Research Policy 52 (2023) 104812

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Big data and dynamic capabilities in the digital revolution: The hidden role of source variety

Mattia Pedota

Politecnico di Milano, Department of Management, Economics, and Industrial Engineering, Via R. Lambruschini 4b, 20156 Milan, Italy

ARTICLE INFO

JEL classification:
O32
O33

Keywords:
Artificial intelligence
Big data
Digitalization
Digital revolution
Dynamic capabilities
Knowledge

ABSTRACT

Recent research frames big data as a resource enhancing dynamic capabilities through improved prediction, decision-making, and data-driven innovation. In contrast, this study frames big data as an evolutionary driver that channels firms' knowledge and attention in specific directions, implying that firms need multiple big data sources to be receptive and dynamically capable. I apply this framework to the context of the digital revolution and focus on the impact of big data on firms' digitalization priorities. By leveraging a large-scale survey of more than twenty thousand Italian firms of all sizes, I find that big data improves the digitalization awareness of firms only if they gather big data from more than one source (otherwise, counterintuitively, it may even decrease it). I also find a positive effect of source variety both on the likelihood of prioritizing individual digitalization factors and on the variety of digitalization factors prioritized. Such effects appear to be stronger for small firms relative to their larger counterparts. Given the path dependence of digitalization trajectories, these findings have relevant policy implications in the context of initiatives like the European strategy for data and the SME strategy for a sustainable and digital Europe.

1. Introduction

Recent developments in artificial intelligence enable multipurpose exploitations of data, spurring new business models and improving the efficiency of existing ones (Garbuio and Lin, 2019; Liang et al., 2018; Reim et al., 2020). As algorithms and techniques for statistical inference improve, the world becomes more interconnected: besides people producing textual, numerical, and audiovisual data through their online activities, increasingly many devices act as vehicles for data sharing and transmission (Guo et al., 2013). The surge in data availability coupled with the development of methods for data analysis easily explains the ubiquity of big data.

The baseline definition of big data refers to structured or unstructured data that is too large for traditional data-processing software (Lansley and Longley, 2016; Sestino et al., 2020). However, the definition can be broadened to include the related data analytics, storage, and management (Boyd and Crawford, 2012; Wamba et al., 2015). In line with this holistic approach, the present work assumes that the act of sourcing big data is almost always coupled with some analysis. Accordingly, I hereafter refer to big data in the singular, denoting the whole phenomenon rather than the data themselves.

Big data is acknowledged to improve various aspects of firm performance (Brynjolfsson and McElheran, 2016; McAfee et al., 2012). In the realm of innovation, recent research suggests that it can enhance a firm's dynamic capabilities (Teece et al., 1997) through improved prediction, data-driven innovation, and better sensing of opportunities (Conboy et al., 2020; Côrte-Real et al., 2017; Rialti et al., 2019). However, while this covers the resource-based side of dynamic capabilities, it overlooks its evolutionary-based nuances, such as bounded rationality, learning, and path dependence (Barreto, 2010; Nelson et al., 2018). Big data underlies information, which channels organizational knowledge and attention and contributes to shaping a firm's perception of the current and future states of the environment (Ocasio, 1997; Zollo and Winter, 2002). Thus, I propose that the variety and typology of big data sources are likely to affect a firm's ability to sense opportunities and reconfigure resources in specific directions. Furthermore, while expecting these effects to hold for all firms, I suggest that they may be even stronger for small firms: being characterized by lower bureaucratization and less coexisting perspectives (i.e. less employees), small firms may be more susceptible to both informational gains and potential biases from big data.

The digital revolution constitutes the ideal context to study these dynamics, as it requires multifaceted adaptation. Several studies underline that not only technological innovation, but also strategic planning, collaboration, skill sourcing, and skill consolidation are essential for firms to thrive in the digital era (Ciarli et al., 2021; Pedota et al.,

E-mail address: mattia.pedota@polimi.it.

https://doi.org/10.1016/j.respol.2023.104812
Received 17 October 2022; Received in revised form 8 May 2023; Accepted 14 May 2023
Available online 25 May 2023

2023). Lacking big data may weaken firms' (dynamic) capabilities of sensing the potential of advanced digital and automation technologies and reconfiguring their strategy and resources accordingly. Also, extracting big data from only few sources may bias firms toward few digitalization factors at the expense of others. Due to the path dependence of knowledge accumulation (Cohen and Levinthal, 1990; Nelson and Winter, 1982) and the hierarchical nature of digital technologies (European Patent Office, 2017; Zolas et al., 2021), both effects may engender self-reinforcing dynamics, ultimately shaping the dynamic efficiency of firms (and in turn productive systems). Thus, investigating the interaction between big data and dynamic capabilities in the context of the digital revolution carries both theoretical and practical relevance.

This study leverages a large cross-sectional survey developed by the Italian National Institute of Statistics (ISTAT) in 2018, covering 21,934 Italian firms of all sizes. Among other topics, the survey investigates whether firms ascribe competitive relevance to digitalization factors from a given list, namely infrastructure, fiscal incentives supporting digitalization, digital initiatives of the government, capability of networking with other firms and research centers, skill sourcing, skill consolidation, development of a digitalization strategy. Dependent variables capture whether respondents flagged a given digitalization factor as important for the competitiveness and development of the firm in the following two years. Regressors of interest capture whether respondents sourced big data from social media, sensors, portable devices, and/or other sources in the year before (thus, although the survey is cross-sectional, the temporal antecedence of regressors is ensured). Control variables include firm size, industry, geographic location, and degree of ICT intensity, at the highest level of detail provided by the database. With this setup, I perform a series of multiple logistic and ordered logistic regressions aimed at determining: 1) whether big data enhances firms' awareness of digitalization factors; 2) if and to what extent the kind and/or variety of sources of big data make a difference in the kind and/or variety of digitalization factors prioritized; 3) whether small firms exhibit any relevant difference in such dynamics relative to their larger counterparts.

I find that firms using big data (regardless of the source) have a significantly lower probability of not regarding any listed digitalization factor as important, as well as a significantly lower probability of being unable to identify priorities among the listed factors. This is coherent with the enhancing effect of big data on dynamic capabilities. However, interestingly, firms that extract big data from only one source have a level of digitalization awareness comparable to that of firms that do not use big data at all (and, in some cases, even lower). Furthermore, not only does source variety increase the probability of regarding any given digitalization factor as important, but it also increases the variety of digitalization factors considered important. As hypothesized, most of these effects are stronger for small firms rather than medium and large ones.

From a theoretical viewpoint, this study contributes to the literature on big data and dynamic capabilities by framing big data as an evolutionary driver rather than a mere resource, thus reconciling the resource-based and the evolutionary traditions in dynamic capabilities research. From this vantage point, the study provides evidence that the typology of big data sources that firms rely on shapes the path ahead. Consequently, firms need big data source variety to be receptive to multiple facets of the environment and thereby dynamically capable. From a practical viewpoint, results highlight an additional reason why big data is a crucial enabler of the digital revolution: not only is big data complementary to other digital technologies functionally, but it also guides firms' digitalization trajectories by shaping firms' digitalization awareness. Furthermore, results draw managerial, entrepreneurial, and institutional attention not only to the opportunities stemming from big data utilization, but also to the traps inherent in relying on too few big data sources. Given the path dependence of digitalization trajectories, this realization matters for both firms and economic systems, thus bearing relevance to initiatives like the "European strategy for data" (European Commission, 2020a).

2. Theoretical background

2.1. Dynamic capabilities and big data

Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments (Teece et al., 1997: p. 516). The concept originally stressed the interdependence between the position of the firm (e.g. its asset endowment), the processes for coordination, learning, and reconfiguration, and the paths lying ahead (Teece et al., 1997). Subsequent elaborations better specified the business dimensions involved (Eisenhardt and Martin, 2000) and the different functions of dynamic capabilities: sensing, seizing, and transforming. Sensing refers to the ability by the firm to scan the environment for opportunities, seizing indicates the ability to exploit them, while transforming encompasses the learning and resource reconfiguration mechanisms underlying competitive advantage renewal (Teece, 2007).

Dynamic capabilities are deeply rooted in the evolutionary view (Nelson and Winter, 1982), stressing path dependence, learning, and innovation. They can be regarded as high-level collections of routines through which a firm dynamically adjusts its lower-level routines and resources as a function of its perceived position in the environment (Winter, 2003). In this respect knowledge is key, as it shapes the firm's awareness of the environment and its expectations about it, including the perceived strategic importance of change (Zollo and Winter, 2002). Furthermore, knowledge underlies the quintessential dynamic capabilities: those related with learning and innovation (Nelson et al., 2018). Absorptive capacity, the ability of the firm to recognize the value of new knowledge, assimilate it, and apply it to commercial ends (Cohen and Levinthal, 1990), is often regarded as a dynamic capability itself (Volberda et al., 2010; Zahra and George, 2002). Knowledge articulation and, to a greater extent, knowledge codification enhance organizational learning, by fostering knowledge sharing and facilitating the identification of causal mechanisms (Nonaka, 1994; Zollo and Winter, 2002). Various studies provide evidence that dynamic capabilities for knowledge absorption, integration, and reconfiguration are drivers of success in innovation-based Schumpeterian competition (Danneels, 2008, 2012; Nelson et al., 2018; Verona and Ravasi, 2003).

The interplay between dynamic capabilities, knowledge, and innovation has recently drawn attention due to globalization and digitalization. Key knowledge is now dispersed across geographies, sources, and media. This reinforces the open innovation paradigm (Bogers et al., 2018; Chesbrough, 2003), by making it easier and more beneficial to tap into external sources of knowledge. As a result, dynamic capabilities become even more important: sensing capabilities become critical to identify relevant external knowledge, as well as licensing out opportunities; seizing capabilities are needed to set incentives, processes, and governance mechanisms to leverage collaboration; transformation capabilities become key factors underlying the dynamic integration of internal and external knowledge (Bogers et al., 2019).

In this highly globalized and digitalized context, big data bears relevance to dynamic capabilities due to its knowledge-related properties (Ferraris et al., 2018). When complemented by machine learning techniques (Zhou et al., 2014), analytical skills (LaValle et al., 2011), and a supportive culture (Frisk and Bannister, 2017), big data brings significant value to firms (Ciampi et al., 2022; McAfee et al., 2012; Wamba and Mishra, 2017). Depending on the effectiveness of analytical capabilities and diffusion mechanisms, big data may translate into knowledge that significantly affects the kind and quality of decisions. When managed through appropriate routines, such knowledge can be leveraged in different instances (Erevelles et al., 2016). Thus, big data has the potential to improve several functional areas, ranging from marketing to supply chain management (Chehbi-Gamoura et al., 2020; Choi and Chen, 2021; Lo and Campos, 2018).

Given these features, recent research on big data often employs a dynamic capabilities perspective. Empirical evidence has been offered that process-oriented dynamic capabilities mediate the relationship between big data analytics capabilities and firm performance (Wamba et al., 2017). Furthermore, several studies underscore the importance of big data for innovation, both directly and indirectly. Data-driven improvements in functional areas allow firms to develop digitally enabled routines for sensing, seizing, and reconfiguring resources. Digitally enabled routines like support scenario-planning practices, agile cross-functional teams, and integration of process and IT know-how foster process innovation (Chirumalla, 2021). As firms master such routines and leverage them to improve the efficiency of their processes, they may be incentivized to develop additional process, product, and/or organizational innovation, due to emerging interdependencies. This is because changes in the constituents of a system (e.g. the introduction of new machinery) may require adjustments in other constituents, and also because the added complexity creates new technological problems stimulating further R&D effort (Szalavetz, 2019). R&D effort is likewise incentivized by data-driven improvements in knowledge building and prediction, which mitigate the risk and uncertainty inherent in innovative projects (Niebel et al., 2019). Furthermore, big data provides direct inputs (e.g. customer data) for the innovation process (Bresciani et al., 2021; Sultana et al., 2021), concurrently enhancing the ability by firms to sense the opportunities that come up to them and reconfigure resources accordingly (Conboy et al., 2020; Mikalef et al., 2021). Improved predictive capabilities also heighten the promptness and effectiveness of firms' reactions to sudden change, leading to information-driven competitive advantage (Côrte-Real et al., 2017; Rialti et al., 2019).

These studies have marked important steps toward understanding the relationship between big data and dynamic capabilities. However, while dynamic capabilities bring together resource-based and evolutionary views (Barreto, 2010), current framings of big data in relation to dynamic capabilities lean heavily toward the former. Big data tends to be regarded as a resource to be deployed through an ad hoc bundle of IT and managerial capabilities, often referred to as big data analytics capabilities (Mikalef et al., 2020). When adequately complemented, big data is acknowledged to improve dynamic capabilities through better decision-making, prediction, and responsiveness, enabling firms to navigate through change. However, this widespread framing has so far overlooked the more evolutionary-based aspects of dynamic capabilities: those related with bounded rationality, learning, and path dependence. Even assuming adequate complements, I argue that the postulation that big data improves dynamic capabilities generically may be too coarse-grained. Given bounded rationality, big data is also a powerful channeler of organizational attention and knowledge search. I advance that the number and typology of big data sources a firm relies on is likely to affect its perception of the environment (including its future states), and in turn its ability to sense opportunities and reconfigure its resources.

Thus, on the one hand, I aim to provide further empirical evidence on the fact that big data enhances firms' dynamic capabilities. On the other hand, more importantly, I aim to take a step more, by investigating the role of big data source typology and big data source variety in shaping the dynamic capability of sensing opportunities and adapting to technological change. To this end, the ongoing digital revolution constitutes the ideal context, as it marks a fundamental shift in the way firms operate, compete, and innovate (Osterrieder et al., 2020; Stornelli et al., 2021). Adaptation to the digital revolution requires firms to innovate technologically, while also adapting operationally and strategically (Ciarli et al., 2021; Pedota et al., 2023). In other words, firms need to simultaneously advance along a series of digitalization factors. I propose that not only the mere adoption of big data, but also the typology and variety of big data sources play a role in this transition, dynamically shaping the digitalization path of firms (and in turn economic systems).

2.2. Hypotheses

Knowledge has a well-established role in shaping firms' evolutionary trajectories (Greiner, 1998; Scott and Bruce, 1987). The bulk of current knowledge is a crucial driver of the intensity and direction of the process of knowledge search. Typically referred to as the absorptive capacity of a firm (Cohen and Levinthal, 1990; Zahra and George, 2002), it is a fundamental enabler of innovation. As stressed by more recent conceptual refinements, the first component of absorptive capacity is the ability to recognize the value of new knowledge (Todorova and Durisin, 2007). Without prior related knowledge, a firm lacks the very cognitive and informational prerequisites to grasp the importance of further knowledge. This is not only due to the difficulty of integrating such new knowledge into extant cognitive structures, but also to the incapability of estimating the prospective implications of that knowledge. Firms enact a series of external routines aimed at enhancing their value recognition capabilities (Lewin et al., 2011). Many of such routines are data-driven, including the mining of patent literature (Cohen et al., 2002) and the administration of end user surveys (Kohli et al., 1993).

Hence, I argue that big data is likely to play a significant role in the ability of firms to recognize the value of digitalization factors. First, given that big data comprises both data sourcing and analytics (Boyd and Crawford, 2012; Wamba et al., 2015), it constitutes a form of embedded knowledge. Firms sourcing large quantity of data also tend to adopt advanced analytical techniques to exploit them (with varying extents of success). Thus, they possess knowledge on digitalization and data analytics. Coherently with the theory of absorptive capacity, this is likely to facilitate the recognition of the value of digital knowledge and thereby the importance of digitalization factors. Second, big data translates into information. By processing large quantities of data, firms can better intercept technoeconomic trends (Perez, 2010), as well as technological trajectories and macrotrajectories (Dosi, 1982; Pedota et al., 2021). At the same time, they are better positioned to assess their strengths and weaknesses relative to their competitive environment. Therefore, big data adopters are also more likely to know which digitalization factors to prioritize based on their needs, which leads to targeted adaptation and resource reconfiguration efforts. Possible examples are the preemptive identification of a competence-destroying technology (Abernathy and Clark, 1985) triggering the prioritization of skill sourcing, or the discovery of a market opportunity foregrounding product-oriented collaboration. This leads to the formulation of the following two hypotheses:

HP1a. Big data allows firms to recognize the competitive relevance of digitalization factors.

HP1b. Big data allows firms to identify which digitalization factors to prioritize.

Extant research has suggested that big data may improve dynamic capabilities through information-related advantages (Conboy et al., 2020; Côrte-Real et al., 2017; Rialti et al., 2019), but it is largely silent on the role of big data source typology and variety in this respect. I maintain that different big data sources lead to different kinds of information, which may affect firms' perception in different ways. Sources of information have been shown to play a pivotal role in a number of different areas, including innovation development (Medase and Abdul-Basit, 2020). Firms relying on a larger variety of sources of information are more likely to develop innovations considered as national or world premieres (Amara and Landry, 2005), with probable underlying reasons being the non-redundancy of the information obtained (Burt, 1992) and the creativity-enhancing properties of knowledge diversity (Taylor and Greve, 2006).

I propose that a greater variety of sources of information provides managers in the firm with heterogeneous knowledge, which stimulates their creativity by expanding their domain-relevant knowledge (Amabile, 1983; Amabile and Pratt, 2016). With more boundary-spanning domain-relevant knowledge, managers are likely to give weight to factors that less knowledgeable individuals would disregard. This is primarily a consequence of the notion that knowledge attracts similar knowledge (Cohen and Levinthal, 1990; Zahra and George, 2002): with more heterogeneous knowledge, managers have a larger number of hooks to recognize the value of further knowledge. However, it is also a consequence of the higher number of connections that they can make and possibly their higher motivation: with boundary-spanning knowledge at their disposal, managers can recognize the value of further knowledge not only for its immediate relevance to the current bulk of knowledge, but also for its prospective recombinatory potential (Fleming, 2001; Pedota and Piscitello, 2022). Furthermore, a higher level of creativity typically entails a surge in intrinsic motivation and positive affect (Amabile and Pratt, 2016). This may further enhance the ability by firms to recognize the value of new knowledge, as eagerness to learn is a crucial component of absorptive effort (Song et al., 2018; Srivastava et al., 2015).

Information also shapes attentional focus. Bounded rationality (Simon, 1991) implies that managers can never attain a complete and objective representation of the world (Bogner and Barr, 2000; Fiol and O'Connor, 2003). Instead, they construct a subjective framing of the external environment based on drivers like firm context (Ocasio, 1997), industry context (Sutcliffe and Huber, 1998), and past performance (March and Shapira, 1992). Depending on whether they perceive the external environment as malleable or fixed, they may adhere to proactive or deterministic causal logics, whereby they attempt to shape the environment through strategic action or merely react to environmental signals, respectively (Nadkarni and Barr, 2008). In both cases, available information forms the basis on which the subjective representation is built, thereby molding perception and in turn action. Low breadth of information may constrain the attentional focus of firms within narrow limits, with direct implications on the comprehensiveness of their environmental perception.

I argue that, by constituting information, big data shapes both knowledge and attention within firms. When relying on a variety of big data sources, firms benefit from heterogeneous knowledge flows, and they are more likely to be receptive to different facets of the environment. Thus, they are better positioned to sense and dynamically build on a wider range of opportunities. In the context of the digital revolution, this may include a reconfiguration of the skill base, the formulation of a digitalization strategy, and the engagement in collaborative opportunities. Furthermore, heterogeneous knowledge boosts organizational creativity, prompting firms to consider a wider range of possibilities (e.g. visionary digitalization strategies or ambitious collaboration plans). Both these effects are likely to increase their proclivity to recognize the value and competitive relevance of digitalization factors. On the side of attention, I maintain that firms relying on various big data sources have a subjective representation of the environment that is richer and more complex than the one they would have by relying on fewer sources. This is likely to reinforce the perceived importance of digitalization factors, both due to a more comprehensive understanding of the current state of the environment and a better ability to anticipate its future states. Therefore, I suggest that relying on a higher variety of big data sources has a twofold effect: not only does it increase the likelihood of considering any given digitalization factor as important, but it also augments the variety of digitalization factors considered important. This is condensed in the following hypotheses:

HP2a. As the variety of sources of big data increases, both the awareness and the capability by firms to identify competitively relevant digitalization factors increases.

HP2b. As the variety of sources of big data increases, the variety of digitalization factors considered important for competitive advantage increases.

I also observe that small firms have a set of distinctive features relative to their larger counterparts. Younger and less resourceful, their geographical, lateral, and vertical scope is typically limited. They have a lower number of employees, a shorter hierarchical chain, and less structured mechanisms for carrying out core and support activities, including knowledge gathering and decision-making (Gibcus et al., 2009; Penn et al., 1998). For all these reasons, they are not (yet) stuck in path-dependent trajectories of organizational development. Instead, they tend to be relatively flexible, forward-looking, and receptive to the surrounding environment, as well as proactive and entrepreneurial (Miller, 2011; Mthanti and Ojah, 2017). Furthermore, lacking dedicated staff to scan the environment for information, they must often rely on heuristics and rules of thumb for making decisions, which makes them prone to biases (Busenitz and Barney, 1997; Gibcus et al., 2009).

This can be condensed into two relevant preculiarities of small firms. On the one hand, they have more to gain from big data. Having a lower initial bulk of information, the marginal benefit of big data is likely to be higher in their case. In other terms, ceteris paribus, I expect a higher informational difference between a small firm with big data and one without than between a large firm with big data and one without. Considering the awareness of competitively relevant digitalization factors, the effect is made even stronger by the entrepreneurial orientation and receptivity of small firms to the external environment, which increases the likelihood of them capitalizing on big data to get acquainted with different digitalization factors. On the other hand, as they are smaller, less structured, and more prone to bias, I also expect small firms to benefit from big data source variety to a higher extent. This is because big data is likely to constitute a relatively large proportion of their information, and such information is going to circulate many times among a restricted number of employees. When lacking variety in data sources, this may engender a sort of echo chamber where priorities and decisions are dictated based on a very partial snapshot of the world. Unlike their larger counterparts, small firms cannot rely on a large corpus of alternative information sources, nor do they have a variety of coexisting perspectives (given the small number of employees). Therefore, I put forward the following hypotheses:

HP3a. Both the awareness-enhancing effect (HP1a) and the identification-enhancing effect (HP1b) of big data are stronger for small firms relative to medium and large ones.

HP3b. The effect of big data source variety on the awareness and capability to identify competitively relevant digitalization factors (HP2a) is stronger for small firms relative to medium and large ones.

HP3c. The effect of big data source variety on the variety of digitalization factors considered important for competitive advantage (HP2b) is stronger for small firms relative to medium and large ones.

3. Empirical analysis

3.1. Description of the sample

The sample comes from the "survey on information and communication technologies in firms", administered by the Italian National Institute of Statistics in 2018 in collaboration with the European Commission.[1] Its objective is to provide comprehensive information on the integration of ICT technologies in Italian companies that have a minimum workforce of 10 employees. Data cover a range of topics, including firms' training of ICT staff, utilization of e-commerce and social media platforms, implementation of electronic invoicing, approach toward the digital revolution, and commitments to emerging technologies (including big data). The survey is organized in four sections: general information (A), ICT competences (B), internet usage and connection (C), cloud computing services (D), 3D

[1] The entire questionnaire is available at the following link: https://listarilevazioni.istat.it.

printing (E), robotics (F), big data analytics (G), invoicing (H), sales through ICT networks (I), determinants of the firm's digital transformation (J). The present study takes its key variables from sections G and J, along with various controls from section A.

The survey aims at the population of Italian firms with at least 10 employees, from any of the following sectors (letters refer to the Italian ATECO classification): manufacturing (C); supply of electricity, gas, steam and air conditioning (D); water supply, sewerage and waste management (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transport and storage (H); accommodation and catering services (I); information and communication services (J); real estate activities (L); professional, scientific, and technical activities (M, except division 75: veterinary services); rental, travel agencies, and business support services (N); repair of computers and communications equipment (group 95.1 of section S: other service activities).

The whole population of firms with at least 250 employees is included. Firms with a lower number of employees are stratified random sampled according to industry (at given levels of aggregation), number of employees (10–49, 50–99, 100–249), and geographical location (northeast, northwest, center, south, islands). The total number of firms is 21,934. To segment the sample according to size, I followed the revenue criterion of the EU recommendation 2003/361 and recognized firms with revenues lower than or equal to 10 million as small firms, firms with revenues between 10 and 50 million as medium-sized firms, and the remaining firms as large ones. This way, I identified 13,761 small firms, 4716 medium-sized firms, and 3457 large firms.

The sample is designed to be representative of the population of Italian firms, which has peculiar features. The Italian production fabric is characterized by high sectorial specialization in traditional sectors (e. g. textile and clothing) and a prevalence of small enterprises (as reflected in the sample), two factors that tend to hamper innovation (Bugamelli et al., 2012). However, as explained in the next subsection, the estimates do control for firm size, sector, and ICT intensity. Furthermore, the large sample size enables the isolation of small firms and the analysis of different subsamples based on firm size (where sector and ICT intensity are always controlled for). The robustness of results to the inclusion of controls for the main peculiarities of Italy enhances their generalizability to different countries.

3.2. Methodology

To test the hypotheses, I relied on selected parts of sections G and J of the survey. Subsection G1 requires firms to indicate whether they have gathered big data from sensors, portable devices, social media, and/or "other sources" in year 2017. Subsection J3 requires firms to indicate which of the following digitalization factors are relevant for the competitiveness and development of the firm during years 2018 and 2019: a) infrastructure and ultra-bandwidth connection (hereafter infrastructure); b) subsidies, financing and fiscal incentives in favor of digitalization (hereafter subsidies); c) digital initiatives of the government (hereafter governmental intervention); d) networking through collaboration with other firms and research centers (hereafter collaboration); e) acquisition of new technological competences through hiring (hereafter skill sourcing); f) development/consolidation of extant technological competences through training of current personnel (hereafter skill consolidation); g) development of a digitalization strategy (hereafter digitalization strategy); h) other factors; i) no digitalization factor matters; j) I don't know. Both sections allow for multiple responses, but subsection J3 requires firms to select at most 3 digitalization factors. While constraining the variability of factors selected, this restriction has the advantage of forcing respondents to reflect more carefully about which factors to include, thereby avoiding the risk that respondents may carelessly flag all (or most) factors as important.

From these sections, I generated a series of key dummy variables. From subsection G1, for each possible source (sensors, portable devices, social media, other), I generated a variable taking the value of 1 if the company gathered big data from it, and zero otherwise (hereafter "source dummy"). To measure the extent to which a firm relies on different big data sources, I also generated a variable that is the sum of the dummy variables associated with each source (hereafter "source variety"). Furthermore, I generated another variable taking the value of 1 if the company gathered big data *exclusively* from that source, and zero otherwise (hereafter "exclusive source dummy"). From subsection J3, for each digitalization factor, I generated a variable taking the value of 1 if the company flagged that factor as important, and zero otherwise (hereafter "digitalization factor dummy"). Moreover, to measure the extent to which a firm considered different digitalization factors as important, I also generated a variable that is the sum of the dummy variables associated with each digitalization factor (hereafter "digitalization factor variety").

Control variables include size, industry, geographical location, and ICT intensity, at the highest level of detail provided by the database. Besides performing separate analyses based on firm size (small, medium/large, whole sample), I used revenue classes to control for size at a higher level of granularity within each subsample. To control for industry, I used dummy variables capturing whether the firm belongs to any of the aforementioned sectors (letters C to S of the ATECO classification). To account for geographical location, and in particular for the technological divide between different regions of Italy, I used dummy variables indicating the position of the firm in the northwest, northeast, center, south, or islands. Finally, I proxied the degree of ICT intensity of the firm through the percentage of ICT workers employed, as ICT intensity may drive both big data adoption and digitalization awareness, thus potentially confounding the estimates.

The analysis starts with three sets of logistic regressions. Each set consists of ten logistic regressions, each of which employs a digitalization factor dummy as a dependent variable (including "I don't know" and "no digitalization factor matters"). The aim is to grasp the effect of a series of regressors of interest (outlined below) on the odds of regarding a digitalization factor as important for the competitiveness and development of the firm in the future. For simplicity, for each set, I estimated all the equations separately through logistic regressions. In the first set, for each regression, I used all source dummies as regressors of interest. In the second set, for each regression, I used all exclusive source dummies as regressors of interest. In the third set, for each regression, I used source variety as a regressor of interest.

I also considered that estimating the equations separately may entail a risk of bias, due to a possible correlation between residuals. This would happen if there were relevant omitted explanatory variables influencing some of the dependent variables jointly. Thus, as a robustness check, I grouped digitalization factors based on the similarity in their possible determinants. I grouped digitalization strategy, collaboration, skill sourcing, and skill consolidation, as they may be jointly influenced by determinants related to the digital proactiveness of the firm. I grouped infrastructure, subsidies, and governmental intervention, as they may be jointly influenced by determinants related to the (real or perceived) lack of enablers by the firm. I grouped "other factors", "no digitalization factor matters" and "I don't know", as they comprise the category of "alternative answers". Then, I performed three sets of multivariate probit regressions (Cappellari and Jenkins, 2003) analogous to the ones described in the previous paragraph, the only difference being the joint estimation for the three aforementioned groups of dependent variables. Coefficients and standard errors are reported in Tables A1 and A2 in Appendix A. The signs of coefficients, the relative magnitudes, and the levels of statistical significance are substantially equivalent to the ones obtained through the separate estimates, leading to the conclusion that the latter are reliable.

Subsequently, I performed three ordered logistic regressions adopting digitalization factor variety as a dependent variable. In the first, I used all source dummies as regressors of interest. In the second, I used all exclusive source dummies as regressors of interest. In the third, I used source variety as a regressor of interest. All controls mentioned previously have been included in every logistic and ordered logistic regression. Finally, I isolated small firms from the rest of the sample and replicated all the analyses separately on each of the two resulting subsamples (small firms vs all the other firms). Results are reported in the next subsection.

3.3. Results

For simplicity, I start by discussing results on the whole sample (the first third of all tables) and proceed to focus on the peculiarities of small firms in the last part of the subsection. As Table I shows, big data coming from any source reduces considerably the probability that a firm dismisses the listed digitalization factors as irrelevant. Gathering big data from either sensors, social media, or "other sources" cuts almost in half[2] the odds of not regarding any listed digitalization factor as important. Although big data coming from portable devices shows both a weaker effect and a weaker statistical significance (still within the 10 % level), it goes in the same direction. At the same time, gathering big data from sensors, social media, or portable devices significantly increments the capability by firms to identify which digitalization factors to prioritize, as it reduces the odds of "not knowing" in a range from 20 % (portable devices) to 31 % (sensors). As for "other sources", the effect is not statistically significant.

Table I also shows that source matters. The effect of big data on the prioritization of digitalization factors strongly depends on the type of source. Big data coming from social media increases the odds of prioritizing collaboration by more than 50 %, whereas it has a weak effect on digitalization strategy and no other statistically significant effect. Big data coming from sensors makes firms lean toward skill sourcing (with an odds increase of 23 %), while it has a weak effect on infrastructure, subsidies, and skill consolidation (and no other statistically significant effect). Big data coming from portable devices significantly affects only the importance ascribed to subsidies, with odds increasing by 20 %. Big data coming from other sources increments the prioritization of collaboration and that of skill sourcing, by 35 % and 43 % respectively (and nothing else).

As hypothesized, source variety plays a key role as well. Insights in this sense come from the last column of Table I and the whole Table II. Table II reports the coefficients of the logit regression of digitalization factors on exclusive source dummies. While all source dummies trigger a significant reduction in the probability of not regarding any listed factor as important and that of ignoring which factors matter most (with only one exception), exclusive source dummies do not (once again, with just one exception). In other words, firms that exclusively gather big data from a single source do not benefit from any increase in digitalization awareness: they are not significantly more prone to recognizing the importance of digitalization factors, nor are they significantly more capable of identifying those with the highest competitive relevance. Gathering big data exclusively from portable devices appears to even reduce digitalization awareness, by doubling the odds of not regarding any listed digitalization factor as important.

The effects of exclusive source dummies on individual digitalization factors reinforce the picture, as the vast majority of them are not statistically significant. Not only are there few positive effects (e.g. big data coming exclusively from sensors and social media weakly increasing the prioritization of skill consolidation), but some are even negative, the most relevant being big data from portable devices reducing by more than half the odds of prioritizing collaboration. Hence, while intuition would suggest that the mere adoption of big data is enough to increase digitalization awareness, the fact that four out of the only seven statistically significant effects here are negative highlights that this is far from being true. For example, gathering big data from sensors increases the odds of prioritizing skill sourcing (see Table I), but gathering big data exclusively from sensors does not (see Table II). Gathering big data from "other sources" increases the odds of prioritizing collaboration (see Table I), but gathering big data exclusively from "other sources" reduces such odds by roughly the same amount (see Table II). This suggests that big data does improve dynamic capabilities related to the sensing of digitalization opportunities and the identification of digitalization priorities, but only when coming from multiple sources. On the contrary, employing a single source may even decrease them.

The last column of Table I complements the findings of Table II by providing a more fine-grained account of source variety. The column reports the coefficients of the logit regression of digitalization factors on source variety (S.V. in the table), a variable counting the number of sources of big data employed. This variable appears to crucially affect digitalization awareness. Adding one source multiplies the odds of not regarding any listed digitalization factors as important and "not knowing" by 0.57 and 0.78, respectively. Thus, going from zero to four sources decimates the odds of not regarding any listed digitalization factors as important, and it reduces the odds of "not knowing" by roughly two thirds. Even considering digitalization factors individually, source variety increments the prioritization of almost all of them in a sizable and statistically significant way, the only two (trivial) exceptions being "other factors" and governmental intervention (which are not impacted by any individual source).

The picture emerging from the previous analyses holds not only for individual digitalization factors, but also for the variety of digitalization factors prioritized, as evidenced by Tables III and IV. All big data sources, and especially source variety, increase the odds of prioritizing a higher number of digitalization factors (see Table III). However, they do so only when used in some conjoint manner: analogously to the individual cases (Table II), the exclusive use of a single big data source does not increase the odds of prioritizing a higher number of digitalization factors and may even decrease them, as in the case of portable devices (see Table IV).

Turning to small firms, it is worth noting the higher prevalence of sizable and statistically significant individual logit coefficients relative to both the medium/large firms subsample and the whole sample (see Table I). Of relevance is the effect of big data coming from social media, which augments the odds of prioritizing skill sourcing and collaboration by 43 % and 79 % respectively, as well as infrastructure (27 %), subsidies (35 %) and digitalization strategy (31 %). However, these effects are completely lost in the case of small firms that gathered data exclusively from social media (see Table II). More generally, not counting "nothing" and "I don't know", small firms feature 12 significant positive source dummies, 2 significant positive exclusive source dummies, and 2 significant negative exclusive source dummies; the whole sample features 9 positive significant positive source dummies, 3 significant positive exclusive source dummies, and 4 significant negative source dummies; medium/large firms feature 4 significant positive source dummies, 3 significant positive exclusive source dummies, and 3 significant negative exclusive source dummies. Of course, statistically significant source and exclusive source dummies vary across subsamples, due to structural differences (e.g. small firms having an inherently stronger need to prioritize infrastructure and subsidies). For brevity, the present work will not delve into such differences. What is interesting to note here, however, is that small firms appear to exhibit the greatest loss in the ability to sense digitalization opportunities when relying on a single source of big data rather than two or more, considering both magnitude and statistical significance.

This is confirmed, from a different angle, also from the last column of Table I. With the exception of collaboration,[3] where the coefficient is roughly the same, the effect of source variety on the prioritization of digitalization factors is always dramatically higher (often nearly double or even more) in the case of small firms relative to both medium/large firms and the whole sample. Small firms also exhibit the highest effect of each big data source, as well as source variety, on the variety of

[2] This and all the subsequent odds estimates are obtained by exponentiating the logit coefficients in the corresponding tables.

[3] Governmental intervention and "other factors" also constitute (trivial) exceptions, as they are not statistically significant.

Table I
Logit coefficients of big data sources and source variety.

Group	Digitalization factor	Sensors	Portable	Social	Other	S.V.
Whole sample	Infrastructure	0.12* (0.07)	0.05 (0.08)	0.04 (0.07)	0.09 (0.07)	0.08*** (0.02)
	Subsidies	0.11* (0.07)	0.18** (0.07)	0.09 (0.07)	−0.01 (0.07)	0.09*** (0.02)
	Gov. interv.	−0.01 (0.10)	0.05 (0.10)	−0.02 (0.10)	0.11 (0.09)	0.32 (0.32)
	Collaboration	0.16 (0.10)	0.12 (0.12)	0.43*** (0.11)	0.30*** (0.10)	0.25*** (0.03)
	Skill sourcing	0.21*** (0.08)	0.04 (0.10)	0.11 (0.09)	0.36*** (0.08)	0.19*** (0.03)
	Skill consolid.	0.13* (0.07)	0.11 (0.08)	0.06 (0.08)	0.10 (0.07)	0.10*** (0.02)
	Dig. strategy	0.06 (0.07)	0.10 (0.08)	0.15* (0.08)	0.11 (0.07)	0.11*** (0.03)
	Other factors	0.15 (0.17)	0.15 (0.19)	−0.20 (0.21)	−0.18 (0.18)	−0.04 (0.06)
	I don't know	−0.37*** (0.11)	−0.22** (0.11)	−0.30** (0.12)	−0.13 (0.10)	−0.25*** (0.04)
	Nothing	−0.60*** (0.21)	−0.37* (0.19)	−0.58** (0.25)	−0.70*** (0.23)	−0.55*** (0.09)
Small firms	Infrastructure	0.12 (0.13)	0.03 (0.12)	0.24** (0.12)	0.23** (0.11)	0.15*** (0.04)
	Subsidies	0.08 (0.13)	0.19* (0.11)	0.30*** (0.12)	−0.23 (0.11)	0.14*** (0.04)
	Gov. interv.	−0.24 (0.19)	0.11 (0.15)	0.11 (0.16)	0.07 (0.14)	0.03 (0.05)
	Collaboration	0.10 (0.21)	0.07 (0.19)	0.58*** (0.17)	0.17 (0.17)	0.24*** (0.06)
	Skill sourcing	0.56*** (0.16)	−0.02 (0.17)	0.36*** (0.14)	0.35*** (0.14)	0.31*** (0.05)
	Skill consolid.	0.40*** (0.13)	0.19 (0.13)	0.13 (0.12)	0.21* (0.14)	0.23*** (0.04)
	Dig. strategy	−0.01 (0.16)	0.10 (0.14)	0.27** (0.14)	0.24* (0.13)	0.16*** (0.05)
	Other factors	0.48 (0.31)	−0.17 (0.31)	−0.16 (0.32)	−0.45 (0.33)	−0.07 (0.11)
	I don't know	−0.35* (0.19)	−0.28* (0.16)	−0.65*** (0.18)	−0.04 (0.14)	−0.32*** (0.06)
	Nothing	−0.65* (0.36)	−0.19 (0.23)	−0.50* (0.30)	−0.70** (0.32)	−0.46*** (0.12)
Medium and large firms	Infrastructure	0.11 (0.08)	0.07 (0.10)	−0.06 (0.10)	0.06 (0.08)	0.05* (0.03)
	Subsidies	0.12 (0.08)	0.17* (0.10)	0.02 (0.10)	0.06 (0.08)	0.09*** (0.03)
	Gov. interv.	0.07 (0.11)	−0.02 (0.13)	−0.10 (0.13)	0.13 (0.11)	0.03 (0.04)
	Collaboration	0.11 (0.12)	0.19 (0.15)	0.34** (0.14)	0.35*** (0.12)	0.24*** (0.04)
	Skill sourcing	0.08 (0.09)	0.02 (0.11)	0.00 (0.11)	0.40*** (0.10)	0.13*** (0.03)
	Skill consolid.	0.05 (0.08)	0.00 (0.10)	0.05 (0.10)	0.08 (0.09)	0.04 (0.03)
	Dig. strategy	0.05 (0.08)	0.11 (0.11)	0.08 (0.10)	0.05 (0.09)	0.07** (0.03)
	Other factors	0.04 (0.22)	0.35 (0.25)	−0.23 (0.28)	−0.05 (0.23)	0.04 (0.08)
	I don't know	−0.28* (0.14)	−0.15 (0.17)	0.00 (0.16)	−0.24* (0.14)	−0.18*** (0.05)
	Nothing	−0.46* (0.27)	−0.75** (0.36)	−0.70* (0.43)	−0.69** (0.33)	−0.62*** (0.14)

This table shows the coefficient of the logit regressions of digitalization factors on source dummies and source variety for each sample group. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

Table II
Logit coefficients of exclusive big data sources.

Group	Digitalization factor	Sensors	Portable	Social	Other	Nothing
Whole sample	Infrastructure	0.17 (0.11)	0.20 (0.13)	0.00 (0.12)	0.21** (0.10)	−0.14** (0.06)
	Subsidies	0.02 (0.10)	0.20 (0.13)	0.00 (0.12)	−0.17* (0.10)	−0.24*** (0.06)
	Gov. interv.	−0.05 (0.15)	0.24 (0.16)	0.10 (0.17)	0.13 (0.14)	−0.04 (0.09)
	Collaboration	−0.28* (0.16)	−0.89*** (0.26)	0.04 (0.17)	−0.28* (0.15)	−0.62*** (0.09)
	Skill sourcing	−0.03 (0.12)	−0.25 (0.18)	−0.20 (0.15)	−0.05 (0.14)	−0.44*** (0.08)
	Skill consolid.	0.19* (0.11)	0.08 (0.14)	0.24* (0.13)	0.10 (0.10)	−0.23*** (0.07)
	Dig. strategy	−0.08 (0.11)	−0.12 (0.15)	0.16 (0.13)	0.02 (0.11)	−0.24*** (0.07)
	Other factors	−0.30 (0.31)	−0.34 (0.38)	−0.25 (0.35)	−0.10 (0.27)	−0.08 (0.17)
	I don't know	−0.32 (0.21)	0.01 (0.20)	−0.55** (0.24)	0.10 (0.17)	0.55*** (0.11)
	Nothing	0.37 (0.36)	0.74** (0.34)	0.49 (0.40)	0.46 (0.36)	1.12*** (0.24)
Small firms	Infrastructure	0.15 (0.21)	−0.08 (0.19)	−0.01 (0.19)	0.10 (0.17)	−0.31*** (0.11)
	Subsidies	−0.08 (0.22)	0.03 (0.19)	0.08 (0.19)	−0.23 (0.17)	−0.35*** (0.11)
	Gov. interv.	−0.43 (0.35)	0.26 (0.24)	0.35 (0.25)	0.04 (0.23)	−0.02 (0.15)
	Collaboration	−0.35 (0.36)	−0.82** (0.38)	−0.04 (0.28)	−0.35 (0.26)	−0.59*** (0.15)
	Skill sourcing	0.42* (0.25)	−0.53* (0.29)	−0.01 (0.23)	−0.31 (0.21)	−0.72*** (0.13)
	Skill consolid.	0.46** (0.22)	−0.02 (0.20)	0.00 (0.20)	0.05 (0.18)	−0.46*** (0.11)
	Dig. strategy	−0.24 (0.26)	−0.37 (0.25)	−0.05 (0.22)	−0.23 (0.20)	−0.39*** (0.13)
	Other factors	0.33 (0.55)	−0.38 (0.59)	0.24 (0.49)	−0.11 (0.48)	−0.42 (0.76)
	I don't know	−0.31 (0.35)	0.18 (0.27)	−0.52 (0.35)	0.54** (0.25)	0.71*** (0.18)
	Nothing	0.34 (0.57)	0.72* (0.43)	0.50 (0.52)	0.45 (0.48)	1.00*** (0.34)
Medium and large firms	Infrastructure	0.13 (0.12)	0.36* (0.19)	−0.06 (0.16)	0.26** (0.13)	−0.09 (0.08)
	Subsidies	−0.02 (0.13)	0.22 (0.19)	−0.11 (0.16)	−0.15 (0.13)	−0.24*** (0.08)
	Gov. interv.	0.06 (0.18)	0.24 (0.24)	−0.13 (0.24)	0.21 (0.17)	−0.04 (0.11)
	Collaboration	−0.30* (0.18)	−0.91** (0.36)	0.13 (0.21)	−0.21 (0.18)	−0.59*** (0.11)
	Skill sourcing	−0.13 (0.14)	−0.13 (0.23)	−0.42** (0.20)	0.08 (0.14)	−0.30*** (0.09)
	Skill consolid.	0.12 (0.13)	−0.02 (0.20)	0.36** (0.17)	0.10 (0.14)	−0.12 (0.08)
	Dig. strategy	−0.05 (0.13)	0.01 (0.20)	0.26 (0.17)	0.14 (0.14)	−0.17** (0.09)
	Other factors	−0.51 (0.39)	−0.17 (0.50)	−0.70 (0.54)	−0.06 (0.33)	−0.23 (0.21)
	I don't know	−0.39 (0.26)	−0.10 (0.33)	−0.50 (0.34)	−0.38 (0.25)	0.41*** (0.14)
	Nothing	0.50 (0.48)	0.59 (0.57)	0.39 (0.68)	0.44 (0.53)	1.22*** (0.34)

This table shows the coefficient of the logit regressions of digitalization factors on exclusive source dummies for each sample group. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

Table III
Ordered logit coefficients of big data sources and source variety.

Group	Sensors	Portable	Social	Other	S. V.
Whole sample	0.31*** (0.06)	0.22*** (0.07)	0.30*** (0.07)	0.37*** (0.06)	0.30*** (0.02)
Small firms	0.45*** (0.13)	0.21** (0.10)	0.54*** (0.11)	0.41*** (0.10)	0.39*** (0.03)
Medium and large firms	0.20*** (0.08)	0.22** (0.10)	0.14 (0.09)	0.38*** (0.08)	0.24*** (0.03)

This table shows the coefficients of the ordered logit regressions of digitalization factor variety on source dummies and source variety for each sample group. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

Table IV
Ordered logit coefficients of exclusive big data sources.

Group	Sensors	Portable	Social	Other	Nothing
Whole sample	−0.09 (0.10)	−0.19* (0.12)	−0.02 (0.11)	−0.02 (0.10)	−0.65*** (0.06)
Small firms	0.10 (0.21)	−0.47*** (0.17)	−0.06 (0.18)	−0.25 (0.17)	−0.85*** (0.11)
Medium and large firms	−0.16 (0.12)	0.02 (0.18)	−0.07 (0.16)	0.16 (0.13)	−0.52*** (0.08)

This table shows the coefficients of the ordered logit regressions of digitalization factor variety on exclusive source dummies for each sample group. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

digitalization factors prioritized (see Table IV). However, neither individual big data sources nor source variety seem to reduce the likelihood of small firms not prioritizing any of the listed digitalization factors in a significantly different way than medium/large firms. The last column of Table II makes it clear that the increase in the odds of not prioritizing any factor prompted by the absence of big data is very high in both subsamples (and even higher in the case of medium/large firms). However, the increase in the odds of "not knowing" is considerably higher in the case of small firms (roughly 100 % vs 50 %).

Taken together, these results confirm hypotheses HP1a and HP1b, with a further specification. Big data seems to improve digitalization awareness in general, as evidenced by the drastic reduction in the probability of not regarding any listed digitalization factor as important and that of not knowing which factors matter most, regardless of source (the only exception being "other sources" in the latter case). Still, different sources of big data affect differently the probability of regarding any individual digitalization factor as important (see Table I). Thus, each source of big data appears to systematically guide firms toward the prioritization of specific digitalization factors. This is in line with the knowledge-shaping and attention-shaping effects postulated in the theoretical background. HP2a and HP2b are also verified (see Tables III and IV), with a most interesting addition: not only does source variety increase the digitalization awareness of firms, but a minimum threshold of source variety also appears to be a necessary condition for it, as gathering big data exclusively from a single source either has no effect on digitalization awareness or even decreases it.

Hypothesis HP3a is only partially verified: as for the overall digitalization awareness, big data seems to affect small firms in roughly the same way as their larger counterparts (despite obvious systematic differences in individual priorities). However, big data enhances small firms' capability of identifying specific digitalization priorities to a considerably higher extent than their larger counterparts. Instead, hypotheses HP3b and HP3c are fully verified: small firms appear to be the ones that lose the most from relying on a single big data source and gain the most from big data source variety.

4. Discussion and conclusion

Big data is famous for being the main complement for artificial intelligence: the availability of multi-source, massive amounts of data is the reason why artificial intelligence has developed exponentially, spurring the emergence of digital-intensive business models (Fanti et al., 2022; Reim et al., 2020). This core complementarity, in turn, induces the adoption of other advanced technologies, such as cloud computing (for data storage) and cyber-physical systems (for further data acquisition). However, findings reveal that the role of big data in shaping digitalization trajectories goes beyond technological complementarities. The digital revolution has induced a rapidly changing business environment requiring the dynamic capability of advancing along a series of digitalization factors (Ciarli et al., 2021; European Patent Office, 2017; Pedota et al., 2023). Big data adopters are much less likely to disregard digitalization factors and more likely to be able to identify which digitalization factors to prioritize for achieving competitive advantage.

Most importantly, results foreground the relevance of source variety. Firms relying on a higher variety of big data sources have a stronger awareness of each individual digitalization factor, and they also tend to prioritize a wider range of digitalization factors. Beyond expectations, empirical evidence goes so far as indicating that reliance on a single big data source may even nullify (and possibly revert) the increase in digitalization awareness prompted by big data adoption. I find this intriguing on two grounds. First, it suggests that big data fosters digitalization also through its ability to shape knowledge and attention: if it were only for technological complementarities, reliance on a single big data source would still enhance digitalization awareness (contrary to the present evidence). Second, it pinpoints the relevance of big data sources instead of merely reasserting the value of big data. Even with its core complements (e.g. artificial intelligence), big data may not be enough to enhance the ability to sense opportunities and adapt to technological change: relying on a single big data source may trap firms in an even narrower mindset than not relying on big data at all.

Thus, the present study contributes to filling an important gap in the research on big data and dynamic capabilities (Conboy et al., 2020; Côrte-Real et al., 2017; Rialti et al., 2019). While results resonate with the proposition that big data enhances dynamic capabilities by helping firms sense and seize opportunities, they highlight that complementarities in big data sources must be in place for this to occur. In this sense, I bring forward the evolutionary-based side of dynamic capabilities (Barreto, 2010; Nelson et al., 2018.). Given bounded rationality and path dependence, I argue theoretically and show empirically that the number and typology of big data sources significantly shape the way firms adapt to technological change. Hence, being exposed to big data coming from various sources is essential to dynamic capabilities. The present results on the adaptation by firms to the digital revolution are coherent with this proposition.

I also contribute to the debate on the digital revolution by shedding new light on the enabling role of big data. Among the enabling technologies of the digital revolution (European Patent Office, 2017; Martinelli et al., 2021), results suggest that big data deserves special consideration. Besides interacting with other digital technologies (thereby functionally enabling them), it also boosts firms' awareness of other digitalization factors. Such factors enable the digital transition both at the level of the firm and at the level of economic systems. Along this line, a potential implication of my findings is a form of path dependence where firms lacking big data (of adequate variety) may fail to integrate digitalization in their vision and high-level routines. Thus, they may be even less prone to and capable of recognizing the value of digitalization in subsequent periods, triggering a vicious circle. Conversely, firms relying on multiple sources of big data are likely to make progress on multiple, complementary digitalization enablers. In subsequent periods, this may increase the amount and variety of big data at the firms' disposal, as well as their proficiency in analyzing them, thus triggering a virtuous circle of technological advancement.

From an economic standpoint, the present results imply that the availability of big data sources of adequate variety may positively affect countries' growth and competitiveness. Given that big data adopters are more likely to identify and prioritize digitalization factors, making big data widely available and incentivizing firms to adopt it may increase both the static and the dynamic efficiency of firms as well as their innovation rate, improving a country's economic fundamentals. This is also because, at the macro level, many digitalization factors are characterized by positive externalities. For example, the macroeconomic benefits of firms prioritizing collaboration are likely to increase more than proportionally with the number of firms prioritizing collaboration, due to network dynamics. Likewise, the prioritization of factors like skill consolidation and infrastructure development on a large scale may endow a country with a skilled workforce and an environment more conducive to innovation. Thus, countries that promote the development of diverse and rich sources of big data (maybe also through ad hoc data centers) are likely to enhance competitiveness, economic growth, and social welfare.

Significant policymaking implications also emerge from the additional findings on small firms. Relative to their larger counterparts, small firms' digitalization awareness seems to be even more sensitive to big data, and especially to big data source variety. The detrimental effect of relying on a single big data source is of particular concern to small firms, in line with the echo chamber effect postulated in the theoretical background. This potential issue is accentuated by the weaker structure and higher adaptability of small firms. On the one hand, the magnitude of the direct effects of big data and source variety is higher for small firms. On the other hand, small firms are even more susceptible to the potential form of path dependence described above: being still in fieri, their dynamic capabilities may be even more big data-dependent, triggering stronger (positive or negative) feedback loops. Small firms endowed with big data are more likely to develop digitally enabled microfoundations of dynamic capabilities, which act not only as hooks for gathering further data in subsequent periods, but also as powerful stimuli for innovation (Chirumalla, 2021). Thus, they are more likely to initiate a virtuous circle of innovation capability development through product and process innovation interdependencies (Szalavetz, 2019), while their non-data-driven counterparts lag behind.

In its “SME Strategy for a sustainable and digital Europe”, the European Commission acknowledges that SMEs do not fully benefit from data (e.g. due to unequal access to big data repositories) and tend to lack familiarity with advanced digital technologies relative to their larger counterparts. This is in line with extant literature recognizing that small firms reap less benefits from digital technologies, due to reduced resources, lower absorptive capacity, and lower availability of complements (Bugamelli et al., 2012; Cirillo et al., 2021; Fabiani et al., 2005). This is especially evident and influential in countries like Italy, where SMEs are prevalent. Thus, the European Commission plans to work on improving SMEs' data accessibility (European Commission, 2020b). The theoretical arguments and empirical evidence advanced here resonate with this plan. While larger firms typically have a higher rate of adoption thanks to their resource endowment, small adopting firms seem to benefit equally (and perhaps even more) from big data adoption, at least in terms of digitalization awareness. Thus, they should be enabled and incentivized to adopt big data.

However, the present results also put novel emphasis on the necessity to have a balanced and varied wealth of data. I suggest that big data may act as a sort of meta-digital enabler by shaping knowledge and attention. Hence, I draw an additional link between the lack of big data by small firms and their tendency to shy away from advanced digital technologies. As this link works through knowledge and attention, it requires further consideration. If firms (particularly small ones) were to rely on very large but narrow quantities of data, they may end up neglecting important pieces of their digital development. For instance, if they gathered big data only from portable devices, they may overemphasize efficiency to the detriment of exploration and networking. Hence, policymakers should become aware that big data, while indeed most valuable, is a double-edged sword, and reliance on multiple big data sources may make the difference between a virtuous or a vicious circle. This should be reflected in current and future initiatives aimed at fostering digitalization, including those focused on SMEs and those larger in scope, both at the level of the single country and beyond (e.g. “a European strategy for data”; European Commission, 2020a). Countries (like Italy) where SMEs are prevalent and innovativeness is structurally hampered require particular care, as big data may deeply affect innovation dynamics.

While this work foregrounds the knowledge-shaping and attention-shaping role of big data, as well as the importance of source variety, it is silent on the organizational moderators of such effects. Future qualitative research should explore the structures and mechanisms that enable an effective integration of big data coming from different sources to enhance dynamic capabilities and minimize biases. Regarding dynamic capabilities, the present analysis mostly relates to the dimensions of sensing opportunities and setting up priorities in terms of strategy and resource reconfiguration. Building on these findings, future quantitative research leveraging longitudinal datasets may inquire into the relationship between big data and other components of dynamic capabilities. As the increasing availability of big data shapes firms' adaptation and innovation tendencies, I do encourage continued research in this area.

CRediT authorship contribution statement

Mattia Pedota: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The manuscript contains a link to the database

Acknowledgements

I would like to thank Alessio Basti, Rocco Mosconi and three anonymous referees for their helpful comments on earlier drafts of this work. I also gratefully acknowledge the attentive and constructive guidance of Editor Martin Kenney throughout the peer review process.

Appendix A

Table A1
Multivariate probit coefficients of big data sources and source variety.

Digitalization factor	Sensors	Portable	Social	Other	S.V.
Infrastructure	0.07* (0.04)	0.03 (0.05)	0.04 (0.05)	0.05 (0.04)	0.05*** (0.01)
Subsidies	0.06* (0.03)	0.11** (0.04)	0.06 (0.05)	−0.01 (0.04)	0.06*** (0.01)
Governmental intervention	−0.01 (0.05)	0.03 (0.06)	−0.01 (0.06)	0.06 (0.05)	0.02 (0.02)
Collaboration	0.10 (0.06)	0.06 (0.06)	0.23*** (0.06)	0.16*** (0.05)	0.13*** (0.02)
Skill sourcing	0.13*** (0.05)	0.03 (0.05)	0.08 (0.05)	0.21*** (0.04)	0.12*** (0.02)
Skill consolidation	0.09* (0.04)	0.07 (0.05)	0.04 (0.05)	0.06 (0.04)	0.07*** (0.02)
Digitalization strategy	0.04 (0.04)	0.06 (0.05)	0.09* (0.05)	0.07 (0.04)	0.06*** (0.02)
Other factors	0.06 (0.08)	0.06 (0.09)	−0.09 (0.09)	−0.07 (0.08)	−0.01 (0.03)
I don't know	−0.17*** (0.06)	−0.10* (0.06)	−0.13** (0.06)	−0.07 (0.05)	−0.12*** (0.02)
Nothing	−0.26*** (0.09)	−0.19** (0.09)	−0.24** (0.10)	−0.33*** (0.09)	−0.25*** (0.04)

This table shows the coefficient of the multivariate probit regressions of digitalization factors on source dummies and source variety. Dependent variables have been grouped as described in the Methodology subsection for joint estimation. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

Table A2
Multivariate probit coefficients of exclusive big data sources.

Digitalization factor	Sensors	Portable	Social	Other	Nothing
Infrastructure	0.10 (0.07)	0.12 (0.08)	0.01 (0.08)	0.13** (0.06)	−0.09** (0.04)
Subsidies	0.00 (0.06)	0.13 (0.08)	0.01 (0.06)	−0.11* (0.06)	−0.14*** (0.04)
Governmental intervention	−0.02 (0.08)	0.15 (0.09)	0.06 (0.09)	0.08 (0.08)	−0.02 (0.05)
Collaboration	−0.15* (0.08)	−0.46*** (0.12)	0.01 (0.09)	−0.15* (0.08)	−0.33*** (0.05)
Skill sourcing	−0.02 (0.07)	−0.16 (0.10)	−0.11 (0.08)	−0.04 (0.07)	−0.27*** (0.04)
Skill consolidation	0.11* (0.07)	0.05 (0.08)	0.15* (0.08)	0.06 (0.07)	−0.14*** (0.04)
Digitalization strategy	−0.05 (0.07)	−0.08 (0.09)	0.09 (0.08)	0.01 (0.07)	−0.15*** (0.04)
Other factors	−0.13 (0.14)	−0.15 (0.16)	−0.11 (0.15)	−0.04 (0.12)	−0.03 (0.07)
I don't know	−0.15 (0.10)	−0.01 (0.11)	−0.28** (0.12)	0.03 (0.09)	0.28*** (0.06)
Nothing	0.18 (0.15)	0.33** (0.15)	0.26 (0.16)	0.21 (0.15)	−0.50*** (0.10)

This table shows the coefficient of the multivariate probit regressions of digitalization factors on exclusive source dummies. Dependent variables have been grouped as described in the Methodology subsection for joint estimation. Standard errors are reported in parentheses. Three stars indicate significance at 1 %, two stars at 5 %, one star at 10 %. All control variables described in the Methodology subsection have been included in each regression.

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