpret and understand information derived from the acquired data. In a data-driven context, assimilation capacity can rely on such roles as business analysts and data scientists specialised in running algorithms (De Mauro et al., 2018).

[1] Hereafter, in this paper, we refer to Lam’s constructs of absorptive capacity.

Transformation capacity refers to the capacity to combine and integrate existing knowledge from the assimilated information in order to create new knowledge (Nonaka, 1994). Finally, application capacity refers to the routines that allow an organisation to refine, extend and leverage on existing competencies or to create new ones by incorporating transformed knowledge extracted from data through algorithms and applying it to new operating procedures and organisational routines (Pentland and Feldman, 2005).

From the absorptive capacity perspective, organisational knowledge creation is a process that amplifies the knowledge created by individuals and crystallises it as a part of the knowledge network of an organisation. As far as the use of data-driven approaches in operational processes is concerned (Wamba, 2017), knowledge creation involves the combination and integration of knowledge outcomes generated by algorithms with the tacit knowledge and the systems of values and beliefs of the line employees that are directly involved in operational processes (Lam et al., 2017). For these reasons, in data-driven contexts, firms are increasingly leveraging on frontline employees in the knowledge creation processes, especially in the assimilation and transformation processes that sustain the absorptive capacity (Lam et al., 2017). In fact, as the knowledge of frontline employees is experiential and tacit (Nonaka, 1994), it can play an essential role in the knowledge conversion processes that companies should enact to extract relevant knowledge from data and algorithms. The absorptive capacity literature has identified three types of combinative capabilities (Van den Bosh et al., 1999; p.556) - (i) coordination capabilities, (ii) system capabilities, and (iii) socialisation capabilities. These capabilities are the main mechanisms of knowledge creation when such knowledge comes from outside a firm's boundaries (Jansen et al., 2005). However, a clear picture is still missing of how such mechanisms operate when the source of information is not external, but instead consists of data generated by sensors on the production assets and analysed by algorithms.

The way coordination, system and socialisation capability dimensions can support the creation of absorptive capacity in a data-driven context is illustrated in the next section, and the grey areas, which are related to what is not known about their effectiveness in supporting knowledge creation processes from data, are dealt with.

2.2. Coordination, system and socialisation capabilities as antecedents of absorptive capacity in a data-driven context.

Coordination capabilities. Coordination capabilities enhance knowledge exchange across functional and hierarchical boundaries (Henderson and Cockburn, 1994). Galbraith (1973) argued that the main dimensions of coordination capabilities are cross-functional integration and participation in decision-making. Cross-functional integration typically occurs with interfaces, such as liaison personnel, and with temporary and permanent teams to enable knowledge exchange. Such integration mechanisms enable a lateral form of communication that can deepen knowledge flows across functional boundaries and authority lines (Jansen et al. 2005), thereby supporting the knowledge articulation mechanisms through which individuals and groups figure out what works and what does not work in the execution of specific organisation knowledge (Levitt and March, 1988). Knowledge articulation is thus the process through which implicit knowledge is articulated, through collective discussion, debriefing sessions and performance evaluation processes, and it is a mechanism through which tacit knowledge can be capitalised on and transformed into articulated statements (Zollo and Winter, 2002). Such a knowledge articulation process is effective when the organisation can process an abundant amount of data and information, when it captures multiple perspectives on a problem that is fuzzy, and when its organisational structure facilitates the development of a common language to discuss problems (MacDuffie, 1997). Davenport (2006), with reference to how data analytics can drive such problem-solving processes, underlined that good analysts can express complex ideas in simple terms and should have the relationship skills necessary to interact with decision-makers, who are generally middle-low level managers (e.g., team leaders or supervisors) and process specialists.

Cross-functional integration makes sense in a data-driven context, due to the entry of new, highly specialised roles, such as that of data scientists, who are in charge of running the algorithms required for predictive and prescriptive analytics (Agrawal et al., 2018). In general, cross-functional integration mechanisms can allow data science and analytics skills to be applied to functional domains that require specific knowledge. Paraphrasing Picasso's above-mentioned statement about the ability of computers to just give answers, it is possible to say that cross-functional integration mechanisms support organisations in problem setting, and in formulating problems and testable questions that may be addressed by data science and analytics through quantitative methods. What we still do not know about cross-functional integration is how the various organisational mechanisms that integrate data science and analytics expertise with business domain knowledge are required in the four absorptive capacity stages. Jansen et al (2005) found that cross-functional integration adds value to the acquisition and assimilation processes of external knowledge since – by promoting nonroutine and reciprocal information processing – they contribute to a firm's understanding of external knowledge. However, in their empirical analysis, the contribution of cross-functional integration to combining sets of existing and newly acquired knowledge was shown to not have a salient role in the knowledge transformation and application processes that support the realised absorptive capacity. Moreover, their theorising was based on the absorption of external knowledge and not on the creation of knowledge from internally generated data. Integration could play a role in transformation and application, since the process of creating knowledge from data can require more knowledge articulation, a process that is iterative, retrospective and based on collective sense-making. With more data being available on internal operations (e.g., data on micro-stoppages of machinery and the conditions that led to them), members of different functional units, such as operations, process engineering data analysis and R&D, should rethink the systematic nature of existing operational processes and approaches to data analysis. For example, algorithms fail when the phenomenon being modelled changes often and requires adaptations (Agrawal et al., 2018). Thus, cross-functional integration may be important for the system-level thinking that is required for the adaptation of algorithms to local operations.

Participation in decision-making is the second main mechanism used in organisations to enhance coordination, and it indicates the extent to which subordinates take-part in operational decision-making processes. Jansen et al. (2005) showed that participation positively affects the acquisition and the transformation components of absorptive capacity, since it increases the range of "receptors" in the environment (Cohen and Levinthal, 1990). Hence, participation enhances more effective mechanisms of new knowledge creation by involving more members of the organisation in the validation and refinement of an idea (Rangus and Slavec, 2017). However, in a data-driven context, it is not clear how decentralised approaches, based on the participation of employees in operational decision-making, can coexist with the centralisation of data collection, storage and analysis that is inherent to the way data science can provide organisations with reliable and accurate predictive and prescriptive analytics. Specifically, the centralisation of data collection and management introduces several scale-related benefits. Helper et al. (2019) showed how the high investments in the cloud infrastructure required for operational decision-making have favoured the rise of companies specialised in data management and analytics. For example, providers of IS solutions for operation management (e.g., Oracle, SAP) and system integrators (e.g., GE with the Predix Platform, Siemens) try to extract value from their manufacturing clients, through centralised approaches to data management enabled by IoT and AI. Such companies can capture value to the extent to which data can be separated from its context, and to the extent to which a detailed understanding of operational processes is unimportant to understand the data generated by such a process (Helper et al., 2019). However, the extent to which centralisation alone can support the transformation capacity in data analysis may be limited, due to the paucity of micro-level and qualitative studies on AI-based automation and a lack of empirical observations that explain how centralisation can be combined with decentralised approaches.

System capabilities. Van den Bosch et al. (1999) referred to system capabilities as programmed behaviour that provides a memory that can be called upon to handle routine situations. These types of capabilities typically exhibit such common features as formalisation. Formalisation is the degree by which rules, procedures, instructions and communication are formalised and written down (Khandwalla, 1977). As such, using formalisation as a means of making sense (Weick, 1979), previous studies on absorptive capacity argued that formalisation tends to limit the intensity and scope of efforts expended in knowledge acquisition and hinders individuals in assimilating new external knowledge. Accordingly, Jansen and colleagues (2005) posited that formalisation negatively influences the acquisition and assimilation of any new external knowledge that underlies the potential absorptive capacity. However, since formalisation supports the retrieval of knowledge that has already been internalised and enhances the causal understanding of a set of tasks, formalisation has been found to support the transformation component of an absorptive capacity (Jansen et al. 2005).

Nevertheless, in a data-driven context, it is unclear how formalisation in operational processes can affect the quality of data introduced by line employees when they accomplish their tasks. At a higher level, this effect can be related to the fact that formalisation is an essential condition to reduce the variance of an operational process to a minimal level (Mintzberg, 1978). Moreover, the influence of formalisation on the absorptive capacity in a context in which algorithms are used to obtain improvements in operations may be different from the one theorised by Jansen et al., since, in such a case, formalisation consists of the application of methodologies and work practices that can be used to detect and eliminate sources of errors in a process (Womack and Jones, 1996).

Socialisation capabilities. Socialisation capabilities create broad, tacitly understood rules for appropriate action, since they contribute to universal codes of communication, and to strong social norms and beliefs (Teece et al., 1997; Verona, 1999). In a work environment in which algorithms assume increasing importance, socialisation is a relevant variable of organisation design and managerial actions, since organisations need to ensure congruence between new approaches to knowledge creation and that systems of values and beliefs that is already in place among the members of the organisation. Ashforth and Saks (1996) pointed out that the main mechanism organisations use to structure shared socialisation experiences among employees is socialisation tactics. In this vein, Jones (1986) showed that socialisation tactics offer newcomers an organisation-specific language that facilitates the comprehension of background knowledge and communication with others. Moreover, Adler and Kwon (2002) and Jansen et al. (2005) showed that socialisation tactics lead to strong social norms and beliefs, which in turn enhance commitment and compliance with the exploitation processes of new knowledge. When knowledge is created through the generation of more granular data and through the analysis of internal data on operational processes, socialisation mechanisms may exert a role in combining and integrating data-driven approaches with approaches based on intuition and experience in operational decision-making. In literature, these two approaches are seen as being based on different and incompatible sets of values, norms, beliefs, knowledge and educational qualifications of the people using them and of their roles (Lanzolla, Pesce and Tucci, 2020). Anecdotal evidence illustrate how such differences in approaches are often correlated with age and qualification (Troilo et al., 2017), with younger and more qualified specialists working on analytics and data science, but with a body of experiential knowledge missing from the regulation of the operational processes that are managed by the algorithms.

It follows from the above discussion that, in order to capture the idiosyncratic implications of socialisation capabilities in a data-driven context, we should focus on the extent to which new data-driven specialists complement the experiential knowledge brought about by legacy roles.

3. Methods

In order to investigate how the organisational mechanisms associated with combinative capabilities influence the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making, we conducted an inductive case study on the electrical sector. The case study originates from a larger research project started in 2017 and promoted by "Utilitalia" – the federation which brings together 450 Italian utilities operating in the Water, Environment, Electricity and Gas sectors and represents them within national and European institutions.

The electrical sector is characterised by a broad use of big data to improve activities related to the installation, maintenance, repairs and monitoring of electrical grids and power generation assets (Chalvatzis et al., 2019), as well as knowledge-intensive activities, such as demand and supply management (i.e., dispatching), and can therefore be considered a "revelatory context" in which a phenomenon of interest can be "transparently observed" (Yin, 1994: 40). The electrical sector, which has been the subject of progressive deregulation since 1999, consists of four distinct segments: (1) generation, (2) transmission, (3) distribution, and (4) retail. In order to cover the entire supply chain, – we focus on Company T, which is responsible for the transmission (i.e., the management, maintenance and development of the Italian high voltage electricity grid) and dispatching of electricity (i.e., managing the electricity flows on the grid at any time). Moreover, this company operates in a natural monopoly system and on a market regulated by the Italian Regulatory Authority for Energy, Networks and the Environment (ARERA). However, to ensure competition on the market, Company T does not operate in the electricity production, distribution or sales sectors. Thus, to cover the other three segments of the supply chain of the electrical sector, we focus on Company E, the most important company involved in the generation, distribution and retail of electricity in Italy, as indicated by Utilitalia (2020).

Furthermore, both Company E and Company T are currently undergoing a profound transformation in the way big data, IoT, analytics and artificial intelligence technologies are improving – and, in some cases, revolutionising the operational processes through which electricity is generated, transported, distributed and sold. On the one hand, Company E (around 60,000 employees throughout the world) operates in a large number of countries in Europe, Africa, and in South and North America, and has the highest number of smart meters in the world, that is, 45.1 million smart meters in 2020, of which 31.4 million are in Italy. Considering that each smart meter generates 96 flows of data per-day per client (e.g., consumption of electric energy, voltage levels, current, and power factor) and Company E had 73 million end users worldwide and 57.8 smart meters worldwide in 2019 – the potential of the firm to become a data-driven company appears evident. On the other hand, Company T (around 5,000 employees) is a monopolist in Italy, but it also operates in Montenegro and South America for a total of around 50 MW of capacity, with 74.669 Km of high voltage energy lines, and more than € 900 million invested between 2015 and 2020 in the digitalisation and innovation of the grid (e.g., centralised data management systems for predictive maintenance; satellites, drones and robots for the efficiency and safety of the system; AI for the "intelligent" maintenance and inspection of the electricity grid; nanomaterials and nanotechnologies for high voltage energy transmission).

As a result of their large-scale relevant investments in IoT, big data analytics and AI technologies at the European level and their leading-edge position in the application of digital technologies for smart grids (Utilitalia, 2020), the two selected companies generally make more distinct, dramatic and observable changes in the operational processes related to data-driven decision-making than other companies. Thus, we compared different observations across the relatively homogeneous cases of Company E and Company T following a theoretical replication logic (Yin, 1994). This allowed us to search for controlled variation as well as to describe, understand and explain the wider characteristics of the specific phenomenon under scrutiny in the paper (Eisenhardt, 1989). The study has employed multiple levels of analysis to permit the induction of rich and reliable models (Yin, 1994), focusing on each firm at two levels: (1) the top management team, and (2) the functional domains of innovation, operations, maintenance and HRM. Table 1 briefly describes the two studied companies.

Table 1 – Description of the two analysed companies.

Company	**Specialisation**	**Number of employees** *(2020)*	**Market cap** *(Euros, March 2021)*	**Number of interviewed informants**
Company E	Generation, transmission, distribution and retailing of electricity	Around 60,000	83.43B	28
Company T	Transmission of electricity	Around 5,000	12.29B	17

3.1 Research Setting

The electrical sector offers an interesting research setting to study the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making. First, this is a continuous process production sector (Bhattacharjee, 2020), where, in both the generation and the distribution and transmission stages, a relatively restricted number of line employees are in charge of operating, controlling and maintaining the plants and machinery involved in the transformation process, with limited involvement of line operators in manual work and routine operations. As such, IoT, drones and digital twins can generate a large amount of data on how the plants and machinery and the assets of the grid (i.e., transformation substations, electric cables and smart meters) operate. The technical complexity of the transformation processes and the limited number of routine operations require more skilled employees than other sectors. This is particularly evident in the generation stage of the industry value chain. On the other hand, the transmission (in high voltage) and distribution (in medium voltage) of electricity are based on organisational configurations whose principles are typical of mechanistic bureaucracy (Adler and Borys, 1996). In other words, formalisation is the primary coordination and control mechanism used to manage the workforce, which is geographically dispersed over the areas where the grid assets (e.g., trellises, transformer substations) are located.

Second, from a technology innovation standpoint, the sector is supplier dominated (Pavitt, 1984), and this may imply that the specialised suppliers of machinery and plants, due to their knowledge, attempt to control the data generation processes related to the assets they produce and sell to electrical companies (Helper et al., 2019). The effort of specialised suppliers to control the generation of data and analytics can make electrical firms more relationally dependent on suppliers (e.g., GE with the Predix Platform), with a consequent negative effect on their absorptive capacity from data (Lam et al., 2017). For example, the Predix Platform developed by GE equips industrial organisations with everything they need to rapidly build, securely deploy, and effectively run IoT applications from the edge to the cloud, thereby turning asset data into actionable insights. One of the strategies larger energy companies can resort to avoid such a dependence is to vertically integrate across the supply chain. However, economies of scope, economies of scale and/or regulation norms do not always favour such integration processes. For this reason, studying the organisational mechanisms that large energy companies have built to contrast the attempts of specialised suppliers to control their clients' operations assumes great importance.

Third, the electrical sector is at present dealing with discontinuities in its competitive environment that increase the competitive importance of using data and algorithms effectively (Neirotti and Pesce, 2019). Such discontinuities are due to the ongoing climate change, which threatens the stability of the electrical grid, especially during the hottest summer days and the coldest winter nights. Stability of the grid and its resilience (intended as the capability to reactivate its correct working after a breakdown) have become success factors in the industry, and have become even more critical after regulation on the continuity of the service became more severe in many European countries. The regulatory policies in such countries oblige the utilities that transmit and distribute energy to pay heavy fines to customers whenever they cause a blackout. Another type of discontinuity is the progressive transition to renewable energy generation sources, such as photovoltaic devices and wind generation. Such generation paradigms are based on a significant decentralisation of the assets involved in the generation process and an increased operational complexity, due to the necessity of having to monitor and control a much larger number of devices than in a traditional thermal generation unit (El-Kassar and Singh, 2019). Lastly, as a result of this transition to renewable energy sources, electrical utility firms are exploring new business and operating models, such as demand-response management (i.e., a customer can accept a change in the power consumption to better match his/her demand for power with the supply). Such models require the utilities to assume an orchestrator role in matching power generation suppliers and customers, and require a specific capability to use data and algorithms to monitor, control and optimise their operations. Each of these discontinuities requires the electrical utilities to resort to the use of IoT, big data technologies and artificial intelligence solutions in order to monitor and control their assets, to achieve a more complex coordination capability with both customers and energy suppliers, and to introduce predictive and prescriptive logics into their grid to improve its overall operational effectiveness. In the absorptive capacity logic, all these factors act as activation triggers (Zahra and George, 2002) as they lead firms to develop a higher absorptive capacity and to search for new knowledge that can improve their decision-making on operational processes.

3.2 Data Collection

Following the prescriptions for case-based research (Yin, 1994), the study relied on multiple sources of data.

Archival research. We used industry reports, industry regulation policies, and national and international business press reports to gather information on the broad electrical ecosystem, in order to triangulate and deepen our analysis on how digital technologies can be applied to deal with the market and with the operational challenges faced by firms in the sector, as well as to track their use of data and algorithms. We then focused on archival documents and presentations on the strategic plans of the two companies to draw up profiles of the companies, trace their recent history, and identify the mechanisms through which data can be converted into knowledge whenever this did not come directly from our primary data sources.

Semi-structured interviews. Resort to archival research helped us prepare semi-structured interviews (see the interview protocol in Appendix A), which were aimed at collecting detailed information on the two selected companies and analysing how algorithms allow these firms to cope with industry-specific challenges related to continuity of the grid and the systems, as well as operational flexibility in generation plants brought about by the uptake of renewable energy sources. We employed an embedded design and focused on each firm at two levels: (1) the top management team, and (2) the functional domains of innovation, operations, maintenance and HRM. The selection of our informants was aimed at collecting data from members who were in an excellent position to be informed about (a) knowledge creation and conversion mechanisms enabled by algorithms. Most of our informants had at least 15 years of experience in the industry. The notable exception was the HRM director of Company T, who had been hired specifically to implement a new HRM system to help support the digital transformation of the company. The interviews generally lasted about one hour and a half. In order to ensure reliability, two researchers were present at all the interviews. Given the content of the interviews, the researchers were not always allowed to use a recorder. However, detailed notes were taken and, after each interview, they were compared, integrated and transcribed. Following Miles and Huberman's prescriptions (1994), the transcriptions were supplemented with contact summary sheets in which the essential data and insightful quotations that could help future theorising were reported. Overall, 45 interviews were conducted – 28 interviews in Company E and 17 interviews in Company T – and qualitative material for more than 66 hours of interviews was collected.

3.3 Data Analysis

The adopted data analysis followed the common prescriptions for case studies (Yin, 1994). Our analysis began with a detailed reconstruction of the history of Company E and Company T and, in particular, of the period covering the adoption of predictive technologies - such as artificial intelligence and machine learning algorithms - to highlight patterns and critical points. This preliminary phase was followed by multiple rounds of coding of our data to search for patterns in the unfolding of the process over time and in the interpretations that our informants proposed for the events they described (Stake, 1995).

We coded for changes in the exploitation of data-driven approaches in the process of converting data into relevant knowledge for operational decision-making. Following Jansen et al. (2005), we searched our data for references to organisational mechanisms associated with combinative capabilities. Two members of the research team proceeded in parallel. In order to ensure internal consistency of the emerging coding structure (Miles and Huberman, 1994), we checked the reliability of our coding through collective check-coding of previously coded texts. This process involved multiple iterations, as the emerging framework was constantly updated and revised on the basis of evidence collected in the subsequent interviews. We also routinely checked emerging interpretations with our contacts at Company E and Company T (Strauss and Corbin, 1998). Throughout the process, triangulation with other sources helped us refine and strengthen our emerging interpretations (Yin, 1994: 97). Internal and external archival sources – such as annual reports, analysts' reports and the business press – were particularly important to triangulate the informants' recollections of the Top Management Teams' (TMTs) efforts to persuade organisation members about the importance and benefits of the new data-driven practices.

From this analysis, we produced a framework of the organisational mechanisms associated with combinative capabilities in the process of converting data into relevant knowledge for operational decision-making. We drew on true statements from multiple informants to "theorise the arrows" that linked the organisational mechanisms associated with combinative capabilities to the absorptive capacity dimensions associated with the process of converting data into relevant knowledge for operational decision-making. Following Lee (1999), we validated our results with a panel of industry experts with at least 20 years of expertise in the electrical sector in managerial roles. Representative quotations are reported in Table 2, following the common prescriptions adopted to report qualitative data, in order to support our categorisation of organisational mechanisms.

Table 2 – Evidence of concepts and representative quotations from the case studies

Combinative capabilities	Concepts (2nd order codes)		Representative quotations in the data (1st order codes)
[A] COORDINATION CAPABILITIES (cross-functional interfaces and integration mechanisms)	A.1	Cross-functional alignment to ensure retention and effective deployment of newly hired data scientists	*"We compete with Google to recruit and retain data scientists. Last year, we organised an international contest to recruit some experienced data scientists. Out of 200 participants, we hired 12. After a few months, some of them left the company. So, to prevent us from losing our data scientist, a lot of coordination efforts were needed between HRM, operations and IT to offer them projects that would be sufficiently challenging and which, even though well paid, would not bore them." (Middle Manager – Head of a HRM unit, Company E)*
	A.2	Low extent of industry-specific knowledge of data scientists	*"We have a lot of data available about the operational effectiveness of the electrical grid to apply predictive maintenance algorithms, but we need to build a new organisational ecosystem around our few data scientists to acquire data that are relevant for our processes and operations." (Top Management Team, Company E)* *"Data scientists conduct work that is highly specialised, and which is characterised by a low level of industry-specific competences on the electrical domain: they do not care about the electrical part, but they are bulimic of data, and they have a high level of technical skills in algorithms." (Middle Manager – Head of a HRM unit, Company E)*
	A.3	Liaison roles between data science specialists and industry specialists	*"Our data scientists are not interested in delving deeply into the understanding of the technical problems of our sector. Provocatively, we can say they are mainly interested in treating data. Moreover, many of them don't even want to talk so much with our technical departments or with the line workers. For this reason, we have created the business translator role. A business translator is accountable for the development of the business questions that need to be addressed by the data analysis run by our scientists." (Top Management Team, Company E)*
	A.4	Task interdependencies around data science activities	*"In a SCRUM session of our business process on engineering endeavours for the marketing area, the two data scientists involved left the rest of the team, went into a corner of the meeting room, and started to run clustering algorithms to try to re-segment our customer base." (Middle Manager - HRM unit, Company E)*
[A] COORDINATION CAPABILITIES (participation/involvement in operational decision-making)	A.5	Employee involvement in the interpretation of information derived from data	*"We are launching communication initiatives about our new strategy of making the grid smarter. In these initiatives, we stress the importance of line involvement in combining their operational knowledge to formulate improvement suggestions for our algorithms." (Middle Manager – Head of a HRM unit, Company T)* *"Employees from our Operations and Maintenance unit in the Apulia region came here (to Milan) and asked us to simulate a typical breakdown they had seen in a particular grid substation. They saw, on the simulated reproduction of the grid, the very same problem they had experienced in the field when the grid had incurred instability problems. In such a way, they were better able to understand the cause-effect linkages related to such breakdowns." (Middle Manager – Head of a R&D unit, Company E)* *"Now that we have digitalised the electrical grid, we monitor it in real-time and run predictive maintenance algorithms, but we need more involvement from our field force to validate what the algorithms are saying. Line workers, given their experiential knowledge, are well equipped to detect false positives of the algorithms or measurement errors due to a problem related to a sensor, for example, a bad position that can determine a measurement error. This is a crucial step for the fine-tuning of our*

			algorithms and for the continuity of our service. Luckily, our field force is engaged and deeply motivated, and we are working on increasing their involvement in innovation." (Top Management Team, Company T)
	A.6	Retrospective sense-making through algorithms and scepticism towards data-driven approaches	*"We have applied machine learning algorithms in a backward logic to let the algorithms understand the reasons for past breakdowns in our generation plants. The reaction has often been defensive. When faced with the diagnostics generated by the algorithm, employees questioned their efficacy in an attempt to prove their lack of mistakes in running or doing the maintenance of the machinery, even when a breakdown or a micro stoppage was not really due to their actions. They did not truly seize the opportunities of learning something new. We want to fight this. It causes stress and a lack of learning. To do this, we are building a no-blame culture where failure is not punished and should be communicated and shared." (Top Management Team – Thermal Generation Unit, Company E)* *"Sometimes, the reaction an employee has to the application of machine learning for the predictive maintenance of our photovoltaic plants is of questioning the efficacy of the algorithms. Once a line worker told me that they do not need big data to understand this type of breakdown failure." (Top Management Team- Green Power Generation Unit, Company E)*
[B] SYSTEM CAPABILITIES (formalisation)	B.1	Job codifiability and formalisation in data entry procedures	*"We are retrieving data about past maintenance operations. Unfortunately, these data are incomplete and inaccurate because no procedures were in place that obliged operators to document the type of intervention done on the grid. We know the past downtimes of our distribution grid, but we did not document the type of spare parts that were replaced or the type of interventions that were conducted. This is a problem because it hinders the application of machine learning, since we cannot train our algorithms by making inference on any type of association between the work done on the grid in the past and its behaviour." (Middle Manager – Maintenance Unit, Company E)*
	B.2	Digital data generation	*"There are some new smart work practices whereby the operator uses tablets or smartphones to access the workflow systems directly from the field. This type of practice improves the quality of the data entered into the system, and thus allows better data to be obtained to feed the predictive algorithms." (Top Management Team, Company T)*
[C] SOCIALISATION CAPABILITIES (socialisation tactics)	C.1	Knowledge transfer between different organisational domains and between digital specialists and industry specialists	*"We have created some internal digital innovation hubs. These hubs internally connect employees with different backgrounds and competencies, and externally connect our company with green start-ups. To make our line worker a digital worker, we want to run challenge-based training initiatives in the hubs. In these training initiatives, senior specialists or heads of our regional units informally explain the causes of our more critical breakdowns or malfunctioning of the stations to our young (future digital) workers. In this way, our future digital workers will be able to understand, thanks to the senior workers, why the grid sometimes breaks down, and thanks to our IoT specialists, how technology can prevent these problems, as they offer new remote monitoring and control logics." (Middle Manager – HRM unit, Company E)*
	C.2	Socialisation between young and senior workers to blend digital and legacy knowledge	*"Last week, I witnessed a discussion between a young and an older installer. The younger one said: 'There is too much voltage on the power line, we have to introduce a new transformer station'. The older one answered: 'How is that possible?' He went to check: no way! It was impossible. The younger one had made a mistake in the calculation. When the older one commented on it, the younger one replied: 'No, the system gave me that answer, I'm sure! You have to build the transformer station'. And the older one said: 'No, electrotechnically speaking, I can carry 20 kW for 700 metres with that section of cable'. In fact, you know what the problem was? There had been a dummy load (a person who was illegally stealing energy from the grid) and the younger installer had miscalculated the load, but couldn't bypass the problem." (Middle Manager – Distribution unit; Company E)*

4. Findings

The following section reports how the two focal companies that were analysed - Company E and Company T - introduced new organisational mechanisms to exploit algorithms in the process of converting data into relevant knowledge for operational decision-making processes. The main elements of these organisational adaptation processes are summarised in Table 2, which reports evidence of the concepts and the most representative quotations collected during the interviews conducted in the two companies.

Company E

The use of big data and algorithms to manage operations was institutionalised at Company E in 2014, when the company launched its digital transformation initiative and communicated its intention of becoming a "data-driven company" to its employees *(Company E, Annual Report, 2014)*. The digital transformation initiative mainly consisted of the reengineering of about 25 business processes that involved the distribution and retail of electricity. On the operational side, the digital transformation was mainly aimed at improving the overall effectiveness of the grid and its resilience in the case of accidental breakdowns due to external factors, such as severe weather conditions (e.g., snowstorms, hot periods, excess supply in the energy generated from wind and solar sources) that could jeopardise the stability of the grid. As reported by a TMT member of Company E:

> "Our goal is to develop a data-driven system that provides a complete, detailed, real-time picture of the state of the entire grid. This means aggregating and cleaning tons and a constantly growing stream of multi-source data, within a "data lake", and then contextualising it. Company E faces this challenge by innovating over two dimensions, modelling and automation. Modelling is based on data science techniques that include unsupervised and supervised machine learning algorithms, which are useful to create models in order to obtain a better estimate of the electricity demand forecasts and to obtain more in-depth knowledge of the consumption habits of each type of customer. On the other hand, the automatic collection process accumulates consumption, weather and market data, at least on a daily basis, and constantly feeds the algorithm, thereby providing a snapshot of the current state of the energy trends." *(Top Management Team – Thermal Generation Unit, Company E)*

The complexity of the power grid and the fact that it is now becoming an order of magnitude more complex with the transition to renewable energies (solar and wind generation) led Company E to intensify the hiring of specialists experienced in the technical and scientific domains of data science. As one of our informants reported:

> "The complexity of developing algorithms requires writing a lot of codes that integrate platform software services, access data from a variety of sources, transform data, correlate data, clean data, aggregate data, and then define services for machine learning, authentication, authorisation, encryption, and processing. There are hundreds of different components that have to be stitched together for the development of one algorithm." (*Middle Manager – R&D Unit, Company E)*

For this reason, between 2015 and 2018, Company E hired an "elite" group of about 15 data scientists for its corporate technical areas. These specialists had at least five years of specific work experience in data science, mostly developed in such digital companies as Google and Amazon (see A.1 in Table 2). As such, their industry-specific knowledge was limited and, according to our informants, they showed limited willingness to develop it in the company (see A.2 in Table 2). Given these characteristics, the retention of this kind of worker in the company is problematic because digital or financial companies usually offer them more attractive professional challenges and better wage conditions.

The retention problems (A.1, Table 2) and the lack of industry-specific knowledge (A.2, Table 2) led the company to deploy this elite group of data scientists in a variety of functional domains, including operation and maintenance of the grid, marketing and customer relationship management (e.g., for fraud detection). For example, the theft of electricity is one of the most important problems for utilities and Company E decided to apply data science to this problem. As a manager from the Top Management Team of the company remarked:

> "We changed our approach to identifying and prioritizing the theft of electricity to drive a step change in the recovery of unbilled energy. This allowed us to improve productivity, but also to stimulate our data scientists. We obtained such a result by building AI and machine learning algorithms to match the performance delivered by our field experts. Our system integrates and correlates 10 trillion rows of data from seven source systems and 22 data integrations into a unified, federated cloud image in near real-time, which runs on the cloud. Using analytics and more than 500 advanced machine learning features, the fraud detection algorithm continuously updates the probability of fraud for each customer's meter." *(Top Management Team, Company E)*

This redeployment of data scientists in an attempt to challenge them with complex tasks in various domains was introduced in order to offer them a greater variety of professional challenges, and in fact, as one of our key informants in the HRM department reported:

> "Data scientists conduct work that is highly specialised, and which is characterised by a low level of industry-specific competences on the electrical domain: they do not care about the electrical part, but they are bulimic of data, and they have a high level of technical skills in algorithms." (Middle Manager – *Head of a* HRM unit, Company E)

It was reported, both in archival documents and by the informants in company E, that the firm, in order to leverage on the highly specialised skills of data scientists, created a "*new organisational ecosystem around data scientists*" (*Company E, Annual Report, 2016*). The company in particular created a new liaison role, that of the "*business translator*", specialised in designing research challenges for data scientists and in transferring the outcome of the data scientists' work to actionable knowledge for the company (see A.3 in Table 2). The employees appointed to this role were identified among the specialists from each functional department (i.e., sales, customer relationship management, operations and maintenance). Then, such specialists underwent technical training on the fundamental aspects of database architecture, data science and algorithms. As pointed out by one of our informants, this role is extremely important in Company E to furnish data scientists with managerial requirements and to send the results of the algorithms back to management for operational decision making:

> "Data science is one element and data management is another one; you need to master both. The third dimension is scaling the life cycle of these AI models, and unless you've got all three elements, you're still in the prototype world and you cannot make any reliable decision" *(Top Management Team, Company E)*

Coordination between data scientists and business translators generally takes place through task interdependencies, which offers the advantage of a reduction in the coordination costs, and through a shared vocabulary related to data science and the main operational problems of each functional domain. In other words, business translators have a general understanding of the potential knowledge that could be drawn from data. Data scientists were also involved in some of the business process re-engineering programmes started by the same company in 2017 to realign the operational processes of the distribution activities with the new competitive requirements and with the improvement opportunities offered by big data and artificial intelligence. In such situations, their role was mainly aimed at categorising customers or breakdowns in order to have more factual knowledge to use as a point of reference to quantify and prioritise inefficiency causes in the processes that were the subject of a more radical re-engineering. However, again in these situations, the data scientists generated their predictive and prescriptive analytics through algorithms with a limited need of interaction with the other people involved in the project team who were accountable for the re-designing of the process (see A.4 in Table 2).

The data-driven approach in company E also significantly changed the training processes in such a way that many training initiatives are now more closely integrated with research activities. Thus, the training initiatives can use the outcome of R&D programmes as a resource for specific training sessions on the basis of the use of algorithms and data-driven approaches. This is well reflected in the creation - within the corporate R&D department - of a "smart-grid lab" that was responsible for creating and updating a digital twin of the distribution grid. This digital twin of the grid consisted of a simulation model that incorporated real past data pertaining to the functioning of the grid and, in particular, to breakdowns and malfunctioning episodes. Data referring to past breakdowns were used, by Company E, to simulate a smaller reproduction of the grid, which was represented by a set of transformer substations located in the same room. This digital twin of the grid was beneficial for two reasons. First, the location of the substations in the same room allowed the employees involved in training to observe the propagation of a breakdown on the grid better than in reality, where substations are on average 30 km from each other. Second, the digital twin became an instrument that could be used to integrate context-specific tacit knowledge on how the grid was performing in a particular geographical area, with structured data embodied in the simulation model. This was beneficial for both the specialists that developed and kept the model updated and for the line workers involved in training sessions in the research lab (see A.5 in Table 2).

There are other examples in which data-driven approaches led to the creation of digital twins that are still used for similar retrospective sense-making routines to the one depicted in the "smart-grid lab". One of the most representative examples reported by our informants concerns the diagnostics of breakdowns in thermal energy generation plants. Here, sensorisation and the use of machine learning algorithms are mainly employed for the real-time detection of breakdowns, to limit interruptions in the supply of energy and to offer satisfactory service levels to customers. On this topic, one of our interviewees mentioned that:

> "The digitalisation of energy begins where energy begins: at the generation plants. Today, not only wind farms and photovoltaic plants, but also old hydroelectric power stations are managed, at least in part, in an automated way. Thanks to sensor technology, signals from a turbine, dam or pipeline can be collected in real time and sent to a central control room. Here, the use of artificial intelligence algorithms makes it possible to observe abnormal data and thus identify potential risks. Moreover, machine learning algorithms, such as the one of Company Gamma, use data and information from multiple plants and allow a single power plant to self-monitor its stress level. This allows you to intervene before damage occurs."
> *(Top Management Team - Thermal Generation Unit, Company E)*

With specific reference to retrospective sense-making, employees are periodically exposed to the simulation of breakdowns and operational problems experienced in the past and documented in the information systems. This is done to uncover the links between employees' actions and performance outcomes, and in particular to unveil the causes of any breakdowns that altered the average operational capacity of the plant. However, when this practice was started, the exposure of line employees to problems from the past put them in a condition of questioning the validity of the algorithms (see A.6 in Table 2). As a result, managers reacted by adopting a "no-blame" culture in the company, which had essentially been lacking when the data-driven approach was first started. As one of our informants reported:

> "We have applied machine learning algorithms in a backward logic to let the algorithms understand the reasons for past breakdowns in our generation plants. The reaction has often been defensive. When faced with the diagnostics generated by the algorithm, employees questioned their efficacy in an attempt to prove their lack of mistakes in running or doing the maintenance of the machinery, even when a breakdown or a micro stoppage was not really due to their actions. They did not truly seize the opportunities of learning something new. We want to fight this. It causes stress and a lack of learning. To do this, we are building a no-blame culture where failure is not punished and should be communicated and shared."
> *(Top Management Team – Thermal Generation Unit, Company E)*

A crucial precondition for retrospective sense-making routines, based on data analytics, was also found in the increased formalisation of the line employees' work (see B.1 in Table 2). Formalisation is now seen as a necessary step to ensure a sufficient quality of the data introduced to document the maintenance of the equipment and which are fed by algorithms for predictive and prescriptive maintenance purposes. In this vein, Company E - in partnership with a provider of advanced analytics and AI-powered data services - created a workforce management system based on an algorithm that identifies an optimal plan for assigning maintenance tasks to teams. In a few minutes the algorithm can identify a schedule that maximizes the amount of time spent working, while also minimizing the time spent on the road. Another example is the use of a predictive algorithm - scalable to all power plants - to predict the fouling curve of photovoltaic panels (based on data from specific probes) to optimise panel cleaning operations. However, it was not easy to introduce a data-driven culture to the company. Apart from the introduction of a workforce management system - which increased the control and the extent of documentation required to accomplish the line workers' tasks – line employees did not willingly accept that these data-driven approaches often challenged or opposed what their experience suggested, in terms of maintenance activities. Unsurprisingly, this was seen as a loss of power by technical specialists in favour of digital specialists sitting in a corporate office. A contextual element that has magnified this negative sense-making of technical specialists consisted in the fact that, since 2007, Company E has only hired line employees if they have a high-school leaving diploma.

In 2016, in order to mitigate this attitude, the company created reverse mentoring programmes and digital innovation hubs in which senior line workers were flanked with workers under 30 years old, but with at least five years of work experience in the company (see C.1 in Table 2). Such a flanking was aimed at facilitating a bidirectional exchange of knowledge: as younger workers in general have a higher attitude towards data, algorithms and data-driven approaches, they were (and still are) put in charge of transferring their skills in using and consulting analytics dashboards to their senior peers. Instead, the more senior line workers were (are till are) asked to transfer their tacit knowledge to younger colleagues about given tasks and the solutions that should be applied for specific technical problems (see C.2 in Table 3).

Company T

The main business of company T consists in the high-voltage transmission and dispatching of electricity. As in the case of company E, most of the operational work done by the company is conducted by a field force that is responsible for operating and maintaining an electrical grid. As in the case of company E, company T experienced a growth in operational complexity, due to the transition to solar and wind generation energy in the countries in which it operates. This transition increased the problems of matching supply and demand and of dispatching electricity, two critical activities that ensure the operational continuity of the grid. As reported by a TMT member of Company T:

> "In the past, it was reasonably easy to predict the energy supply and demand, align the energy supply, and distribute energy to satisfy the demand. But now, with smart grid transitions, solar panels, batteries and accumulators, it is harder to know how much energy you will need at any given time. Machine learning algorithms allow us to forecast the demand at each individual customer point and aggregate that demand to predict the supply requirements. However, it is not enough for us to have an algorithm that is 80% reliable, we need a risk consideration close to zero. So, we are looking at various alternatives. With artificial intelligence, we can set up new ways of forecasting the demand and of avoiding congestion."
> *(Top Management Team, Company T)*

As in the case of company E, the strategy adopted to cope with this increasing complexity in operational processes was a wider use of sensors and IoT technologies to monitor and control the condition of the grid. As one of our informants reported:

> "The growing number of distributed resources and sensors weighing on the distributors' networks certainly represents a great opportunity for the system, but it also requires a revision of our monitoring and control tools. To this end, Company T is acquiring advanced Artificial Intelligence algorithms that are capable of estimating all the so-called distributed generation (around one million plants) through a small and manageable number of measurements from the field, thus minimising the costs of the system. In addition, we are currently experimenting with integrating new data into the algorithm. For example, we have data from robots for network maintenance, drones for network monitoring and cable analysis that would further reduce monitoring and control the costs." *(Middle Manager – Head of a HRM unit, Company T)*

Another example concerns the monitoring of infrastructures using satellite data processed by means of Artificial Intelligence techniques and big data analytics. As explained by one of our interviewees, the aim of the project is to derive useful information from the automatic analysis of satellite images in order to obtain an increasingly efficient management of Company T's assets. However, our informant pointed out that although the network will become increasingly intelligent, thanks to sensors and the use of analytics and artificial intelligence, this transformation process requires the formalisation of data-driven approaches for line employees to make sense of the data collected by the sensors. The growth in the formalisation of work began with the mandatory use of tablets and smartphones for field workers in the second half of the 2000s (see B.2 in Table 2). At first, the line workers did not willingly accept the digital support tools or their use, which they associated with an increasing importance of a workforce management system – and which, they believed, introduced standards into timetables and the pace of many operational tasks conducted in the field. However, employee acceptance was facilitated by the fact that the tablets and smartphones used in conjunction with the new workforce management system were also the means of retrieving information and analytics that could facilitate their work and reduce the idle time required to retrieve and access the information that is stored in the paper-based archives of some central offices. Data-driven approaches also became the way to make the knowledge extracted from the database available to line employees in the operational line in order to alert them, in a timely manner, about whenever the portion of the grid for which they are accountable is likely approaching a state of malfunctioning.

Between 2016 and 2018, company T intensified its efforts in feeding algorithms with new data from such IoT technologies as drones and robots. Moreover, Company T also increased its efforts to realign its Human Resource Management system to encourage a broader involvement of the line workers in continuous improvement strategies (see A.5 in Table 2). The company now adopts augmented and virtual reality systems to improve the efficiency of the line workers when field operations are required. One informant reported that:

> "Using augmented and virtual reality systems, the technicians carry out digital simulations and receive training that is comparable with that of aircraft pilots. Through this training, once in the field, they control the situation with more elements at their disposal and provide immediate feedback to their peers." (*Middle Manager - Operations Unit, Company T).*

The adoption of such technologies helped the company to increase the reliability of input data on breakdowns and malfunctioning and stimulated the company to engage them for the validation of the output of algorithms. On this, one of our informants reported:

> "Now that we have digitalised the electrical grid, we monitor it in real-time and run predictive maintenance algorithms, but we need more involvement from our field force to validate what the algorithms are saying. Line workers, given their experiential knowledge, are well equipped to detect false positives of the algorithms or measurement errors due to a problem related to a sensor, for example, a bad position that can determine a measurement error. This is a crucial step for the fine-tuning of our algorithms and for the continuity of our service. Luckily, our field force is engaged and deeply motivated, and we are working on increasing their involvement in innovation." *(Top Management Team, Company T)*

The line workers were thus considered as being better equipped than specialised suppliers of electrical systems and components – such as GE with the Predix Platform – to control whether the data generated by sensors and the information produced by machine learning algorithms were plausible and correct, and whether the prescriptive and predictive analytics inferred by the algorithms suggested appropriate courses of action. This was because line workers can rely on tacit experiential knowledge that is context-specific, and a technology supplier that offers data analytics and AI-based solutions can find it hard to capture and internalize such knowledge. Moreover, another reason that emerged is related to the fact that line workers and electrical companies have better systemic knowledge about how a sensorised electrical machine performs in a complex electrical system, such as an electrical grid or a power generation plant.

Our records on company T also suggest that the motivation and engagement of line employees in continuous improvement is critical to integrate their systemic and practical knowledge with the information generated by the algorithms (see A.5 in Table 2). The greater importance given to the involvement of line employees in programmes aimed at improving the efficacy of the data-driven approaches led company T to hire a new HRM director, who had had experience in an automotive company, where the lean production programmes were based on broad bottom-up participation in work practices of continuous improvement. In 2018, the new HRM director started a programme oriented towards introducing new variable compensation mechanisms in order to incentivise and reward the actual contribution of line employees to the continuous improvement of the algorithms. As the new HRM director reported:

> "We are launching communication initiatives about our new strategy of making the grid smarter. In these initiatives, we stress the importance of line involvement in combining their operational knowledge to formulate improvement suggestions for our algorithms." *(Middle Manager – Head of a HRM unit, Company T)*

5. Discussion

In the previous section, we reported a narrative description of the organisational mechanisms associated with the exploitation of data-driven approaches at Company E and Company T, in which we reflected on the informants' interpretations of how the process of converting data into relevant knowledge for operational decision-making evolved over time. In this section, we present a framework that builds on our analysis to theorise how organisational mechanisms associated with combinative capabilities influence the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making. Our framework is depicted in Figure 1.

Our evidence shows that, starting from data and prior legacy knowledge algorithms, such as data analytics, the most immediate impact of AI and machine learning is at the operational decision-making level. However, the operational decision-making process involves six organisational mechanisms in the absorptive capacity dimensions of converting data into relevant knowledge (see Figure 1). The organisational mechanisms (1,2,5) streamline the process of acquiring relevant data to generate a prediction based on the firm's prior legacy knowledge. By combining machine learning and human judgment through supervised/unsupervised training, the algorithm returns the prediction information. The information produced by the algorithm is then analysed and interpreted on the basis of the organisational mechanisms (2,3). Combining prior legacy knowledge and insights from the assimilated information, horizontal integration mechanisms (4) allow new knowledge to be created. Such new knowledge is then incorporated into frontline activity procedures through socialisation tactics (6). Finally, these frontline activities lead to an outcome, which is a consequence of the operational decision-making process. The operational decision-making process can also provide feedback to help improve the next prediction. In this way, new decisions are made, prior legacy knowledge is updated, new data are acquired, new information is generated, and new knowledge is created and recombined in a continuous closed-loop system.

Table 3 provides a synthesis of how the organisational mechanisms matter in the four distinct phases of an absorptive capacity process and highlights the key resources, roles and activities involved in a data-driven context for each phase.

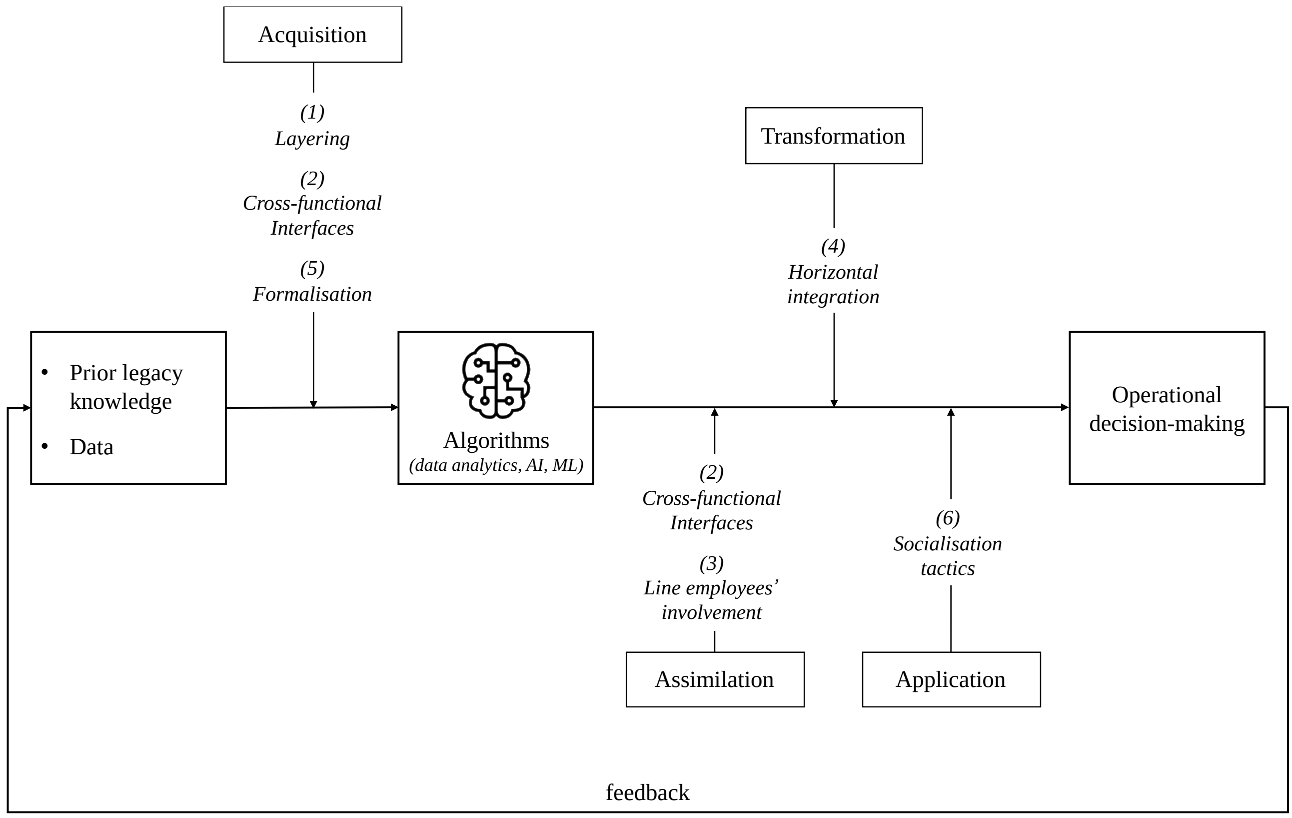

Figure 1 - Towards a comprehensive framework of the organisational mechanisms involved in the absorptive capacity dimensions of converting data into relevant knowledge for operational decision-making.

Table 3 – Organisational mechanisms used to support the dimensions of absorptive capacity in a data-driven context.

<table>
<tr><td colspan="2"></td><td colspan="4">Absorptive capacity dimensions</td></tr>
<tr><td colspan="2"></td><td>Acquisition</td><td>Assimilation</td><td>Transformation</td><td>Application</td></tr>
<tr><td colspan="2"></td><td>Identify and acquire critical data for operations through sensors</td><td>Analyse, process, interpret and understand the information derived from algorithms</td><td>Combine existing knowledge and insights from the assimilated information to create new knowledge</td><td>Incorporate transformed knowledge extracted by algorithms into frontline activity procedures</td></tr>
<tr><td rowspan="4">Combinative capabilities associated with absorptive capacity dimensions</td><td rowspan="2">Coordination capabilities</td><td>(1) – Layering
Data acquisition is a general-purpose activity characterised by high levels of technical specialisation, which does not depend on the extent to which data scientists have accumulated industry-specific knowledge.</td><td>(3) – Line employees' involvement
Line employees' involvement results in system-level and context-specific knowledge being used to fine-tune and validate the output generated by algorithms.</td><td rowspan="2">(4) – Horizontal integration
Horizontal integration mechanisms allow the recombination and internalization of line employees' tacit and codified knowledge resulting from algorithms.</td><td rowspan="2"></td></tr>
<tr><td colspan="2">(2) – Cross-functional interfaces
Cross-functional interfaces realised through new liaison roles (i.e., business translator) allow the internal search of relevant data and the interpretation and understanding of the information derived from algorithms.</td></tr>
<tr><td>System capabilities</td><td>(5) - Formalisation
The formalisation of operational work increases the accuracy and the quantity of the data that can feed algorithms.</td><td></td><td></td><td></td></tr>
<tr><td>Socialisation capabilities</td><td></td><td></td><td></td><td>(6) - Socialisation
Socialisation tactics instil a data-driven culture in the workforce and allows legacy experiential approaches to be blended with data-driven approaches when dealing with operational decisions.</td></tr>
<tr><td colspan="2">Key resources in a data-driven context</td><td>Data</td><td>Information</td><td>Knowledge</td><td>Learning</td></tr>
<tr><td colspan="2">Key roles in a data-driven context</td><td>Data architects and data engineers (for the design of large-scale datasets)
+
Business translators (for the internal search of relevant data)
+
Managers (for the formalisation of the operational processes)</td><td>Data scientists (for the fine-tuning of algorithms)
+
Business translators (for the interpretation and understanding of the information derived from algorithms)
+
Line employees (for the interpretation of the operational process underlying the algorithms)</td><td>Boundary spanning units between research, operation and training (for the recombination of knowledge)
+
Line employees (for the internalisation of knowledge)</td><td>Functional middle managers (for decision-making processes)
+
Line employees and the cross fertilisation of approaches based on seniority (for the implementation of the prescriptive and predictive logics in their operational processes)</td></tr>
<tr><td colspan="2">Key activities in a data-driven context</td><td>Internal search and organisation of the relevant data</td><td>Interpretation and understanding of the information produced by algorithms</td><td>Recombination and internalisation of new and existing knowledge</td><td>Knowledge use and exploitation</td></tr>
</table>

5.1 Organisational mechanisms associated with coordination capabilities.

A high level of specialisation in data science skills emerged. Surprisingly, the level of industry-specific knowledge that data scientists have is somewhat limited, and this reduces the extent of a common language with the rest of the technical specialists and the line operators.

Lam et al. (2017) and Marr (2016) highlighted that the acquisition capacity is made by knowledge agents who identify data that are crucial for their operations. Conversely, our evidence seems to indicate that data acquisition can be separated from the operational context, with no consequence on the acquisition capacity. This is related to how data science and analytics approaches can identify what companies can do in terms of running the algorithms required for predictive and prescriptive analytics from the data generated by their sensorised and connected assets (Iansiti and Lakhani, 2020; Agrawal et al., 2018). In this sense, our results show that data acquisition can be considered as a general-purpose activity and can be layered, with just a marginal adaptation, for a vast array of business domains (Lanzolla et al., 2020). Hence, in a data-driven context of operation management, the digital knowledge domains related to the acquisition capacity from data can be layered upon the legacy ones, since they do not depend on the extent to which roles specialised in data science have accumulated industry-specific knowledge (see 1 in Figure 1 and Table 3).

However, the general-purpose nature of data acquisition critically challenges the value of the collected data. In fact, firms risk information overload, as data acquisition, for the sake of acquisition, significantly increases the messiness of the data (Lam et al., 2017). For this reason, data engineering tasks are necessary to define the structure of databases (Snijders et al, 2012), which should be based on context specific knowledge expressed by such agents as business translators. Hence, business translators play a crucial role in absorptive capacity acquisition routines (Zahra and George, 2002). They share a common language with data scientists; they ask questions and require solutions, and this can be of the utmost importance for the acquisition capacity of a company, which is related to understanding where algorithms can offer a contribution to gather new knowledge that can then be applied to the operational processes (Trantoupulos et al., 2017).

Moreover, our results show that the role of the business translator is also crucial to articulate the requirements of the analysis that the data scientists can run through algorithms. Business translators play a remarkable role in interpreting the outcome of algorithms in order to improve and redesign the existing business processes (Roßmann et al., 2018). In this vein, cross-functional interfaces (Gupta and Govindarajan, 2000) favour the integration of new codified information with explicit knowledge that can be readily articulated, codified, stored and accessed, thus easing its access by the whole organisation (Kleis et al., 2012). This activity is crucial for the subsequent transformation of information into knowledge through its recombination with knowledge already owned by the firm. On the basis of these elements, in a data-driven context of operation management, cross-functional interfaces realised through new liaison roles (i.e., business translator), facilitate the internal search of relevant data and the interpretation and understanding of the derived information, thus enhancing the firm's knowledge acquisition and the assimilation capacity from data, respectively (see 2 in Figure 1 and Table 3).

Our evidence suggests that such an assimilation capacity in a data-driven context also requires companies to maintain a high degree of control over their assets, IoT platforms, and over the algorithms that define their prescriptive and predictive analytics. This means companies have to reduce their relational dependence on the specialised suppliers of integrated machine-data analytics solutions (e.g., the Predix Platform, an industrial IoT software platform from GE Digital).

However, reducing relational dependence entails dealing with a great quantity of data and information that have to be assimilated into organisational memory to create new knowledge (Nonaka et al., 1996; Nonaka et al. 2001). Our results show that the involvement of line employees is the main mechanism that is adopted to mitigate both relational dependence and data assimilation problems. In fact, line workers participate in the interpretation and understanding of predictive and prescriptive analytics through which potential issues related to quality and cost efficiency can be mitigated, or even entirely avoided (Philip, 2018). This allows the company to integrate their system-level and context-specific knowledge with the information generated by their assets.

On the one hand, when work is conducted in a context of geographical dispersion and "in the field", employee involvement in the assimilation of information extracted from algorithms seems to make sense, due to the line workers' context-specific knowledge, which is mainly in tacit form (Lam et al., 2017). On the other hand, when work occurs in a context of continuous production flows, as in the case of power generation plants, employee involvement also introduces system-level knowledge that is hard to formalise and embody in the algorithms that govern IoT solutions. Therefore, system-level knowledge and context-specific knowledge put employees in a position whereby they can apply “common sense” rules to decide on the appropriateness of the decision outcome suggested by algorithms (e.g., understanding which algorithms can be used for asset maintenance). Such common-sense rules may derive from the fact that when organisations are exposed to situations that are rarely encountered, line employees can take into consideration more data and information than the big data collected by an IoT platform and analysed by an algorithm. This eases the interpretation and understanding of the predictive and prescriptive analytics produced by data scientists within the existing internal knowledge of a firm (Trantopoulos et al., 2017). This process is reflected in the “broken-leg rule” (Meehl, 1957), according to which judgmental approaches can be more effective than formulas and algorithms for rare circumstances, due to their capacity to take into consideration additional information that may be relevant.

Thus, humans are better equipped than algorithms to take into consideration additional context-specific information that is relevant for the accuracy of the information or to choose the appropriate course of action. In other words, in a data-driven context of operation management, the involvement of line employees in the fine tuning and validation of the output generated by an algorithm facilitates the firm's assimilation capacity from data (see 3 in Figure 1 and Table 3).

Two key components necessary for the transformation of information assimilated from algorithms are internalisation and conversion (Lam et al., 2017), both of which occur through the integration of new insights, the erasure of obsolete knowledge, and/or the interpretation of the possessed knowledge in a different light (Zahra and George 2002).

Our evidence shows that, in the present case, these processes emerged through horizontal integration mechanisms which entailed the creation of boundary spanning units between research, operations and training - such as the smart grid lab at company E - and favoured the transformation of codified knowledge gathered through algorithms into organisational common knowledge (Zander and Kogut, 1995). Horizontal integration mechanisms -such as the smart-grid lab- are likely to gather individuals together from different domains to favour the integration of their knowledge and technical expertise (Vaccaro et al. 2009). In fact, the smart-grid lab is an applied R&D unit which has the aim of building digital twin models of the grid behaviour through the data acquired by sensors. This lab plays an important role in the transformation of the information assimilated from data collected by sensors and the knowledge derived from the algorithms to inform the operations and management units.

The knowledge transfer mechanism refers to the formal training that occurs in the lab and the balancing of the physical and digital assets (the substations in the lab and the simulation model, respectively). More specifically, digital twins are used to support knowledge articulation at company E, where they help in the understanding of the performance implications of the routines and actions followed by line workers during their operations in the field. The informants reported that this helped the company to integrate the context-dependent and practical knowledge of the line employees with the knowledge embodied in the digital model of the grid and helped employees to articulate the causes of some performance outcomes of the portion of the grid they controlled. This process increases technical discussions and encourages common interpretations and collaborative problem solving in a firm (Majchrzak and Wang 1996; Tippins and Sohi 2003), which results in a full recombination and internalisation of tacit and codified knowledge within the whole organisation.

In other words, the smart grid lab operated as a template (Jensen and Szulanski, 2007), thereby favouring the recombination of the specific knowledge of the line specialists, the data acquired by data scientists and analysts and the information they generated thanks to the interaction with business translators. Therefore, horizontal integration mechanisms allowed an efficient transformation to take place of new and already existing organisational knowledge (Nonaka et al., 1996; Nonaka et al., 2001). It can thus be suggested that, in a data-driven context of operation management, horizontal integration mechanisms entail the recombination and internalisation of the tacit knowledge of line employees and the codified knowledge resulting from algorithms, thus enhancing the firm's transformation capacity from data (see 4 in Figure 1 and Table 3).

5.2 Organisational mechanisms associated with system capabilities.

The involvement of line employees in the fine-tuning of algorithms and in knowledge articulation routines becomes regular and habitual in a data-driven organisation, once it is institutionalised in the HRM system by managers. Our evidence from Company T clearly illustrates that the codification and the formalisation of operational work, through a mandatory use of smartphones and tablets, is one of the steps an organisation should take before becoming data-driven. Specifically, job codifiability, here intended as the extent to which work can be formalised in a set of rules that determines the workflow of activities an employee must accomplish when doing a given task, is a critical factor to ensure data accuracy and to increase data quantity. Hence, formalisation is a prerequisite for the acquisition capacity an organization can develop from its algorithms and not merely a condition through which a principal can exert bureaucratic control over an agent (Kellogg et al., 2020).

In a data-driven context, the formalisation of operational work plays a role that was highlighted in past studies on knowledge creation (MacDuffie, 1997), which underlined that formalisation leads to an extremely detailed and prescriptive specification of a process. Such a specification provides a crucial baseline of data against which all future improvement efforts will be evaluated, and codifies the gains made since improvement efforts have been introduced. As such, contrary to what has been predicted for the absorptive capacity (Jansen et al., 2005), in a data-driven context, formalisation is the beginning and not the end of a learning process that is built on data. These arguments have stronger implications on the absorptive capacity an organisation develops from algorithms when operational work occurs in a situation of geographical dispersion (such as the operation and maintenance of an electrical grid), where hierarchical control and coercive surveillance cannot be as effective as in a plant (Kellogg et al., 2020). Therefore, in a data-driven context of operation management, the formalisation of operational work favours the accuracy and the volume of the data acquired and documented, thus increasing the firm’s acquisition capacity from data (see 5 in Figure 1 and Table 3).

5.3 Organisational mechanisms associated with socialisation capabilities.

Previous studies on absorptive capacity showed that an efficient application of new process knowledge to a firm’s production depends on the cost of applying such knowledge to the line employees (Alavi and Leidner 2001; Alavi and Tiwana 2002; Masini and van Wassenhove 2009; Jansen et al., 2005). In a data-driven context, algorithms can reduce the cost of exploiting the acquired, assimilated and transformed knowledge in a firm, since they offer line employees searchable repositories of explicit knowledge that can be accessed whenever needs arise in production (e.g., Heim and Peng, 2010; Hendricks et al., 2007; Lam et al., 2017). However, although firms may attempt to act instantly on ready-made and codified knowledge from algorithms, previous studies showed that, in order to exploit such knowledge, firms must rely on sharing tactic elements and learning skills among managers, engineers and floor operators (Robertson et al. 2012; Szulanski 1996; von Hippel and Tyre 1995). Our evidence shows that this problem is also exacerbated by the generational differences between employees with different roles and qualifications.

Specifically, our data show that line employees become driven by analytics, even in their day-to-day work, and not only when they are involved in knowledge creation activities – such as the fine-tuning of algorithms – or in specific knowledge articulation routines. This may limit the use of judgmental approaches driven by the accumulation of tacit knowledge and experience. Such a change requires new attitudes and skills, especially for older workers, who are sometimes less willing to accept the use of tablets and workforce management systems to impose the pace of their work. Socialisation tactics – such as the reverse mentoring programme used in Company E – are mechanisms that have been found useful to instil the attitudes necessary to espouse a data-driven culture and skills for the collaborative use of computer and analytics software. In this vein, in the reverse mentoring programme adopted by Company E, young workers are put in charge of transferring digital literacy skills and a data-driven culture, because they often have higher educational qualifications than more senior workers, who perhaps entered the company when the educational requirements were lower and somewhat different. Therefore, in a context in which organisations try to generate more knowledge from their data, younger workers are the recipients of knowledge flows from senior workers, and the knowledge being transferred is practical, tacit and derived from the accumulation of experience. Socialisation tactics further foster communication between communities of practice in a firm, thereby allowing a rapid identification of groups of experts who may hold important tacit knowledge on how to solve context-specific problems (Brown and Duguid 2001; Huber 1990; Majchrzak et al. 2007).

In sum, managers can use socialisation tactics to win over scepticism and create a no-blame culture through behaviour modelling with self-awareness and self-efficacy, and to blend experiential, theoretical and data-driven knowledge. In the workplace, reverse mentoring is aimed at making senior and less qualified employees still feel important and not replaced or deskilled by algorithms and data-driven approaches. In this vein, socialisation tactics facilitate the application of the explicit knowledge acquired from algorithms, a process that relies on communication between different operational functions, ranging from R&D to operations and full-scale production environments (Pisano 1997). These arguments suggest that, in a data-driven context of operation management, socialisation tactics ensure that the knowledge produced from algorithms can complement the operational work of line workers by acting on the commitment and value systems that are relevant to blend digital and legacy knowledge (see 6 in Figure 1 and Table 3).

6. Conclusion

This paper extends the extant literature on the organisational mechanisms at the origin of absorptive capacity in a data-driven context. In particular, the paper illustrates how the organisational mechanisms associated with combinative capabilities influence the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making. By doing so, we contribute to the existing literature in two ways. First, we contribute to research regarding the link between combinative capabilities and absorptive capacity (Kogut & Zander, 1992; Van den Bosch et al., 1999; Jansen et al., 2005). We empirically examine how common features of combinative capabilities affect the dimensions of absorptive capacity in a data-driven context, whenever the knowledge is generated internally – and not externally – as examined in previous studies (cf. Jansen et al., 2005). Hence, this study reveals how organisational antecedents matter and examines the linkage between specific organisational mechanisms, such as common features of combinative capabilities and the dimensions of absorptive capacity in a data-driven context - when the source of knowledge is not external, but instead consists of the data generated by sensors installed and connected to a firm's production assets. Second, we contribute to the literature on process innovation in the area of digital competences of the workforce (e.g., Bala and Venkatesh, 2017; Chalvatzis et al., 2019; El-Kassar and Singh, 2019; Lam et al., 2017) by investigating the organisational configurations and roles required to integrate the knowledge generated from data with operational decision-making processes. We do so by developing a framework that may offer a baseline to continue the investigation of process improvements and the organisational configurations of firms in a data-driven operational environment. We discuss the implications of the framework hereafter. Our considerations are summarised in Table 4.

Table 4 – Summary of the contributions of the paper to the research gaps on absorptive capacity in a data-driven context

Research gaps on absorptive capacity in a data-driven context	**Insights from this research**
What are the mechanisms that integrate data science and analytics expertise with business domain knowledge in the four stages of absorptive capacity?	• The assimilation capacity from data is based on cross-functional mechanisms, such as liaison roles. • Liaison roles act as cross-functional knowledge brokers between new digital specialised roles and legacy technical ones. • The assimilation capacity is not based on approaches that increase the multidisciplinary attitude and skills of data scientists and business domain experts, but is instead based on a layering of the two.
How can decentralised approaches entailing the participation of employees in operational decision-making coexist with the centralisation of data collection, storage and analysis?	• Decentralisation facilitates knowledge creation from data, since line employees introduce system-level knowledge that algorithms capture less effectively. • The larger the scope of the task is, the less employees are able to understand the interdependencies between all the involved activities.
How does formalisation in operational processes affect the quality of data introduced by line employees when they accomplish their tasks?	• Formalisation facilitates data acquisition, as it obliges line workers to comprehensively and accurately document any relevant events that occur in the tasks they perform. • When formalisation is poor, or is not effectively enforced, the quality of the data fed to prescriptive and predictive algorithms is low, with negative implications on the created knowledge.
How can socialisation tactics be used to complement (and not to substitute) data-driven specialists with legacy roles?	• Socialisation tactics facilitate such tasks as data creation, algorithm validation and the use of knowledge created from algorithms. This happens since socialisation tactics are aimed at instilling new values and beliefs of applying a data-driven culture in the operational work of line employees. • Socialisation tactics ensure that the knowledge produced from algorithms can converge with the operational work of line employees as a result of blending digital and legacy knowledge. • Socialisation tactics act on the cognitive and emotional sense-making of line employees by favouring reverse mentoring processes to align employees' behaviour with a data-driven culture.

Cross-functional approaches are necessary because algorithms require new digital specialised roles (i.e., data architects, data engineers, and data scientists), which see as inefficient for their performance the absorption of industry-specific knowledge. As such, and quite surprisingly, the assimilation capacity from algorithms of a firm does not seem to be based on approaches that are aimed at increasing the multidisciplinary attitude and skills of some of the roles involved in the assimilation capacity. Such a capability instead seems to be founded more on cross-functional mechanisms, and in particular on liaison roles, which act as knowledge brokers between the "new digital" specialised roles and legacy technical ones.

The paper also sheds new light on the reasons why participation in operational decision-making processes, in the form of line workers' involvement, is one of the organisational mechanisms through which firms can build an absorptive capacity in a data-driven context. In the study conducted by Jansen et al. (2005), the effect of participation was linked to the benefit of involving a great number of receptors of some single elements of the environment that are relevant for the creation of new knowledge. In their interpretation of small data, Lam et al (2017) enriched this view by positing that line workers mainly introduce contextual knowledge that cannot easily be structured in databases or in the formulae of an algorithm. Our evidence suggests that, in a data-driven context of continuous production flows – such as that of power generation plants where line workers are relatively high-skilled and run more complex plants and systems than other organisational configurations (Bhattacharjee, 2020) – employees introduce system-level knowledge that algorithms capture less effectively in their knowledge integration routines. This effect of employee involvement on knowledge conversion from algorithms might become more evident when firms build organisational configurations based on multifunctional skills and job rotation practices in the operational line.

As far as this latter point is concerned, the paper offers another salient aspect, that is, the effectiveness through which employee involvement leads to legacy experiential approaches in the transformation process of information derived from data into knowledge depends on the extent to which the scope of the tasks controlled by algorithms is broad vs. narrow (Zollo and Winter, 2002). The larger the scope of the task is, the less employees are able to understand the interdependencies between all the involved activities (Fleming and Sorenson, 2001). In such a situation, employees could introduce tacit knowledge elements that are less relevant to create new knowledge for operational decision-making processes. This effect can also be observed in the case of the IoT solutions that generate data, especially when sensors and algorithms control the tasks remotely and can only capture what a machine can do in a broader and complex system, but they may find it difficult to understand the performance of the system as a whole. In such a situation, our evidence suggests that knowledge articulation mechanisms, supported and mediated by the digital representation of broad tasks or processes (e.g., digital twin models of the grid in Company E), might be more effective in creating knowledge than those approaches in which knowledge is produced at a distance from the context where the data were generated (e.g., industrial IoT software platform - such as GE with the Predix Platform - which provides secure edge-to-cloud OT/IT data connectivity, processing, analytics and services to support industrial applications from third-parties). We have brought to light that the ground for such mechanisms is the digital representations of operational processes and that - in such a setting – the involvement of line employees is the main lever of transformation capacity.

Finally, such organisational mechanisms as formalisation and socialisation seem to play a more circumscribed role in knowledge creation than what the existing studies on absorptive capacity have shown (Jansen et al. 2005). In other words, in a data-driven context of knowledge creation, formalisation seems to be a key prerequisite for the quality of the data created by line workers when documenting their work. When formalisation is poor or is not effectively enforced, the quality of the data used to feed prescriptive and predictive algorithms is low, with negative implications on the created knowledge. This confirms the well rooted idea in process improvement studies that formalisation is the first step of a learning process, rather than simply being the end (MacDuffie, 1997).

Although the specific contribution of formalisation to knowledge creation from data lies in the first part of the absorptive capacity process (i.e., related to the acquisition capacity), socialisation seems to play a salient role in the last part of the process (i.e., related to the application capacity). Our evidence shows that socialisation capabilities are mainly aimed at instilling the new beliefs and principles of applying a data-driven culture to the operational routines of line workers (Carillo, 2017). This is a crucial step to ensure that the produced knowledge can be packaged into algorithms that drive the operational work of line workers, and which alert them when the assets they run are approaching conditions that algorithms associate with situations of inefficiency or of poor process quality. However, this result can also be the fruit of certain specificities, as in the case of the two considered companies. In other firms or industry contexts, such socialisation mechanisms as a community of practices could, for example, also play a role in the assimilation or transformation roles.

In illustrating these points, the paper offers several implications on the organisational configurations that firms should build when business process management becomes more data-driven and is based more on algorithms. The main point in this regard stems from the importance that formalisation and employee involvement have on knowledge creation from predictive and prescriptive analytics, and it implies that, to become more data-driven, firms should balance the “enabling” and “coercive” elements of employee empowerment, as illustrated by Adler (2012) in reference to how bureaucratic configurations support deliberate learning. In the same way, new beliefs and principles should drive employees’ behaviour, such as learning orientation, through data and experimentation, and a “no blame” culture pertaining to how data on mistakes and the breakdowns of assets should be shared to foster knowledge articulation routines (de Araújo Burcharth, et al., 2015).

Although we believe we have made a contribution to the understanding of how organisational mechanisms influence the way algorithms can be exploited in the process of converting data into relevant knowledge for operational decision-making, it is important to acknowledge the limited generalisability of our results. Despite our specific choice of the electrical sector, we believe our study provides insights that can advance scholars’ understanding of how organisations build an absorptive capacity that is specifically aimed at generating knowledge from the multitude of data generated in operational processes by plants and machinery. Against the backdrop of today’s digital transformation, we hope our findings will encourage further research on the microprocesses that can explain the way organisational structures should be designed to grasp the knowledge creation potential from predictive and prescriptive analytics generated by algorithms. In this vein, our evidence suggests that vertical integration choices can be expected to foster knowledge articulation mechanisms that are based on algorithmic approaches by reducing the role of cloud-based platforms-as-a-service, such as Predix by GE. Furthermore, we hope our findings will encourage more qualitative studies on the knowledge creation dynamics from algorithms in industry settings where line employees are highly skilled, as in the case of professional work, or alternatively, where work is characterised by a high routinisation and low skills. Finally, as remarked by Lam et al. (2017), we hope our study will encourage scholars to develop new scales that will be able to capture the absorptive capacity dimensions in a data-driven context. In this way, such scales will be able to further quantitatively test and provide a contribution on how organisational mechanisms can influence the way algorithms can be used to convert data into valuable knowledge for firms.

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Appendix A

Semi-structured interview protocol

Introduction and background information

- How long have you been working in your current role, and what are your main tasks?
- Do you have any tasks and/or responsibilities that are related directly to big data, algorithms and AI?
- Can you illustrate the extent to which IoT is triggering the generation and use of big data in your organisation?
- Can you describe the explorative projects related to the Internet of Things, Big data and artificial intelligence that you have launched? What have been the main outcomes? How have these projects been extended?
- How do you think algorithms can be leveraged on in the process of converting data into relevant knowledge for decision-making?

Main questions

- What do you think are the functional domains in which your company engages the most with data collection (for monitoring and predicting tasks)?
- Has your company enrolled any new employees specialised in data analysis and algorithms? If so, how did you recruit them? Can you describe the projects and initiatives on which they have been deployed? In such initiatives, how have the integration and coordination between such new roles and well-established roles in the technical or operational units of your organisations been ensured?
- How have big data and algorithms changed the practices related to data collection in the operational and maintenance processes of your organisation? What specific data provide the greatest value, and under what conditions?
- How is the use of big data and algorithms affecting the work of the operational workers? Have such logics affected the skills of the operational workers and operational middle managers? What skill shortages and forms of reluctance have been produced? How are you coping with this?
- With reference to the skill shortage, have you created any ad-hoc practices or training programmes? Have you seen a change in the culture of your organisation (e.g., values, social norms, systems of beliefs)? At a managerial level, have you taken any steps to facilitate the diffusion of a data-driven culture within your company?
- How are big data and algorithms generating new knowledge in the way operations are run (e.g., identifying the root causes of breakdowns and inefficiencies)? Have you seen any systematic change in the way the organisation is learning?
- Can you illustrate how standard operating procedures have been affected as a result of insightful information derived from algorithms?
- What is the degree to which your company has prioritised data-driven decision-making for frontline processes in its strategy?

Conclusion

- Have we forgotten anything? Is there anything else you would like to discuss?
- Could we get back to you in case we have any (minor) further questions about our data analysis?