International Journal of Operations & Production Management

331

Received 26 August 2025
Revised 6 January 2026
7 April 2026
18 May 2026
Accepted 19 May 2026

# Sociotechnical synergy: how employee involvement unlocks the value of data analytics

Bart Alex Lameijer and Jeroen De Mast
*Amsterdam Business School, University of Amsterdam, Amsterdam, The Netherlands*
Leopoldo Gutierrez
*Department of Business Administration, University of Granada, Granada, Spain, and*
Gopesh Anand
*Gies College of Business, University of Illinois Urbana-Champaign, Champaign, Illinois, USA*

## Abstract

**Purpose** – Despite high expectations about the benefits of data analytics (DA), our understanding of the mechanisms that drive value creation from the implementation of DA in firms remains incomplete. While some studies have suggested that innovation prowess, human resources and operational capabilities are pieces of the puzzle of DA effectiveness, how these pieces fit together remains an open question. In this research, we study the mechanisms that explain value creation through DA implementation in firms, focusing on the use of DA in operations management.

**Design/methodology/approach** – We empirically address this question by analyzing firm-level data from the European Company Survey (ECS) 2013 (19,470 managers) and 2019 (18,616 managers and 1,848 employees), covering 28 European countries. We conduct four sets of robustness tests: (1) comparisons of results among the three subsamples (2013-manager, 2019-employee and 2019-manager); (2) multiple endogeneity checks; (3) alternative model specifications and (4) alternative model assessments.

**Findings** – We present evidence showing that DA impacts firm performance primarily through the enhancement of capabilities for process and product innovation. Further, in line with sociotechnical systems (STS) theory, our moderated mediation analyses show that the value created from DA is contingent upon the presence of employee involvement practices including empowerment, development and team orientation.

**Originality/value** – This research integrates DA, innovation capabilities and employee involvement within an STS framework to explain firm performance, using three large-scale, cross-sectional European datasets, going beyond the conceptual and empirical examination of DA in prior studies.

**Keywords** Data analytics, Employee involvement, Innovation, Sociotechnical systems theory

**Paper type** Research article

## 1. Introduction

Using data analytics (DA) in operational and strategic decision-making is imperative for firms to remain competitive (Forbes, 2024). Firms such as American Express, Coca-Cola, Disney, and Walmart use DA technologies such as mobile analytics, social media analytics, machine learning, and artificial intelligence (AI) to improve in areas such as revenue management, new product development, supply chain management and risk management (Choi *et al.*, 2018). At the same time, adopting DA technologies also carries risks associated with security and



This publication is part of the R + D + I project PID2021-124725NB-I00, funded by MICIU/AEI/10.13039/501100011033 and by “ERDF A way of making Europe” and the grant C-SEJ-148-UGR23 by ERDF Andalusia Program 2021–2027.

International Journal of Operations & Production Management
Vol. 46 No. 13, 2026
pp. 331-356
Emerald Publishing Limited
e-ISSN: 1758-6593
p-ISSN: 0144-3577
DOI 10.1108/IJOPM-08-2025-0810

regulatory compliance, and presents challenges of integrating such technologies with existing systems (Legenvre and Hameri, 2024; Ogbuke *et al.*, 2022). It is therefore not surprising that the high expectations from implementing DA technologies are not always realized (e.g. Lee, 2018). While in some firms, DA has led to decreased expenses and/or increased revenues, in other firms, the performance effects of DA have remained unclear (Bean, 2017). Challenges in achieving measurable performance benefits from DA commonly include the need for cultural change, alignment around outcomes, high-quality data, appropriate talent, and well-integrated processes (Gartner, 2025; McKinsey, 2016). Therefore, a better understanding of the mechanisms that drive value creation from DA is called for (Dremel *et al.*, 2020; Maroufkhani *et al.*, 2019; Mikalef *et al.*, 2020, 2021; Roy *et al.*, 2022; Song *et al.*, 2023).

DA is defined as the processing of data by mathematical, statistical and machine learning techniques to generate actionable insights (Choi *et al.*, 2018). DA can be divided into four groups (De Mast *et al.*, 2023): (1) Descriptive DA, which is the processing of data into aggregate statistics and visual displays, (2) Predictive DA, defined as the use of data in statistical or machine learning models for making forecasts or predictions, (3) Diagnostic DA, consisting of the use of data to establish the causes of observed phenomena, and (4) Prescriptive DA, which is the use of mathematical optimization techniques to find actions or settings that maximize the achievement of desired outcomes. Data may be sourced internally from a firm’s operational practices and systems such as enterprise resource planning (ERP), customer relationship management (CRM), and manufacturing execution system (MES) systems, or externally from outside sources. In recent years, the words big data and big data analytics are used to describe the sharp increase in volumes of data, the velocity with which data becomes available, and the variety of the types of data and the structures of datasets (McAfee *et al.*, 2012). Common areas within Operations Management (OM) where DA is applied include inventory management, manufacturing, revenue management, demand forecasting, new product development, supply chain management, and risk analysis (Choi *et al.*, 2018; Lavalle *et al.*, 2010).

Existing research has covered the uses of DA in OM (Feng and Shanthikumar, 2018; Roehrich *et al.*, 2025), studying how DA facilitates innovation for operations and supply chain management (Lee, 2018; Legenvre and Hameri, 2024), and describing the advantages of DA for decision-making in different contexts including restaurants and retail businesses (Choi *et al.*, 2018). Related research on the perceived value potential of DA highlights the importance of the “action possibilities” DA may “afford” (Leonardi, 2011) and suggests that DA predominantly enhances learning and innovation (Angelopoulos *et al.*, 2023; Mikalef *et al.*, 2020). However, empirical evidence on the effectiveness of DA remains inconclusive due to (1) the omission of its effects on operational performance, (2) the use of mediating constructs that resemble innovation capability (e.g. dynamic capabilities, corporate agility, and disruptive business models) but capture this concept imprecisely, and (3) limitations in the analytical methods used. Moreover, research on the value of DA is relatively silent on the mechanisms through which DA facilitates innovation, and on the role of the human component in the DA-performance relationship (Dremel *et al.*, 2020; Mikalef *et al.*, 2020). While Mikalef *et al.* (2021), Sainam *et al.* (2022), and Yasmin *et al.* (2020) introduce the perspective of employees’ roles in DA, they do not operationalize this construct and overlook the impact of DA on innovation capability. We argue that studying the implementation of DA in firms through the lens of STS theory (Trist and Bamforth, 1951) can provide important insights into how technical and human resource capabilities jointly explain the enhancement of business value from DA (Dremel *et al.*, 2020; Oesterreich *et al.*, 2022). By doing so, we go beyond conceptualizing DA solely as a performance-enhancing tool and focus on its broader organizational and human implications (Roehrich *et al.*, 2025).

In this study, we use data from the third (2013) and fourth (2019) editions of the European Company Survey (ECS), which is considered a valid and reliable source as evidenced from its use in past studies (Addison and Teixeira, 2020; Erro-Garcés and Aramendia-Muneta, 2023). The 2013 dataset consists of 19,470 management responses, and the 2019 dataset consists of

18,616 management and 1,848 employee responses, both covering 28 European countries. We use a conditional indirect effects model based on ordinary least squares (OLS) hierarchical linear regression to test (1) the mediating role of innovation capability in the relationship between DA and firm performance, and (2) the moderating role of employee involvement in the DA–innovation relationship (moderated mediation) (Hayes, 2018; Preacher *et al.*, 2007). We reinforce our findings by conducting several robustness analyses that include assessing the risks of misinterpretations due to model misspecifications, and mitigating endogeneity concerns.

We make three contributions to theory and practice. First, we refute the notion that DA implementation directly creates value in the form of firm performance by showing that value from DA is derived through the strengthening of innovation capabilities in firms. Second, focusing on the factors that influence when DA facilitates innovation capability, we reveal the role of employee involvement, operationalized through employee empowerment, employee development and team orientation, in line with the social subsystem design principles of STS theory (Cherns, 1976, 1987; Clegg, 2000). Third, we study these relationships empirically using survey data from management respondents ($n$ = 19,470) collected in 2013, and management respondents (MR) ($n$ = 18,616) and employee respondents (ER) ($n$ = 1,848) collected in 2019, by the ECS. We analyze the 2013 and 2019 samples separately, not as a longitudinal study, but to leverage two high-quality cross-sectional datasets that capture key technological and organizational changes, ensuring data comparability, and allowing us to test the robustness of our findings across two time periods. This provides a level of conceptualization and an empirical basis that exceeds that of prior studies on the topic. Our use of this data resembles previous OM research based on (supra)national survey data (Cassiman and Veugelers, 2006; Choo *et al.*, 2021). Prior research using ECS 2019 company data has provided preliminary evidence of correlation between a general construct of digitalization and firm performance (Erro-Garcés and Aramendia-Muneta, 2023), which was also documented in the survey report-out (Eurofound and Cedefop, 2020).

Our results indicate that the direct effect of DA on firm performance is marginal; the value of DA is realized when it is embedded in a sociotechnical context characterized by (1) a culture of employee-involvement operationalized through employee empowerment, employee development and team orientation, that supports second-order problem solving (continuous improvement and organizational learning) (Leonardi, 2011; Tucker *et al.*, 2002) and (2) well-developed product and process innovation capabilities. In participatory, team-based settings with greater autonomy, frontline employees leverage their situated knowledge to interpret data and translate analytical outputs into locally meaningful innovations (Gutierrez *et al.*, 2022). The positive moderating effect of employee involvement supports a view of DA-enabled, decentralized innovation: DA performance benefits depend on how organizations mobilize and empower employees to integrate actionable insights generated by DA systems and tools into everyday problem solving and innovation activities (Gaimon and Carrillo, 2022).

## 2. Literature review and proposed contribution

A substantial and rapidly expanding body of literature in OM and Information Systems (IS) highlights the strategic value of DA (e.g. Cozzolino *et al.*, 2018), including its role in enabling new business models and value propositions (e.g. Lavalle *et al.*, 2010). Illustrative examples include data as a service (DaaS), analytics as a service (AaaS), the enhancement of products and services through data-driven functionalities, and servitization strategies (Chen *et al.*, 2012). A review of 34 studies published between 2016 and 2024 (see Supplementary File 1) mostly points to a positive association of DA with firm performance and with related outcomes such as competitive advantage and market performance. This is often attributed to improved decision-making, forecasting accuracy, and operational adaptability (Chatterjee *et al.*, 2023; Oesterreich *et al.*, 2022; Wu *et al.*, 2024). The findings in these studies have been interpreted through several theoretical lenses, such as the resource-based view (Awan *et al.*, 2022), dynamic capabilities theory (Chatterjee *et al.*, 2023; Song *et al.*, 2023; Wu *et al.*, 2024), contingency theory (Olabode *et al.*, 2022), affordance theory (Dremel *et al.*, 2020), and STS theory (Oesterreich *et al.*, 2022). Our study specifically focuses on the use of DA in operations, i.e. its application in process execution and decision support for innovating and improving production and service delivery processes, and on its impact on firm performance (Lee, 2018). We mainly invoke STS theory, supplemented by affordance theory, to uncover the mechanisms for value creation from DA. In the following paragraphs, we place our research in the DA literature that uses these two theoretical perspectives.

### *2.1 Affordance theory*

The affordance-theory perspective recognizes DA technologies and tools as means to collect, store and process different types of data (Dremel *et al.*, 2020; Leonardi, 2011). Consequently, affordances (i.e. realizing DA value potential through action possibilities) on the task level emerge through impacts such as improved, processes, products, and services, which in turn, result in higher business value. Prior research on DA affordances identifies several categories including “creating transparency”, “enabling experimentation to discover, expose, and improve”, “segmenting to customize actions”, “replacing or supporting human decision making”, and “innovating new business models, products, and services” (Dremel *et al.*, 2020). To deepen the understanding of DA affordances, literature reviews (Mikalef *et al.*, 2020) and empirical studies have explored the role of mediating variables for the DA-performance relationship including dynamic capabilities (Wu *et al.*, 2024), knowledge management (Wang *et al.*, 2018), market orientation (Song *et al.*, 2023), and agility (Awan *et al.*, 2022; Wamba *et al.*, 2020). Although these studies suggest that DA enhances (“affords”) innovation, ultimately boosting firm performance, they leave important questions unanswered. These studies either (1) do not empirically study subsequent effects on firm performance (Awan *et al.*, 2022; Mikalef *et al.*, 2019), or (2) adopt market-based proxies for firm performance (Song *et al.*, 2023), or (3) adopt mediators that resemble but imprecisely capture innovation capabilities (Awan *et al.*, 2022; Song *et al.*, 2023; Wamba *et al.*, 2020; Wang *et al.*, 2018; Wu *et al.*, 2024), or (4) rely on limited empirical bases for their findings (Awan *et al.*, 2022; Wamba *et al.*, 2020; Wang *et al.*, 2018; Wu *et al.*, 2024). Overall, although the existing literature on DA value effects is dominated by conceptual and technologically focused studies, the mechanisms through which DA facilitates innovation remain underexplored, and the human component in this association is seldom accounted for (Dremel *et al.*, 2020; Mikalef *et al.*, 2020).

### *2.2 Sociotechnical systems theory*

STS theory (Trist and Bamforth, 1951), applied in our context, suggests the existence of two subsystems for value creation from DA (Dremel *et al.*, 2020; Oesterreich *et al.*, 2022): (1) the technical subsystem, consisting of software, hardware, and methods, as well as the tasks for which the technology is used, and (2) the social subsystem, consisting of human and structural factors, including employees with relevant skills and knowledge. STS theory views technological artifacts (here: DA systems) as an interplay of technical and social subsystems. While the technical subsystem comprises the technical components required for running the system and the tasks for which the system is used, the social subsystem encompasses the organizational structure as well as the people, including their attitudes, knowledge, skills, values, and interrelationships (Closs *et al.*, 2008; Tong *et al.*, 2023).

STS posits that optimal performance arises from the joint development of the two subsystems (Hadid and Mansouri, 2014). While existing research (Mikalef *et al.*, 2021; Sainam *et al.*, 2022; Yasmin *et al.*, 2020) introduces the perspective of employees’ roles in DA it does not operationalize the construct and thus omits to study its impact on innovation capabilities. We propose that the development of innovation capabilities is contingent upon the existence of the two STS sub-systems. While technology affords new informational possibilities, people are required to interpret and implement the insights that emerge

(Detert *et al.*, 2000). Based on the core principles of STS theory applied to work systems (Cherns, 1976, 1987; Clegg, 2000), we argue that interpreting DA through the STS lens provides important details of the sociotechnical amplifiers of DA value realization. When firms involve employees through empowerment, learning, development and teamwork, they amplify the innovative potential of DA. In our theoretical reasoning (Section 3.2), we draw upon these principles for the effects of employee involvement on DA and innovation (Clegg, 2000). Figure 1 depicts our proposed conceptual model.

Our conceptual model is grounded in OM research that has examined the interaction between technology and human agents (Bendoly and Oliva, 2024; Roehrich *et al.*, 2025). Interest in this association has persisted with the evolution of DA technologies—towards big data, cloud computing, and machine learning (Raj *et al.*, 2025). Data-driven improvement has been central to improved product design, process optimization, and supplier evaluation (Kim *et al.*, 2012; Zu *et al.*, 2008), and OM theory has emphasized innovation and employee involvement as key mechanisms and supporters for the impact of DA on firm performance (Gutierrez *et al.*, 2022).

Beyond the theoretical contributions, our study offers significant empirical value that exceeds the level of representation in prior studies. Most of the existing OM and IS literature relies on ad hoc surveys of smaller, single-country samples, collected at a single point in time (31 of 34 studies we reviewed; three also include interviews or Delphi methods), while the remaining rely on case studies. An additional differentiator of our study comes from our use of the ECS datasets which are an exogenous source—an externally administered survey whose design and question formulation follow a rigorous quality-assurance framework and are independent of our research objectives. Compared to author-designed instruments, this choice helps mitigate biases associated with item wording and effects of researcher expectancy. This strengthens the credibility, robustness, and generalizability of our evidence, enabling us to validate prior findings and extend them with important nuances.

## 3. Hypotheses development

### *3.1 Product and process innovation*

Product innovation refers to the introduction of new goods or services designed to meet external market needs, and process innovation is defined as the incorporation of novel elements in operations to improve their efficiency and effectiveness (Damanpour, 1991). Both forms of innovation depend heavily on timely and relevant information. From an affordance-theory perspective, DA systems surface patterns, anomalies, and predictive insights that “afford” new ways of problem-solving, experimenting, and updating products and processes. These affordances exist not merely in the technology itself but in the relationship between the DA tools and their users. DA enhances innovation capabilities by expanding the set of actionable possibilities that organizational actors perceive and enact (Dremel *et al.*, 2020). DA serves as a mechanism for transforming data into actionable knowledge for product and process innovation.

First, DA is fundamental for driving *product* innovation. The ability to manage and analyze large volumes of data from customers, internal processes, and markets enables

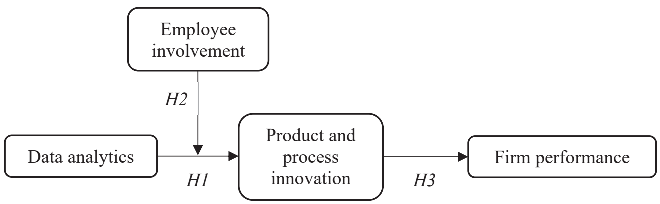


**Figure 1.** Conceptual model. Source: The authors

firms to identify opportunities for improvement and develop better product offerings (Kim *et al.*, 2012). By bridging internal and external knowledge flows, DA enables firms to respond more rapidly and thoroughly to evolving customer preferences and competitive pressures (Sullivan and Wamba, 2024). Moreover, DA allows firms to generate insights and become more innovative, based on voluminous, diverse, and dynamic operational data availability (Ghasemaghaei and Calic, 2019). For example, Rolls-Royce employs DA to monitor engine performance and recommend predictive maintenance services (Chen *et al.*, 2022), and Gillette leverages social media analytics to develop innovative products such as the TREO, a razor designed for caregivers to shave persons requiring assistance (Cheng and Sheu, 2024).

Second, *process* innovation relies on robust information management infrastructures, including data collection systems, real-time monitoring tools, and operational databases (Anand *et al.*, 2009). DA plays a key role in identifying non-value-added activities, shortening development cycles, reducing costs, and enhancing responsiveness to market changes (Kim *et al.*, 2012). DA technologies enable process automation, pattern recognition, and the exploration of previously unrecognized improvement opportunities, thereby supporting operational redesign and optimization (Lee, 2018). As firms increasingly operate under dynamic and uncertain conditions, data becomes indispensable for understanding complex operational systems and informing effective decision-making (Feng and Shanthikumar, 2018). An example is Amazon's "Anticipatory Shipping" system, which leverages predictive analytics to pre-position inventory based on forecasted demand, significantly reducing delivery times and logistics costs (Kopalle, 2014). Accordingly, we propose:

*H1*. DA is positively related to product and process innovation.

### *3.2 Employee involvement*

The benefits of DA for product and process innovation depend not only on technological capabilities but also on organizational conditions that support their adoption (Dremel *et al.*, 2020). A substantial body of empirical research has confirmed that employee involvement plays a key role in data handling, product design, and process improvement (Bessant and Caffyn, 1997; Horvat *et al.*, 2025; Kim *et al.*, 2012; Van Dun and Kumar 2023). Firms that actively involve employees can make more effective use of analytical tools (Escrig-Tena *et al.*, 2021). To unpack the mechanisms in our theoretical reasoning on the enabling role of employee involvement in the relationship between DA and innovation, we draw on STS theory (Trist and Bamforth, 1951) and its principles for work-system design (Cherns, 1976, 1987; Clegg, 2000).

First, key STS design principles cover *employee empowerment*, and granting autonomy to employees or work groups. That is, work structures must be consistent with sociotechnical values of autonomy, participation, learning, and adaptability (Principle [P] 1: Compatibility, and P8: Design and Human Values, Cherns, 1976, 1987). Empowered employees possess the discretion to experiment, adjust workflows, and implement data-driven ideas without rigid managerial control, and have room for local interpretation and adaptation (P2: Minimal Critical Specification, Cherns, 1987; Clegg, 2000). Presenting information to those employees who need it allows employees to not only learn from system generated feedback, but also act on problems and innovate (P5: Information Flow, Cherns, 1976, 1987; Clegg, 2000). In contemporary data-rich environments, empowerment ensures that DA insights do not remain abstract recommendations but are translated into practical innovations through employee-led local adaptation and experimentation (Leonardi, 2011). Moreover, participation in decision-making and incentives for idea generation are found to be critical for capitalizing on digital transformation (Galeazzo *et al.*, 2024).

Second, *employee development* reflects the learning dimension of sociotechnical adaptation. Continuous development initiatives enhance employees' technological competence and absorptive capacity by means of on-the-job learning and feedback mechanisms (P3: Variance Control and P8: Design and Human Values, Cherns, 1976, 1987). Allowing workers to see beyond fragmented tasks and see the whole piece of work (P7: Multifunctionality, Cherns, 1987) enables employees to interpret complex analytical outputs and link them to the operational context (Clegg, 2000; Hadid and Mansouri, 2014; Tong *et al.*, 2023). Within STS theory, employee training and skill building are mechanisms for knowledge integration, bridging codified data knowledge, and including tacit experiential knowledge. When employees develop the skills to use DA meaningfully, they can identify improvement opportunities, test innovative ideas, and support the diffusion of best practices (Furlan *et al.*, 2019). Moreover, training existing employees and hiring data-literate staff are important conditions to realize the benefits of DA for product and process innovation (Mikalef *et al.*, 2021; Yasmin *et al.*, 2020). Thus, firms that invest in employee development arguably strengthen their capacity to turn data-driven insights into tangible innovations.

Finally, *team orientation* plays a central role in achieving the sociotechnical synergy between DA systems and human collaboration. STS theory states that participative, interdependent teams are critical for joint optimization because they enable effective communication, mutual learning, and system-wide coordination (P4: Boundary Location, Cherns, 1976, 1987). In team-oriented settings, employees engage in collective sense-making, interpreting DA-generated insights through dialog and shared problem-solving (Pasmore *et al.*, 1982). Prior research supports the idea that participatory environments with suggestion systems, teamwork, and autonomy foster learning routines that support innovation (Gutierrez *et al.*, 2022). Such collaboration allows diverse functional perspectives to converge on data-driven opportunities for process or product innovation. Empirical studies confirm that shared mental models and cooperative behaviors enhance proactive problem-solving and creativity (Carraro *et al.*, 2025). Hence, when team orientation is high, firms are better able to integrate DA insights into coordinated innovative actions. For instance, Booking.com built a data-driven innovation model around customer preferences, supported by a culture of experimentation and employee autonomy (Gaimon and Carrillo, 2022). In data-intensive environments like Booking.com, employees design and interpret thousands of A/B tests using a digital infrastructure that supports experimentation and decentralized innovation (Gaimon and Carrillo, 2022). This integration ensures that DA is embedded in everyday routines and decisions, sustaining continuous innovation. Thus, we propose:

*H2.* Employee involvement positively moderates the relationship between data analytics and product and process innovation.

### *3.3 Firm performance*

The positive relationship between product and process innovation and firm performance has been widely supported in the literature (e.g. Choo *et al.*, 2021). This relationship is attributed to several mechanisms: first-mover advantage (Lieberman and Montgomery, 1988), improved market responsiveness (Porter, 1985), protection from imitation (Ansoff and Edward, 1988), and value creation through new or improved products and processes (Anand *et al.*, 2009). Capurro *et al.* (2022) suggest that product innovation generates competitive advantage by introducing new products, services, or solutions that may differ significantly from established customer demand, thereby enhancing firm performance. Choo *et al.* (2021) provide justification for this positive impact by highlighting mechanisms such as the generation of new revenue streams, increased perceived customer value, and competitive differentiation. Similarly, Mikalef *et al.* (2019) emphasize the role of process innovation, describing how it enables firms to improve adaptability, achieve greater efficiency, and make better-informed decisions, all of which contribute to enhanced performance. Supported by these lines of reasoning, we propose:

*H3.* Product and process innovation is positively related to firm performance.

## 4. Data and measures

Our research objective is to study the interrelationships between DA adoption, employee involvement, innovation capability, and performance at the firm level. We use data from the third and fourth editions of the European Company Surveys (ECS 2013 and 2019), as executed by Eurofound, a tripartite European Union Agency for the improvement of living and working conditions (Eurofound, 2023). The ECS uses a strict quality assurance framework to monitor and document all phases of the data collection and ensures adherence to quality criteria outlined in the European Statistical System (Eurostat, 2024). The quality assurance framework includes measures related to sampling, translation, pretesting, piloting, interviewer selection and training, fieldwork implementation, and data processing and storage. An additional external quality assessment further affirmed the ECS MR/ER 2013; 2019 as robust and nationally representative surveys of workplace practices in the EU 27 member states and the United Kingdom (UK) (Eurofound and Cedefop, 2020). We provide details on the (1) sampling procedure, (2) survey design and measurement error mitigation, (3) descriptive statistics, and (4) non-response and response bias mitigation in supplementary files 5.1-5.4.

### *4.1 Survey design and measures*

We used questions (abbreviated as Q) from the ECS MR 2013 (Eurofound, 2015) and ECS MR/ER 2019 surveys (Eurofound and Cedefop, 2020) as items for our measurement constructs. Due to inverse scaling of several question-responses in the surveys, we used recoding following the guidance in the ECS 2013; ECS 2019 technical notes (Eurofound and Cedefop, 2019a). We include the full ECS MR/ER 2013; MR 2019 surveys as supplementary documents (2-4) and present our development of factors in Table 2 shown in Section 4.3 (for the ECS MR 2019), and supplementary documents 6a (for the ECS MR 2013) and 6b (for the ECS ER 2019). We used the latest survey (2019) as our main data source and the earlier survey (2013) mainly for verification, and thus our discussions of the data appear in reverse chronological order in several instances.

*4.1.1 Firm performance.* In the ECS MR 2019, the reflective firm performance measures for growth in production, employees and profitability consisted of items validated in past research (Fullerton *et al.*, 2014). After recoding, these items are scored using scales of 0–2 (0 = decreased, 1 = stayed the same, 2 = increased) or 0–1 (0 = no, 1 = yes). Recoding led to a reversing of order to increasing (2 greater than 1 greater than 0). Firm performance was similarly assessed in the ECS MR 2013, and covered development in profitability and output on scales of 0–4 (0 = very bad/decreased to 4 = very good/increased) and 0–1 (0 = no, 1 = yes). Our main measure for firm performance consists of four scale items (Table 2).

*4.1.2 Operational data analytics.* The ECS MR 2019 included formative measures of DA adoption for operations improvement that we validated based on past research (Bag *et al.*, 2021) and that were measured using scales of 0–1 (0 = no, 1 = yes) and 0–2 (0 = decreased, 2 = increased). The ECS MR 2013 included a measure for the use of analytical information systems for workflow management on a 0–1 scale (0 = no, 1 = yes), and a measure for the intensity of quality monitoring for product and service delivery processes on a 0–2 scale (0 = no, 2 = continuously). Our main DA measure is constructed from these two scale items. To mitigate measurement item validity concerns, we also fitted our models based on the ECS MR 2013 data without the second item and got largely similar results (Table 4).

*4.1.3 Innovation capability.* Innovation capability was measured using formative scale items in the ECS MR 2019, and covered newly introduced products, services and processes (i.e. operations improvement oriented), on a 0–2 scale (0 = no, 1 = new to the firm, 2 = new to the market). The ECS MR 2013 survey captured the same information on a 0–1 scale (0 = no, 1 = yes). We use process and product innovation combined in our main analysis, and separately for each of the two items in supplementary analyses (Section 5).

*4.1.4 Employee involvement.* For measuring employee involvement, we relied on validated measures proposed by Denison (1990) that comprise *team orientation*, *employee development* and *employee empowerment.* We selected ECS questions that (1) closely followed the original items in Denison (1990), (2) were largely similar in the ECS MR/ER 2019 and MR 2013, and (3) best captured the essence of the STS theory mechanisms (Cherns, 1976, 1987; Clegg, 2000).

The ECS MR 2019 included measures for *team orientation* (covering the peer learning and collective sense-making mechanisms under STS); employee participation in teams, and team autonomy, measured on a 0–1 range (0 = single team/non-autonomous, 1 = more than one team/autonomous). The ECS MR 2013 had the same items. *Employee development* (covering the knowledge integration mechanism under STS) was measured on a 0–6 range (0 = no employees, 6 = all employees) in the ECS MR 2019, and similarly in the ECS MR 2013. *Empowerment* (covering the empowerment mechanism under STS) is recognized as the extent of freedom, independence, and discretional decision rights that employees experience in scheduling and selecting their work, selecting the equipment (i.e. methodologies, technologies) to use, and the procedures to follow (Sims *et al.*, 1976). Empowerment was measured in the ECS MR 2019 by autonomy in task distribution and work management (0 = not at all, 3 = to a great extent) and was related to increasing degrees of employee influence on management decisions (0 = not at all, 3 = to a great extent). The ECS MR 2013 similarly captured the dimensions for empowerment and for employee participation in management decision making. The main employee involvement measure that we used in our analyses is constructed from six scale items (Table 2).

*4.1.5 Control variables.* We included the following control variables from the ECS MR 2019 survey: international orientation (Q7; proportion of foreign sales (0 = 0%, 3 = 50% or more)), firm growth (Q12; change in employees (0 = decreased beyond 10%, 4 = increased beyond 10%), after recoding), presence of DA employee monitoring (Q23; to account for adversary effects of DA implementation (0 = no, 1 = yes), after recoding), hierarchical complexity (Q25; hierarchical levels in the company [open question]), industry concentration (competition) (Q66 (0 = not competitive, 3 = very competitive)) following Zhu *et al.* (2021), and demand dynamism (stability) (Q67 (0 = not predictable, 3 = very predictable) following Xue *et al.* (2012). The ECS MR 2013 included the following two similar control variables: firm growth (Q7; change in employees (0 = decreased, 2 = increased), after recoding) and hierarchical complexity (Q24; hierarchical levels in the company [open question]). Finally, we included dummy-coded variables to account for industry (NACE 1-digit) and country (28 countries) fixed effects.

### *4.2 Data collection and sample description*

The target sample sizes for management and employee interviews for the ECS surveys varied from 250 firms in the smallest countries to 1,500 firms in the largest countries. Target firms were contacted by phone, with interviewers requesting to speak with the most senior person in charge of personnel. If a formal employee representative was available, who was responsible for negotiating working conditions with management in the same establishment, that person was also interviewed (Eurofound and Cedefop, 2019b, p. 20). The target respondents for the ECS MR/ER 2019 were selected based on their knowledge of the topics under investigation (i.e. a key-informant approach) (Kumar *et al.*, 1993). In 16% of the firms, a management respondent agreed to participate, out of which 35% completed the questionnaire online, leading to an overall yield rate of 5%. The proportion of subsequently interviewed employee representatives per company varied between 60% (Finland) and 8% (Cyprus) (Table 1) (Eurofound and Cedefop, 2019b, p. 91).

The initial samples comprised 27,019 (ECS MR 2013) and 21,869 (ECS MR 2019) management respondents, and 3,073 (ECS ER 2019) employee respondents. As part of our data preparation, we removed cases with missing data. For the ECS MR/ER 2019 versions, we removed “skipped” (coded 3), “not applicable” (7), and “out of range” (9) responses in the ECS MR/ER 2019 sub-samples, yielding 18,616 management responses and 1,848 ECS 2019 employee responses. In addition to similar deletions in the ECS 2013 sub-sample, we removed

**Table 1.** Descriptive statistics of ECS MR 2013; MR/ER 2019

| | ECS 2019 management respondents Firms size[a] | | | Industry[b] | | | | | ECS 2013 management respondents[c] | | ECS 2019 employee respondents[c] | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Frequencies per country | 10–49 | 50–249 | >250 | Primary | Secondary | Tertiary | Total | | Total | | Total | |
| Austria (AT) | 524 | 245 | 103 | 4 | 344 | 524 | *872* | 4.7% | *733* | 3.8% | *95* | 5.10% |
| Belgium (BE) | 505 | 185 | 136 | 1 | 320 | 505 | *826* | 4.4% | *671* | 3.4% | *62* | 3.40% |
| Bulgaria (BG) | 522 | 244 | 102 | 3 | 343 | 522 | *868* | 4.7% | *312* | 1.6% | *49* | 2.70% |
| Cyprus (CY) | 75 | 17 | 9 | 0 | 26 | 75 | *101* | 0.5% | *377* | 1.9% | *2* | 0.10% |
| Czech Republic (CZ) | 369 | 288 | 78 | 2 | 364 | 369 | *735* | 3.9% | *775* | 4.0% | *26* | 1.40% |
| Germany (DE) | 352 | 170 | 54 | 6 | 218 | 352 | *576* | 3.1% | *1,093* | 5.6% | *34* | 1.80% |
| Denmark (DE) | 622 | 152 | 88 | 1 | 239 | 622 | *862* | 4.6% | *692* | 3.6% | *82* | 4.40% |
| Estonia (EE) | 255 | 125 | 67 | 3 | 189 | 255 | *447* | 2.4% | *381* | 2.0% | *10* | 0.50% |
| Greece (EL) | 327 | 74 | 33 | 3 | 104 | 327 | *434* | 2.3% | *793* | 4.1% | *4* | 0.20% |
| Spain (ES) | 777 | 380 | 92 | 11 | 461 | 777 | *1,249* | 6.7% | *1,162* | 6.0% | *123* | 6.70% |
| Finland (FI) | 574 | 269 | 116 | 2 | 383 | 574 | *959* | 5.2% | *746* | 3.8% | *310* | 16.80% |
| France (FR) | 763 | 284 | 102 | 3 | 383 | 763 | *1,149* | 6.2% | *1,154* | 5.9% | *261* | 14.10% |
| Croatia (HR) | 270 | 156 | 70 | 3 | 223 | 270 | *496* | 2.7% | *351* | 1.8% | *37* | 2.00% |
| Hungary (HU) | 497 | 251 | 125 | 1 | 375 | 497 | *873* | 4.7% | *670* | 3.4% | *23* | 1.20% |
| Ireland (IE) | 182 | 49 | 18 | 2 | 65 | 182 | *249* | 1.3% | *369* | 1.9% | *3* | 0.20% |
| Italy (IT) | 731 | 528 | 63 | 3 | 588 | 731 | *1,322* | 7.1% | *1,226* | 6.3% | *125* | 6.80% |
| Lithuania (LT) | 226 | 132 | 54 | 2 | 184 | 226 | *412* | 2.2% | *304* | 1.6% | *52* | 2.80% |
| Luxembourg (LU) | 152 | 16 | 29 | 0 | 45 | 152 | *197* | 1.1% | *313* | 1.6% | *27* | 1.50% |
| Latvia (LV) | 269 | 122 | 69 | 4 | 187 | 269 | *460* | 2.5% | *318* | 1.6% | *2* | 0.10% |
| Malta (MT) | 101 | 23 | 3 | 0 | 26 | 101 | *127* | 0.7% | *197* | 1.0% | *3* | 0.20% |
| The Netherlands (NL) | 618 | 236 | 82 | 2 | 316 | 618 | *936* | 5.0% | *710* | 3.6% | *202* | 10.90% |
| Poland (PL) | 311 | 301 | 60 | 2 | 359 | 311 | *672* | 3.6% | *812* | 4.2% | *23* | 1.20% |
| Portugal (PT) | 475 | 309 | 92 | 7 | 394 | 475 | *876* | 4.7% | *782* | 4.0% | *9* | 0.50% |
| Romania (RO) | 335 | 248 | 108 | 9 | 347 | 335 | *691* | 3.7% | *323* | 1.7% | *33* | 1.80% |
| Sweden (SE) | 634 | 100 | 132 | 0 | 232 | 634 | *866* | 4.7% | *701* | 3.6% | *206* | 11.10% |
| Slovenia (SI) | 272 | 164 | 60 | 2 | 222 | 272 | *496* | 2.7% | *384* | 2.0% | *19* | 1.00% |
| Slovakia (SK) | 195 | 74 | 24 | 0 | 98 | 195 | *293* | 1.6% | *338* | 1.7% | *11* | 0.60% |
| The United Kingdom (UK) | 395 | 121 | 56 | 0 | 177 | 395 | *572* | 3.1% | *918* | 4.7% | *15* | 0.80% |
| | 11,328 (61%) | 5,263 (28%) | 2,025 (11%) | 76 (<1%) | 7,212 (38%) | 11,328 (61%) | *18,616* | 100% | *19,470*[d] | 100% | *1,848* | 100% |

**Note(s):** [a]By employees. For the ECS MR 2019 sample firm ages vary; 13% ≤ 10 years, 22% between 11 and 20 years, 25% between 21 and 30 years, and 39% => 30 years or more. For the ECS MR 2013 sample firm ages vary similarly; 16% < 10 years, 67% between 10–49 years, and 17% > 50 years, [b]NACE industry code based. Industry representation for the ECS MR 2013 sample was similarly distributed (primary (<1%), secondary (manufacturing) (42.3%) and tertiary (services) (57.6%) sectors), [c]ECS 2019 employee and ECS 2013 management respondent descriptives condensed for brevity purposes. ECS MR 2019 roles of respondents centered around either hierarchical general- and owning managers (31.7%) and supportive human resource-, finance, operations, etc. managers (68.3%). This is similar to the ECS MR 2013: 33.7% = of hierarchical general- and owning managers, 66.3% = supportive human resource-, finance, operations, etc. managers, [d]ECS MR 2013 also included 9.5% responses from Iceland, Norway, Liechtenstein and Switzerland (the results in Table 4 with- and without this group are consistent) data from public-sector organizations given that the ECS 2019 data did not include public-sector organizations, yielding 19,470 responses. We present the descriptives by sub-samples in Table 1.

*4.3 Data exploration and construct development*

We used internal consistency checks and principal component analyses to corroborate the validity of our firm performance and employee involvement measures. We treated the measures for DA and innovation as formative, given their objectively assessable nature (e.g. “we are making use of data analytics, or not”, etc.) (Spector, 2006) and their consistency in item-scaling (no-yes) (Ford and Scandura, 2023). To mitigate validity concerns, however, we subjected these measures to the same statistical consistency assessments (Table 2 and supplementary files 6a-b).

Results of the principal component analyses (PCA; varimax rotation), and normality and reliability tests (Hensley, 1999) are presented in Table 2. With a Kaiser-Meyer-Olkin (KMO) measure of 0.69 (ECS MR 2013 = 0.65), the sampling adequacy was good, signaling a high consistency of correlation patterns across the items, making subsequent factor analysis feasible (Kaiser and Rice, 1974). We scrutinized the three factor components loadings that were below 0.5, and after considering their impact on content and face validities, eliminated the three items. Cronbach’s alpha scores for the five constructs were satisfactory ($\geq$0.50 threshold) (Kline, 2023) supporting their internal consistency. Robustness analyses for factor loadings using oblimin and varimax rotation confirmed the reported measurement indices.

**Table 2.** Data exploration and construct development (ECS 2019 management respondents)

| Factor and item factor loading | PCA |
|---|---|
| *Factor 1: Firm performance (FP)* | *α*[a] *= 0.59* |
| 1.1 Current company financial performance (0–2, Q-69)[c] | 0.81 |
| 1.2 Profit expectation this year (0–1, Q-70)[c] | 0.75 |
| 1.3 Change in production volume (goods/services) in last three years (0–2, Q-68)[c] | 0.61 |
| 1.4 Projected change in employees in the next three years (0–2, Q-71)[c] | 0.51 |
| *Factor 2: Data analytics (DA)* | *α = 0.85* |
| *2.1 Data analytics usage for process and product improvement (0–1, Q-22)*[c] | |
| *2.2 Change in use of data analytics in last three years (0–2, Q-24)* | |
| *Factor 3: Innovation capability (INNOVATION)* | *α = 0.70* |
| *3.1 Significant change in products or services in last three years (0–2, Q-9)*[c] | |
| *3.2 Significant change in processes in last three years (0–2, Q-10)*[c] | |
| *Factor 4: Employee involvement (INVOLVEMENT)* | *α = 0.64* |
| *Team orientation* | |
| 4.1 Employees working in single team vs. working in more than one team (0–1, Q-17) | 0.63 |
| 4.2 Employees’ team autonomy in dividing the work within teams (0–1, Q-18)[c] | 0.66 |
| *Employee development* | |
| 4.3 Employee participation in training during paid working time (0–6, Q-37) | 0.50 |
| 4.4 Employee participation in on-the-job training (0–6, Q-38) | 0.54 |
| *Empowerment* | |
| 4.5 Employee tasks controlled by managers vs. facilitation autonomous execution (0–1, Q-26) | (0.40)[b] |
| 4.6 Employee independence in organizing and scheduling own time and tasks (0–6, Q-30) | (0.44)[b] |
| 4.7 Involvement of employee suggestions in management decision making (0–1, Q-54)[c] | (0.36)[b] |
| 4.8 Involvement of employees in work organization changes (0–3, Q-56)[c] | 0.50 |
| 4.9 Involvement of employees in management decision making (0–3, Q-57A-D)[c] | 0.51 |

**Note(s):** [a]Cronbach’s alpha, [b]Deleted from the final scale due to low component factor loading, [c]Item recoded into reversed (increasing) order

We computed a composite index for each of the factors calculated as the average of the items ultimately selected per factor (Ford and Scandura, 2023) (Table 2). In the process of composite factor development, the item data were rescaled to range between 0 and 1 (i.e. absolute max scale-correction), where 1 is the most positive score (García *et al.*, 2015). This helped to mitigate collinearity biases stemming from scale differences and enabled comparative interpretations of effects (Cohen *et al.*, 2013). To further mitigate collinearity issues in analyzing interaction terms, we used mean-centering transformations (Kline, 2023; Ryu, 2015). To assure correct coefficient interpretation, we re-estimated all reported models using the original measurement scales, and the results confirmed the reported effects, both in direction and magnitudes. We followed the same procedure for the ECS 2013 management and ECS 2019 employee data (supplementary files 6a-6b).

We constructed composite factors based on the arguments that (1) not all constructs of interest have been measured by at least three items, (2) moderators (interaction terms) are included in the modeling approach, and (3) thorough procedures to mitigate measurement error in the study design were applied (additional file 5.2.) (Biemer *et al.*, 2013; Kline, 2023). Moreover, parameter estimate differences between composite factor and multiple item latent factor structural equation modeling are evidently negligible under the conditions of sufficiently representative sample sizes and rational study designs (Liang *et al.*, 1990). Finally, discriminant validity assessment of the composite factors revealed no problematic correlations (all <0.90 with a maximum correlation of 0.28) (Kline, 2023) (Table 3, see supplementary file 7a for ECS MR 2013 and supplementary file 7b for ECS ER 2019 correlations).

### *4.4 Common method bias*

Common method bias (CMB) was minimized using procedural and statistical methods, including survey pre-tests to avoid ambiguity (Eurofound and Cedefop, 2020; Podsakoff *et al.*, 2003). Our variables of study represent reasonably objectively assessable information (e.g. “we are making use of DA, or not”, etc.), further mitigating the risks for CMB (Spector, 2006). In addition, we assessed CMB using Harman’s single factor test, which resulted in low explained variance (21.57%).We performed a common latent factor analysis and found that the variance explained by a common latent factor in the measurement model was low (0.004%), thereby reducing the possibility of the distorting effect of CMB (Richardson *et al.*, 2009).

## 5. Regression analyses and results

We used ordinary least squares (OLS) hierarchical linear regression based conditional indirect effects modeling to test our hypotheses (Salem *et al.*, 2022; Stekelorum *et al.*, 2022) as we study the relationship between DA and firm performance (FP) dependent on other variables (Process Model #7 in Hayes, 2018). Specifically, we analyzed a first stage moderation model, comprising two linear regressions, one with the mediator (INNOVATION) and the second with FP as dependent variables (Edwards and Lambert, 2007). First, testing the effect of DA

**Table 3.** Descriptive statistics and correlations

| Factor | Mean | S.D. | Min | Max | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|
| 1. Firm performance | 2.32 | 0.37 | 1.00 | 2.80 | | | |
| 2. Data analytics | 1.67 | 0.64 | 1.00 | 2.50 | 0.12 *** | | |
| 3. Innovation | 1.48 | 0.62 | 1.00 | 3.00 | 0.16 *** | 0.28 *** | |
| 4. Involvement | 2.43 | 0.67 | 0.50 | 4.30 | 0.16 *** | 0.27 *** | 0.21 *** |

**Note(s):** Pearson correlation is significant at the 0.05 level (**) or 0.01 level (***) (2-tailed) ($n$ = 18,616)
Original ECS 2019 management respondents’ data reported

and the interaction of DA and INVOLVEMENT on INNOVATION, we inferred that INVOLVEMENT positively affects the relation between DA and INNOVATION. Next, we analyzed how the interaction indirectly affects FP, by regressing FP on INNOVATION, DA, INVOLVEMENT and the interaction of DA and INVOLVEMENT. We conducted supplementary analyses separating the samples for manufacturing (MAN) and services (SERV) firms, and separating process innovation and product innovation (full results in supplementary file 8, Tables 8.1-8.6)

To assess the robustness of our results, we used maximum-likelihood covariance-based, multilevel moderated mediation structural equation modeling (MSEM) (Table 6 and supplementary file 9) (Edwards and Lambert, 2007). Compared to hierarchical OLS analysis, MSEM accounts for the nested structure of the data and allows for estimation of all moderating and mediating effects in one model (Preacher *et al.*, 2007). The replicated results, presented in supplementary file 9, corroborate our findings in direction, comparative effects, and significance.

First, our results (Table 4) confirm direct positive albeit small effects (ECS MR 2019: $b = 0.01$ and 2013: $b = 0.04$) of DA on FP, indicating that DA marginally contributes to firm performance and that DA's primary impact materializes through intermediate mechanisms. This is an important finding. Based on two representative samples of data, we present evidence against the notion that the effect of DA on firm performance is primarily direct. This adds nuance to the findings of 12 of the 34 reviewed studies that report predominantly direct effects (e.g. Chatterjee *et al.*, 2023; Supplementary File 1).

Second, the direct effects of DA on INNOVATION (H1) in our results appear to be larger (ECS MR 2019: $b = 0.10$ & 2013: $b = 0.19$) than the DA direct effects on firm performance, confirming the hypothesized innovation-enhancing effect of DA. We find corroborative results (significance, effects size and direction) for the direct effect of DA on INNOVATION (H1) using the ECS 2019 survey data from employee respondents (see Section 5.1). These results provide evidence of the learning- and innovation-enhancing character of DA (e.g. Olabode *et al.*, 2022; supplementary file 1). Taken together, our results for H1 offer an important insight. The prominence of the mediated effect over the direct effect means that the value afforded by DA facilitates what Tucker *et al.* (2002) call second-order problem solving: issues are signaled and addressed by using DA to make value adding changes to processes or products, that is, through process or product innovation. The minor direct effect of DA on FP suggests that reacting to data by fixing the immediate issue, but without preventing recurrence by changing the process or product (i.e. first-order problem solving) (Tucker *et al.*, 2002), is a rather ineffective mode of applying DA, creating little value for firm performance.

Third, INVOLVEMENT is found to significantly and positively moderate the relation between DA and INNOVATION (H2) (ECS MR 2019: $b = 0.18$ and MR 2013: $b = 0.08$), stronger for the ECS MR 2019 sub-sample. To dig deeper into this effect, we conducted additional analyses: *services* vis-á-vis *manufacturing*, and *process*-vis-á-vis *product* innovation (supplementary file 8, Tables 8.1 - 8.6). MR 2013 interaction effects of DA and INVOLVEMENT on INNOVATION are significant and largest primarily for manufacturing. For services we do not find the interaction effects in 2013 (supplementary file 8, Tables 8.4 - 8.6). Conversely, MR 2019 interaction effects of DA and INVOLVEMENT on INNOVATION are all significant (across sectors) and larger than DA direct effects on FP (supplementary file 8, Tables 8.1 - 8.3).

These results show that realizing value from DA depends on a habit and culture of employee involvement practices (empowerment, development, team orientation) as emphasized by our STS theory based reasoning. We found these results to be stronger for the 2019 sub-sample as compared to the 2013 sub-sample, which may point to an interesting phenomenon. By 2019, DA had become more widely adopted and less of a competitive differentiator *per se* (Tumbas *et al.*, 2017). Thus, it appears that the culture of wider employee involvement practices increasingly facilitated organizational sense-making processes through DA functional affordances of transparency, and enablement of experimentation (Dremel *et al.*,

**Table 4.** ECS MR 2013 and 2019 conditional indirect effect moderated mediation results

| ECS MR 2019 results[a] Management respondents | Innovation capability Mediator *Coeff* | *SE* | *95% CI* | Firm performance Dependent variable *Coeff* | *SE* | *95% CI* |
|---|---|---|---|---|---|---|
| Intercept | −0.04 *** | (0.01) | −0.06, −0.02 | 0.05 *** | (0.01) | 0.03, 0.07 |
| Data analytics (H1) | *0.10* *** | (0.01) | *0.09, 0.11* | *0.01* *** | (0.00) | *0.00, 0.02* |
| Involvement | *0.21* *** | (0.01) | *0.19, 0.23* | - | – | - |
| Data analytics × Involvement (H2) | *0.18* *** | (0.03) | *0.12, 0.23* | - | – | - |
| Innovation (H3) | - | – | - | *0.05* *** | (0.00) | *0.04, 0.06* |
| *Control variables* | | | | | | |
| Firm growth | 0.11 *** | (0.00) | 0.09, 0.12 | 0.24 *** | (0.00) | 0.24, 0.26 |
| International orientation | 0.08 ** | (0.00) | 0.07, 0.09 | 0.02 *** | (0.00) | 0.01, 0.02 |
| Hierarchical complexity | 0.05 *** | (0.01) | 0.02, 0.08 | 0.01 | (0.01) | −0.01, 0.02 |
| Demand dynamism | 0.03 *** | (0.00) | 0.01, 0.04 | −0.06 *** | (0.01) | −0.07, −0.05 |
| Industry concentration | −0.04 *** | (0.00) | −0.05, −0.02 | −0.01 *** | (0.01) | −0.02, −0.00 |
| Employee monitoring | 0.11 *** | (0.00) | 0.09, 0.12 | 0.01 ** | (0.00) | 0.00, 0.02 |
| Industry dummies | Included | | | Included | | |
| Country dummies | Included | | | Included | | |
| $R^2$ *(adj)* | 0.17 | | | 0.23 | | |
| *F-value* | 94.96 *** | | | 138.45 *** | | |
| *n* | 18,616 | | | | | |

| ECS MR 2013 results Management respondents | Innovation capability Mediator *Coeff* | *SE* | *95% CI* | Firm performance Dependent variable *Coeff* | *SE* | *95% CI* |
|---|---|---|---|---|---|---|
| Intercept | −0.04 *** | (0.01) | −0.05, −0.03 | 0.09*** | (0.01) | 0.08, 0.10 |
| Data analytics (H1) | *0.19* *** | (0.01) | *0.17, 0.21* | *0.04* *** | (0.01) | *0.03, 0.06* |
| Involvement | *0.30* *** | (0.01) | *0.28, 0.32* | - | – | - |
| Data analytics × Involvement (H2)[b] | *0.08* * | (0.05) | *−0.01, 0.18* | - | – | - |
| Innovation (H3) | - | – | - | *0.05* *** | (0.00) | *0.05, 0.06* |
| *Control variables* | | | | | | |
| Firm growth | 0.08 *** | (0.01) | 0.06, 0.09 | 0.22 *** | (0.00) | 0.21, 0.22 |
| Hierarchical complexity | 0.40 *** | (0.00) | 0.31, 0.50 | 0.12 *** | (0.03) | 0.06, 0.17 |
| Industry dummies | Included | | | Included | | |
| Country dummies | Included | | | Included | | |
| $R^2$ *(adj)* | 0.15 | | | 0.30 | | |
| *F-value* | 88.19 *** | | | 215.25 *** | | |
| *n* | 19,470 | | | | | |

**Note(s):** Robust standard errors in parentheses, two tailed significance (* = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$). CI: Confidence interval, [a]The ECS MR 2019 model was also reassessed based on the same control variables that are available for the ECS MR 2013 survey data, confirming the DA, INVOLVEMENT, and DA × INVOLVEMENT coefficients, [b]Interaction effects are significant at the 1% level for *process* innovation specifically (supplementary file 8.5) and at the 5% level for manufacturing (supplementary file 8.4)

2020). These DA functional affordances of information democratization are known to facilitate the identification, provision, analysis, and interpretation of company information (Seidel *et al.*, 2013). Consequently, we can say that the direct main effects of the technological subsystem weaken, and the moderated or conditional social subsystem effects become more salient (confirmed by the larger and stronger moderation effects in the ECS MR 2019 model, Figure 2).

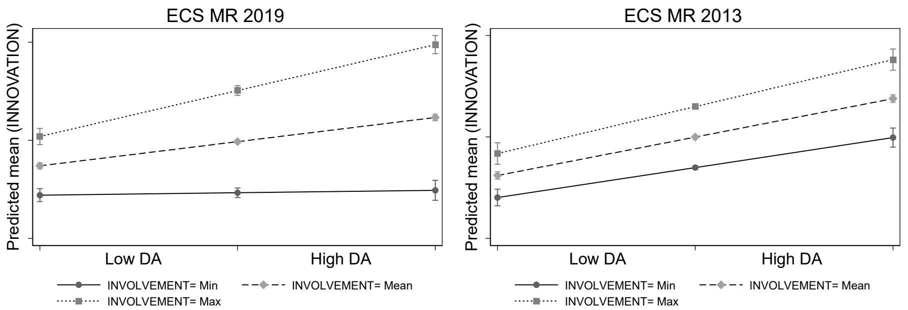


**Figure 2.** Marginal effects plot at minimum, mean and maximum employee involvement levels

Fourth, consequent effects of INNOVATION on FP (H3) are significant and appear moderate (ECS MR 2019: $b = 0.05$ & 2013: $b = 0.05$). These results are consistent among industries and specific types of innovation (supplementary file 8, Tables 8.1-8.6). Finally, almost all the control variables appear to be significant.

Next, following Malhotra's *et al.* (2014) recommendation to explicitly test mediation effects, we conducted causal mediation analyses to confirm the indirect effect of DA on FP via INNOVATION (ECS MR 2019: *coeff:* 0.004 $^{***}$, *SE:* 0.000, *95%CI:* 0.003, 0.004, ECS MR 2013: *coeff:* 0.008 $^{***}$, *SE:* 0.000, *95%CI:* 0.006, 0.009). The indirect albeit small indirect effects suggest that DA's primary impact is on enhancing innovation capability, but the subsequent effect—the yield of these innovations on firm performance—also depends on additional organizational factors. Figure 2 demonstrates the interaction effect of DA and INVOLVEMENT, via the simple slopes at their minimum vis-á-vis maximum values on INNOVATION.

Next, we analyzed bias-corrected bootstrapping-based confidence intervals (CIs) to further understand the moderating effect of INVOLVEMENT on the relationship between DA and FP mediated by INNOVATION (Hayes, 2018). Results shown in Table 5 reveal an absence of zero values in the bias-corrected CIs, signaling meaningful indirect effects of DA on FP at various levels of INVOLVEMENT for both ECS MR 2013; 2019 data (Preacher *et al.*, 2007). The moderated mediation index (regression slope quantifying how the DA-FP relation is affected by low vis-á-vis high employee INVOLVEMENT) (Hayes, 2018) reveals statistical significance for the ECS MR 2019 (at 1%) and 2013 (at 10%) (Table 5).

### *5.1 Robustness analyses and post-hoc assessments*

We conducted several additional analyses to assess the risks for misinterpretations due to model misspecification and endogeneity (Ketokivi and McIntosh, 2017; Lu *et al.*, 2018; Rohrer *et al.*, 2022). First, we followed three approaches generally used to mitigate potentially endogeneity-biased results: (1) included control variables (i.e. the "full information approach"), (2) used instrument variables, and (3) applied statistical approaches (i.e. instrument free approaches such as generalized methods of moments or Gaussian Copula estimation) (Park and Gupta, 2012). Second, we considered alternative models to explain the relations between DA, INNOVATION and FP for the ECS MR 2013/2019 responses. Third, we triangulated our findings with the ECS (ER) 2019 survey data that was conducted amongst employees, representing different topics (predominantly oriented towards employee representation) albeit based on a smaller sample. We summarize the results of the robustness and post-hoc analyses in Table 6, and for brevity, provide the elaborate reports in the supplementary files 9, 10.1, and 10.2.

**Table 5.** Indirect effects of DA and INVOLVEMENT interaction via INNOVATION on FP

| ECS MR 2019 results<br>Management respondents<br>Moderator: Employee involvement | Effect on firm performance<br>*Coeff* | *Bootstrap SE*[a] | *95% CI*[b] |
|---|---|---|---|
| Low: −1 standard deviation | 0.003 *** | (0.000) | 0.002, 0.005 |
| High: +1 standard deviation | 0.006 *** | (0.000) | 0.005, 0.008 |
| Index of moderated mediation[c] | 0.009 *** | (0.001) | 0.006, 0.012 |

| ECS MR 2013 results (robustness)<br>Management respondents<br>Moderator: Employee involvement | Effect on firm performance<br>*Coeff* | *Bootstrap SE*[a] | *95% CI*[b] |
|---|---|---|---|
| Low: −1 standard deviation | 0.009 *** | (0.000) | 0.007, 0.011 |
| High: +1 standard deviation | 0.011 *** | (0.001) | 0.008, 0.013 |
| Index of moderated mediation[c] | 0.004 * | (0.002) | −0.000, 0.009 |

**Note(s):** Standard errors in parentheses, two tailed significance (* = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$). CI: Confidence interval, [a]Boostrapping based on 1,000 replications, [b]Coefficient is significant when the confidence interval excludes zero, [c]The moderated mediation index indicates the indirect effect of DA on FP, mediated by INNOVATION as INVOLVEMENT changes by one unit (Hayes, 2018)

## 6. Discussion

The OM and IS literatures have generally recognized the association between DA and firm performance. In trying to add specificity to this association and uncover the underlying mechanisms, scholars have studied various mediators and moderators, mainly supported by survey data and case studies. Although past results have suggested fragments of a theory, a satisfactory explanation, with an overarching theoretical framework, has not yet emerged. Approaching this question from the STS perspective in this research, we have tried to understand how DA improves decisions taken by professionals working in complex, sociotechnical production systems, and how this might create value (Bendoly and Oliva, 2024).

### *6.1 Theoretical contributions*

First, we have argued against the notion that DA directly affects firm performance. Our results show small positive direct effects, thereby adding nuance to the findings of 12 of the 34 reviewed studies that report predominantly direct effects (e.g. Chatterjee *et al.*, 2023; supplementary file 1).

Second, we have corroborated the notion that DA value effects materialize mainly through the affordance of enhanced innovation capabilities in firms. In so doing, we have supported prior similar (Mikalef *et al.*, 2019) and related notions on the learning and innovation enhancing character of DA (e.g. Olabode *et al.*, 2022; supplementary file 1). We find subsequent firm performance effects, thereby providing support for the mediating mechanism of innovation capability in the DA – firm performance relationship (Mikalef *et al.*, 2019).

Third, and perhaps most important, we have provided an original and detailed theoretical substantiation of the sociotechnical mechanisms through which DA facilitates innovation capabilities, by operationalizing the role of employee involvement following the STS theory social subsystem design principles that capture the importance of employee empowerment, employee development and team orientation (Cherns, 1976, 1987; Clegg, 2000). In so doing, we have integrated the perspective of employees' roles in DA (Mikalef *et al.*, 2021; Sainam

Table 6. Robustness analyses and post-hoc assessments

| Procedure | ECS MR 2019 results | ECS MR 2013 results |
|---|---|---|
| *Alternative estimation approach* | | |
| 1. Multilevel moderated mediation structural equation modeling (supplementary file 9) | Confirmation of results directions, comparative effects and significances | Confirmation of results directions, comparative effects and significances |
| *Endogeneity assessments* | | |
| 2. Multilevel moderated mediation structural equation model error term correlation assessment (supplementary file 9) | Weak and insignificant correlations between DA, INNOVATION($\varepsilon$) and FP($\varepsilon$) | Weak and insignificant correlations between DA, INNOVATION($\varepsilon$) and FP($\varepsilon$) |
| 3. Instrument variable based 2-stage model estimation (*supplementary file 10.1*) | Significant evidence DA is exogeneous to FP | Significant evidence DA is exogeneous to FP |
| 4. Instrument-free Gaussian Copula model estimation (supplementary file 10.1) | Not applicable | Significant evidence DA is exogenous to FP |
| *Alternative model assessments* | | |
| 5. Moderating vs. mediating effect of innovation on DA-FP relation (supplementary file 10.2) | Insignificant interaction effect ($b = -0.02$, $p = 0.12$) | Insignificant interaction effect ($b = 0.00$, $p = 0.73$) |
| 6. Moderating effect of involvement on DA-FP relation (supplementary file 10.2) | Insignificant interaction effect ($b = 0.01$, $p = 0.42$) | Insignificant interaction effect ($b = 0.00$, $p = 0.96$) |
| 7. Mediating effect of involvement on DA-INNOVATION relation (supplementary file 10.2) | Significant but marginal indirect effect (*proportion* = 0.18, $p = 0.00$) | Significant but marginal indirect effect (*proportion* = 0.01, $p = 0.00$) |
| *Triangulation of results with ECS 2019 employee representative survey data* | | |
| 8. Effect of DA on INNOVATION (supplementary file 10.2) | Significant effect ($b = 0.16$, $p = 0.00$). | No item data available |
| 9. Effect of INVOLVEMENT on DA-INNOVATION (moderation) (supplementary file 10.2) | Insignificant interaction effect | No item data available |

**Note(s):** The complete descriptions of the approaches and the results of the robustness analyses and post-hoc assessments are reported in supplementary files 9, 10.1, and 10.2

*et al.*, 2022; Yasmin *et al.*, 2020) in an explanation coherent with existing theory and specified the role of the human component in DA value effects (Dremel *et al.*, 2020; Mikalef *et al.*, 2020). Based on our reasoning rooted in STS theory (Closs *et al.*, 2008; Tong *et al.*, 2023), our findings offer an original and more complete understanding of DA value effects. Our results suggest that DA has little benefit unless it is adopted in conjunction with process and product innovation and an employee involvement-oriented culture that is promoting "second-order problem solving" (e.g. continuous improvement, organizational learning) (Leonardi, 2011; Tucker *et al.*, 2002). The understanding that emerges is that participatory environments based on teamwork and autonomy foster learning routines that support innovation (Gutierrez *et al.*, 2022). Interpreting data and translating it to findings and insights relevant to the processes under study requires mobilization and enactment of specific knowledge that frontline employees have and management may not have (Molina *et al.*, 2007). Our findings corroborate this conjecture of decentralized innovation (Wu *et al.*, 2019) as evident from the positive moderating effect of employee involvement. Perhaps our perspective frames DA as a reincarnation and further specification in the evolution of the total quality management (TQM) framework and its component of statistical process control (SPC), which were widely discussed in the 1980s and 90s (Dean and Bowen, 1994). The mechanisms that explain why SPC is valuable may also be foundational for explaining why and how DA could be valuable, namely, by collocating DA with employees who have the knowledge to use DA for process innovation (Kent *et al.*, 2024), and to recognize new opportunities for product innovation.

Interestingly, comparing our results from analyzing the data from two periods also suggests that between 2013 and 2019, the integration of DA with employee involvement for strengthening innovation capabilities grew in importance. The period of 2013–2019 represents a time of growing prominence of DA capabilities, with companies across sectors investing in managerial capabilities to develop digital technologies and derive insights to monetize internal and external data sources (Tumbas *et al.*, 2017). While manufacturing has had a tradition of data-driven process- and product-improvement, for other sectors, this competency has traditionally resided in finance and marketing functions (McKinsey Global Institute, 2016). In this period, manufacturing companies reoriented DA capabilities from analyzing internal processes to the analysis of user- and external data in support of new business models. This shift required new modes of collaboration between the information technology departments and the rest of the businesses, and companies developed their DA capabilities (e.g. business acumen, analytics and technical capabilities) and visions about the role of data as success factors (Dremel *et al.*, 2017). The notion that effective DA capabilities require more than technology alone was initially only understood as interdisciplinary data analytics teams (Vidgen *et al.*, 2017). Further conceptualizations identified the need for integrated business perspectives, cultural adjustment, and the involvement of people, emphasizing the integration of human workers and digital DA technologies (Parker and Grote, 2022).

### *6.2 Managerial implications*

An important practical implication of our results is that DA should not be implemented as an initiative solely driven by experts, managers or consultants *per se*. Instead, it should be adopted as a decentralized initiative implemented at the frontline-level in manifestations such as dashboards, business intelligence applications, and predictive algorithms that support decision-making by empowered and trained rank-and-file employees. Frontline employees have the knowledge to recognize the implications of patterns in data, and the improvement opportunities they present. In team-oriented settings, employees can engage in collective sense-making, interpreting DA-generated insights through dialog and shared problem-solving (Carraro *et al.*, 2025). When trained and empowered, these employees can better point to additional data that may be needed and how best it may be collected, and have the absorptive capacity to best identify the ways in which the results from DA can be translated into product and process changes that can actually be implemented (Furlan *et al.*, 2019).

Also, initiatives to adopt DA should be connected to the purpose and structures of process and product innovations, as the effects of DA on firm performance are closely tied to such innovation capabilities. While the roles of DA in figuring out customer trends that can be useful for product development and in pointing to optimization levels of process settings that can be valuable for process improvements are more well-known (Wu *et al.*, 2020), our results show the value of developing and mobilizing the knowledge of frontline employees so that they can better engage in product and process innovations.

Finally, our findings warrant a cautionary note for the current debate on advanced emerging technologies for DA in organizations, such as deep-learning based predictive analytics and generative AI systems that augment or automate analytical decision-making (Horvat *et al.*, 2025). We conjecture that advanced DA systems and tools diffuse across organizations following a similar trajectory: competitive advantage will hinge less on making use of advanced DA systems *per se*, and more on how work systems are designed to enable employees in improving processes and products (Parker and Grote, 2022). Our findings imply that managers should not only invest in advanced technical DA capabilities but also in the sociotechnical conditions of employee empowerment, development, and team orientation, to enable employees to integrate the actionable insights generated by advanced DA systems and tools into everyday problem solving and innovation (Gaimon and Carrillo, 2022).

## 7. Conclusion

Motivated by established theory on the interaction between technological and social subsystems, we conjecture and confirm that DA affects performance through innovation capabilities, with the involvement of employees as a positive moderator. The empirical basis for our study is European Company Survey (ECS) data spanning multiple years (2013 and 2019) and dual perspectives (management and employees). Our study connects operational DA and its benefits to established theory in OM.

Despite the evidence base and our extensive robustness analyses, limitations remain. First, given the anonymity of the responses, our results could not be corroborated by alternative proxies from other sources of secondary data. Therefore, our study is bound by the measures that were available from the ECS survey items, which were somewhat inconsistent between the datasets, and for measuring data analytics and innovation capabilities allowed only two-item formative scales, potentially limiting measurement breadth and reliability. Second, our firm-level analyses provide meso-level insights and take only a first step from *what* to *how* explanations about the effects of DA adoption on firm operations. Future research is encouraged at the micro-level, within firms, for instance, to study the potentially mediating role of employee involvement on the effect of DA on innovation capabilities. Third, the sub-sample analysis using only the ECS ER 2019 data did not confirm the moderating effect of employee involvement. Future research using matched manager–employee dyads or multi-source designs to adjudicate perceptual differences and strengthen causal inference could provide more insights. Fourth, our results are limited by the 28 countries included in our sample, the 27 countries of the EU and the UK, for the 2013 and 2019 surveys. Nevertheless, the replication of results over these datasets does give confidence in the generalizability of our findings. Finally, the cross-sectional nature of our data does not allow for conclusive explanations about DA adoption patterns over time, and the nature and reciprocity of causality. We have applied robustness tests to account for potential endogeneity biases. Future research using panel data would be better suited to addressing these remaining limitations.

### Supplementary material

The supplementary material for this article can be found online.

### References

Addison, J.T. and Teixeira, P. (2020), “Trust and workplace performance”, *British Journal of Industrial Relations*, Vol. 58 No. 4, pp. 874-903, doi: 10.1111/bjir.12517.

Anand, G., Ward, P.T., Tatikonda, M.V. and Schilling, D.A. (2009), “Dynamic capabilities through continuous improvement infrastructure”, *Journal of Operations Management*, Vol. 27 No. 6, pp. 444-461, doi: 10.1016/j.jom.2009.02.002.

Angelopoulos, S., Bendoly, E., Fransoo, J., Hoberg, K., Ou, C. and Tenhiälä, A. (2023), “Digital transformation in operations management: fundamental change through agency reversal”, *Journal of Operations Management*, Vol. 69 No. 6, pp. 876-889, doi: 10.1002/joom.1271.

Ansoff, I. and Edward, J.M. (1988), *The New Corporate Strategy*, Wiley, doi: 10.2307/258179.

Awan, U., Bhatti, S.H., Shamim, S., Khan, Z., Akhtar, P. and Balta, M.E. (2022), “The role of big data analytics in manufacturing agility and performance: moderation–mediation analysis of organizational creativity and of the involvement of customers as data analysts”, *British Journal of Management*, Vol. 33 No. 3, pp. 1200-1220, doi: 10.1111/1467-8551.12549.

Bag, S., Gupta, S., Kumar, A. and Sivarajah, U. (2021), “An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance", *Industrial Marketing Management*, Vol. 92, pp. 178-189, doi: 10.1016/j.indmarman.2020.12.001.

Bean, R. (2017), "How companies say they're using big data", *Harvard Business Review*, Vol. 95 No. 2, pp. 36-40.

Bendoly, E. and Oliva, R. (2024), "Holding North: recognizing identity and advancing contribution in operations management", *Journal of Operations Management*, Vol. 70 No. 4, pp. 518-522, doi: 10.1002/joom.1306.

Bessant, J. and Caffyn, S. (1997), "High-involvement innovation through continuous improvement", *International Journal of Technology Management*, Vol. 14 No. 1, pp. 7-28.

Biemer, P.P., Groves, R.M., Lyberg, L.E., Mathiowetz, N.A. and Sudman, S. (2013), *Measurement Errors in Surveys*, Vol. 548, John Wiley & Sons, doi: 10.1002/9781118150382.

Capurro, R., Fiorentino, R., Garzella, S. and Giudici, A. (2022), "Big data analytics in innovation processes: which forms of dynamic capabilities should be developed and how to embrace digitization?", *European Journal of Innovation Management*, Vol. 25 No. 6, pp. 273-294, doi: 10.1108/ejim-05-2021-0256.

Carraro, M., Furlan, A. and Netland, T. (2025), "Unlocking team performance: how shared mental models drive proactive problem-solving", *Human Relations*, Vol. 78 No. 4, pp. 407-437, doi: 10.1177/00187267241247962.

Cassiman, B. and Veugelers, R. (2006), "In search of complementarity in innovation strategy: internal R&D and external knowledge acquisition", *Management Science*, Vol. 52 No. 1, pp. 68-82, doi: 10.1287/mnsc.1050.0470.

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U. and Bag, S. (2023), "Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm", *Technological Forecasting and Social Change*, Vol. 196, 122824, doi: 10.1016/j.techfore.2023.122824.

Chen, H., Chiang, R.H. and Storey, V.C. (2012), "Business intelligence and analytics: from big data to big impact", *MIS Quarterly*, Vol. 36 No. 4, pp. 1165-1188, doi: 10.2307/41703503.

Chen, M., Pu, X., Zhang, M., Cai, Z., Chong, A.Y.-L. and Tan, K.H. (2022), "Data analytics capability and servitization: the moderated mediation role of bricolage and innovation orientation", *International Journal of Operations and Production Management*, Vol. 42 No. 4, pp. 440-470, doi: 10.1108/ijopm-10-2021-0663.

Cheng, C.C.J. and Sheu, C. (2024), "Social media analytics and product innovation: mediating effects of knowledge exploration and exploitation competences", *International Journal of Operations and Production Management*, Vol. 44 No. 1, pp. 229-259, doi: 10.1108/ijopm-08-2022-0537.

Cherns, A. (1976), "The principles of sociotechnical design", *Human Relations*, Vol. 29 No. 8, pp. 783-792, doi: 10.1177/001872677602900806.

Cherns, A. (1987), "Principles of sociotechnical design revisted", *Human Relations*, Vol. 40 No. 3, pp. 153-161, doi: 10.1177/001872678704000303.

Choi, T.M., Wallace, S.W. and Wang, Y. (2018), "Big data analytics in operations management", *Production and Operations Management*, Vol. 27 No. 10, pp. 1868-1883, doi: 10.1111/poms.12838.

Choo, A., Narayanan, S., Srinivasan, R. and Sarkar, S. (2021), "Introducing goods innovation, service innovation, or both? Investigating the tension in managing innovation revenue streams for manufacturing and service firms", *Journal of Operations Management*, Vol. 67 No. 6, pp. 704-728, doi: 10.1002/joom.1136.

Clegg, C.W. (2000), "Sociotechnical principles for system design", *Applied Ergonomics*, Vol. 31 No. 5, pp. 463-477, doi: 10.1016/s0003-6870(00)00009-0.

Closs, D.J., Jacobs, M.A., Swink, M. and Webb, G.S. (2008), "Toward a theory of competencies for the management of product complexity: six case studies", *Journal of Operations Management*, Vol. 26 No. 5, pp. 590-610, doi: 10.1016/j.jom.2007.10.003.

Cohen, J., Cohen, P., West, S.G. and Aiken, L.S. (2013), *Applied Multiple regression/Correlation Analysis for the Behavioral Sciences*, LEA, London, UK, doi: 10.4324/9781410606266.

Cozzolino, A., Verona, G. and Rothaermel, F.T. (2018), "Unpacking the disruption process: new technology, business models, and incumbent adaptation", *Journal of Management Studies*, Vol. 55 No. 7, pp. 1166-1202, doi: 10.1111/joms.12352.

Damanpour, F. (1991), "Organizational innovation: a meta-analysis of effects of determinants and moderators", *Academy of Management Journal*, Vol. 34 No. 3, pp. 555-590, doi: 10.2307/256406.

De Mast, J., Steiner, S.H., Nuijten, W.P. and Kapitan, D. (2023), "Analytical problem solving based on causal, correlational and deductive models", *The American Statistician*, Vol. 77 No. 1, pp. 51-61, doi: 10.1080/00031305.2021.2023633.

Dean, J.W. Jr and Bowen, D.E. (1994), "Management theory and total quality: improving research and practice through theory development", *Academy of Management Review*, Vol. 19 No. 3, pp. 392-418, doi: 10.2307/258933.

Denison, D.R. (1990), *Corporate Culture and Organizational Effectiveness*, Wiley, New York, NY, doi: 10.1016/j.orgdyn.2003.11.008.

Detert, J.R., Schroeder, R.G. and Mauriel, J.J. (2000), "A framework for linking culture and improvement initiatives in organizations", *Academy of Management Review*, Vol. 25 No. 4, pp. 850-863, doi: 10.2307/259210.

Dremel, C., Wulf, J., Herterich, M.M., Waizmann, J.C. and Brenner, W. (2017), "How AUDI AG established big data analytics in its digital transformation", *MIS Quarterly Executive*, Vol. 16 No. 2, pp. 81-100, doi: 10.1016/j.im.2018.10.007.

Dremel, C., Herterich, M.M., Wulf, J. and Vom Brocke, J. (2020), "Actualizing big data analytics affordances: a revelatory case study", *Information and Management*, Vol. 57 No. 1, 103121, doi: 10.1016/j.im.2018.10.007.

Edwards, J.R. and Lambert, L.S. (2007), "Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis", *Psychological Methods*, Vol. 12 No. 1, pp. 1-22, doi: 10.1037/1082-989x.12.1.1.

Erro-Garcés, A. and Aramendia-Muneta, M.E. (2023), "The role of human resource management practices on the results of digitalisation. From Industry 4.0 to Industry 5.0", *Journal of Organizational Change Management*, Vol. 36 No. 4, pp. 585-602, doi: 10.1108/jocm-11-2021-0354.

Escrig-Tena, A.B., Segarra-Ciprés, M. and García-Juan, B. (2021), "Incremental and radical product innovation capabilities in a quality management context: exploring the moderating effects of control mechanisms", *International Journal of Production Economics*, Vol. 232, 107994, doi: 10.1016/j.ijpe.2020.107994.

Eurofound (2015), *Third European Company Survey: Workplace Practices - Patterns, Performance and well-being*, Publications Office of the European Union, Luxembourg.

Eurofound (2023), "European foundation for the improvement of living and working conditions", available at: https://www.eurofound.europa.eu/en/home (accessed 21 November 2023).

Eurofound and Cedefop (2019a), *European Company Survey 2019: Coding Report*, Publications Office of the European Union, Luxembourg.

Eurofound and Cedefop (2019b), *European Company Survey 2019: Technical Report*, Publications Office of the European Union, Luxembourg.

Eurofound and Cedefop (2020), *European Company Survey 2019: Workplace Practices -unlocking Employee Potential*, Publications Office of the European Union, Luxembourg.

Eurostat (2024), "Quality assurance framework", available at: https://ec.europa.eu/eurostat/web/quality/european-quality-standards/quality-assurance-framework (accessed 8 July 2024).

Feng, Q. and Shanthikumar, J.G. (2018), "How research in production and operations management May evolve in the era of big data", *Production and Operations Management*, Vol. 27 No. 9, pp. 1670-1684, doi: 10.1111/poms.12836.

Forbes (2024), “Unlocking the power of analytics: how to adopt A data-driven mindset”, *Par Chadha*, available at: https://www.forbes.com/sites/forbesbusinesscouncil/2024/04/12/unlocking-the-power-of-analytics-how-to-adopt-a-data-driven-mindset/(accessed 21 May 2024).

Ford, L.R. and Scandura, T.A. (2023), *The SAGE Handbook of Survey Development and Application*, SAGE Publications, doi: 10.4135/9781529617757.n1.

Fullerton, R.R., Kennedy, F.A. and Widener, S.K. (2014), “Lean manufacturing and firm performance: the incremental contribution of lean management accounting practices”, *Journal of Operations Management*, Vol. 32 Nos 7-8, pp. 414-428, doi: 10.1016/j.jom.2014.09.002.

Furlan, A., Galeazzo, A. and Paggiaro, A. (2019), “Organizational and perceived learning in the workplace: a multilevel perspective on employees’ problem solving”, *Organization Science*, Vol. 30 No. 2, pp. 280-297, doi: 10.1287/orsc.2018.1274.

Gaimon, C. and Carrillo, J. (2022), “Successful innovation and the alignment of knowledge workers at the executive, management, and technical specialist levels”, *Production and Operations Management*, Vol. 31 No. 12, pp. 4589-4598, doi: 10.1111/poms.13853.

Galeazzo, A., Furlan, A., Tosetto, D. and Vinelli, A. (2024), “Are lean and digital engaging better problem solvers? An empirical study on Italian manufacturing firms”, *International Journal of Operations and Production Management*, Vol. 44 No. 6, pp. 1217-1248, doi: 10.1108/ijopm-06-2023-0477.

García, S., Luengo, J. and Herrera, F. (2015), *Data Preprocessing in Data Mining 72*, Springer International Publishing, Cham, Switzerland, pp. 59-139, doi: 10.1007/978-3-319-10247-4.

Gartner (2025), “Lack of AI-ready data puts AI projects at risk”, available at: https://www.gartner.com/en/newsroom/press-releases/2025-02-26-lack-of-ai-ready-data-puts-ai-projects-at-risk (accessed 27 November 2025).

Ghasemaghaei, M. and Calic, G. (2019), “Does big data enhance firm innovation competency? The mediating role of data-driven insights”, *Journal of Business Research*, Vol. 104, pp. 69-84, doi: 10.1016/j.jbusres.2019.07.006.

Gutierrez, L., Lameijer, B.A., Anand, G., Antony, J. and Sunder, M.V. (2022), “Beyond efficiency: the role of lean practices and cultures in developing dynamic capabilities microfoundations”, *International Journal of Operations and Production Management*, Vol. 42 No. 13, pp. 506-536, doi: 10.1108/ijopm-02-2022-0086.

Hadid, W. and Mansouri, A. (2014), “The lean-performance relationship in services: a theoretical model”, *International Journal of Operations and Production Management*, Vol. 34 No. 6, pp. 750-785, doi: 10.1108/ijopm-02-2013-0080.

Hayes, A.F. (2018), “Partial, conditional, and moderated moderated mediation: quantification, inference, and interpretation”, *Communication Monographs*, Vol. 85 No. 1, pp. 4-40, doi: 10.1080/03637751.2017.1352100.

Hensley, R.L. (1999), “A review of operations management studies using scale development techniques”, *Journal of Operations Management*, Vol. 17 No. 3, pp. 343-358, doi: 10.1016/s0272-6963(98)00051-5.

Horvat, D., Jäger, A. and Lerch, C.M. (2025), “Fostering innovation by complementing human competences and emerging technologies: an industry 5.0 perspective”, *International Journal of Production Research*, Vol. 63 No. 3, pp. 1126-1149, doi: 10.1080/00207543.2024.2372009.

Kaiser, H.F. and Rice, J. (1974), “Little jiffy, mark IV”, *Educational and Psychological Measurement*, Vol. 34 No. 1, pp. 111-117, doi: 10.1177/001316447403400115.

Kent, P., Siemsen, E. and Shao, X. (2024), “The impact of co-location on production knowledge transfer in collectivist and individualist cultures”, *International Journal of Operations and Production Management*, Vol. 44 No. 1, pp. 179-205, doi: 10.1108/ijopm-06-2022-0354.

Ketokivi, M. and McIntosh, C.N. (2017), “Addressing the endogeneity dilemma in operations management research: theoretical, empirical, and pragmatic considerations”, *Journal of Operations Management*, Vol. 52 No. 1, pp. 1-14.

Kim, D.Y., Kumar, V. and Kumar, U. (2012), "Relationship between quality management practices and innovation", *Journal of Operations Management*, Vol. 30 No. 4, pp. 295-315, doi: 10.1016/j.jom.2012.02.003.

Kline, R.B. (2023), *Principles and Practices of Structural Equation Modelling*, The Guilford Press, New York.

Kopalle, P.O. (2014), "Why Amazon's anticipatory shipping is pure genius", *Forbes*, available at: https://www.forbes.com/sites/onmarketing/2014/01/28/why-amazons-anticipatory-shipping-is-pure-genius/(accessed 8 July 2025).

Kumar, N., Stern, L.W. and Anderson, J.C. (1993), "Conducting interorganizational research using key informants", *Academy of Management Journal*, Vol. 36 No. 6, pp. 1633-1651, doi: 10.2307/256824.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2010), "Big data, analytics and the path from insights to value", *MIT Sloan Management Review*, Vol. 52 No. 2, pp. 21-32.

Lee, H.L. (2018), "Big data and the innovation cycle", *Production and Operations Management*, Vol. 27 No. 9, pp. 1642-1646, doi: 10.1111/poms.12845.

Legenvre, H. and Hameri, A.P. (2024), "The emergence of data sharing along complex supply chains", *International Journal of Operations and Production Management*, Vol. 44 No. 1, pp. 292-297, doi: 10.1108/ijopm-11-2022-0729.

Leonardi, P.M. (2011), "When flexible routines meet flexible technologies: affordance, constraint, and the imbrication of human and material agencies", *MIS Quarterly*, Vol. 35 No. 1, pp. 147-167, doi: 10.2307/23043493.

Liang, J., Lawrence, R.H., Bennett, J.M. and Whitelaw, N.A. (1990), "Appropriateness of composites in structural equation models", *Journal of Gerontology*, Vol. 45 No. 2, pp. S52-S59, doi: 10.1093/geronj/45.2.s52.

Lieberman, M.B. and Montgomery, D.B. (1988), "First-mover advantages", *Strategic Management Journal*, Vol. 9 No. S1, pp. 41-58, doi: 10.1002/smj.4250090706.

Lu, G., Ding, X., Peng, D.X. and Hao-Chun Chuang, H. (2018), "Addressing endogeneity in operations management research: recent developments, common problems, and directions for future research", *Journal of Operations Management*, Vol. 64 No. 1, pp. 53-64.

Malhotra, M.K., Singhal, C., Shang, G. and Ployhart, R.E. (2014), "A critical evaluation of alternative methods and paradigms for conducting mediation analysis in operations management research", *Journal of Operations Management*, Vol. 32 No. 4, pp. 127-137, doi: 10.1016/j.jom.2014.01.003.

Maroufkhani, P., Wagner, R., Wan Ismail, W.K., Baroto, M.B. and Nourani, M. (2019), "Big data analytics and firm performance: a systematic review", *Information*, Vol. 10 No. 7, p. 226, doi: 10.3390/info10070226.

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D. (2012), "Big data: the management revolution", *Harvard Business Review*, Vol. 90 No. 10, pp. 60-68.

McKinsey (2016), "How companies are using big data and analytics", available at: https://www.mckinsey.com/capabilities/quantumblack/our-insights/how-companies-are-using-big-data-and-analytics#/(accessed 27 November 2025).

McKinsey Global Institute (2016), *The Age of Analytics: Competing in a data-driven World*, McKinsey Global Institute, Research.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019), "Big data analytics and firm performance: findings from a mixed-method approach", *Journal of Business Research*, Vol. 98, pp. 261-276, doi: 10.1016/j.jbusres.2019.01.044.

Mikalef, P., Pappas, I.O., Krogstie, J. and Pavlou, P.A. (2020), "Big data and business analytics: a research agenda for realizing business value", *Information and Management*, Vol. 57 No. 1, 103237, doi: 10.1016/j.im.2019.103237.

Mikalef, P., van de Wetering, R. and Krogstie, J. (2021), "Building dynamic capabilities by leveraging big data analytics: the role of organizational inertia", *Information and Management*, Vol. 58 No. 6, 103412, doi: 10.1016/j.im.2020.103412.

Molina, L.M., Lloréns-Montes, J. and Ruiz-Moreno, A. (2007), "Relationship between quality management practices and knowledge transfer", *Journal of Operations Management*, Vol. 25 No. 3, pp. 682-701, doi: 10.1016/j.jom.2006.04.007.

Oesterreich, T.D., Anton, E., Teuteberg, F. and Dwivedi, Y.K. (2022), "The role of the social and technical factors in creating business value from big data analytics: a meta-analysis", *Journal of Business Research*, Vol. 153, pp. 128-149, doi: 10.1016/j.jbusres.2022.08.028.

Ogbuke, N.J., Yusuf, Y.Y., Dharma, K. and Mercangoz, B.A. (2022), "Big data supply chain analytics: ethical, privacy and security challenges posed to business, industries and society", *Production Planning and Control*, Vol. 33 Nos 2-3, pp. 123-137, doi: 10.1080/09537287.2020.1810764.

Olabode, O.E., Boso, N., Hultman, M. and Leonidou, C.N. (2022), "Big data analytics capability and market performance: the roles of disruptive business models and competitive intensity", *Journal of Business Research*, Vol. 139, pp. 1218-1230, doi: 10.1016/j.jbusres.2021.10.042.

Park, S. and Gupta, S. (2012), "Handling endogenous regressors by joint estimation using copulas", *Marketing Science*, Vol. 31 No. 4, pp. 567-586, doi: 10.1287/mksc.1120.0718.

Parker, S.K. and Grote, G. (2022), "Automation, algorithms, and beyond: why work design matters more than ever in a digital world", *Applied Psychology*, Vol. 71 No. 4, pp. 1171-1204, doi: 10.1111/apps.12241.

Pasmore, W., Francis, C., Haldeman, J. and Shani, A. (1982), "Sociotechnical systems: a North American reflection on empirical studies of the seventies", *Human Relations*, Vol. 35 No. 12, pp. 1179-1204, doi: 10.1177/001872678203501207.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Porter, M.E. (1985), *Competitive Advantage Free*, Vol. 33, press, New York, p. 61.

Preacher, K.J., Rucker, D.D. and Hayes, A.F. (2007), "Addressing moderated mediation hypotheses: theory, methods, and prescriptions", *Multivariate Behavioral Research*, Vol. 42 No. 1, pp. 185-227, doi: 10.1080/00273170701341316.

Raj, A., Kumar, R.R., Narayanan, S., Kirca, A.H. and Jeyaraj, A. (2025), "Analytics capability, supply chain capabilities, and operational performance: a meta-analytic investigation", *Journal of Operations Management*, Vol. 71 No. 6, pp. 786-805, doi: 10.1002/joom.1376.

Richardson, H.A., Simmering, M.J. and Sturman, M.C. (2009), "A tale of three perspectives: examining post hoc statistical techniques for detection and correction of common method variance", *Organizational Research Methods*, Vol. 12 No. 4, pp. 762-800, doi: 10.1177/1094428109332834.

Roehrich, J., Schleper, M.C. and Lam, H.K. (2025), "Balancing continuity and change in operations and supply chain management research", *International Journal of Operations and Production Management*, Vol. 45 No. 12, pp. 1969-1988, doi: 10.1108/ijopm-12-2025-017.

Rohrer, J.M., Hünermund, P., Arslan, R.C. and Elson, M. (2022), "That's a lot to process! pitfalls of popular path models", *Advances in Methods and Practices in Psychological Science*, Vol. 5 No. 2, 25152459221095827, doi: 10.1177/25152459221095827.

Roy, D., Spiliotopoulou, E. and de Vries, J. (2022), "Restaurant analytics: emerging practice and research opportunities", *Production and Operations Management*, Vol. 31 No. 10, pp. 3687-3709, doi: 10.1111/poms.13809.

Ryu, E. (2015), "The role of centering for interaction of level 1 variables in multilevel structural equation models", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 22 No. 4, pp. 617-630, doi: 10.1080/10705511.2014.936491.

Sainam, P., Auh, S., Ettenson, R. and Sung Jung, Y. (2022), "How well does your company use analytics", *Harvard Business Review*, pp. 1-11.

Salem, M., Van Quaquebeke, N. and Besiou, M. (2022), "Aid worker adaptability in humanitarian operations: interplay of prosocial motivation and authoritarian leadership", *Production and Operations Management*, Vol. 31 No. 11, pp. 3982-4001, doi: 10.1111/poms.13798.

Seidel, S., Recker, J. and Brocke, J.V. (2013), "Sensemaking and sustainable practicing: functional affordances of information systems in green Transformations1", *MIS Quarterly*, Vol. 37 No. 4, pp. 1275-1300, doi: 10.25300/misq/2013/37.4.13.

Sims, H.P. Jr, Szilagyi, A.D. and Keller, R.T. (1976), "The measurement of job characteristics", *Academy of Management Journal*, Vol. 19 No. 2, pp. 195-212, doi: 10.2307/255772.

Song, J., Xiang, Y., Huang, B., Xie, Y. and Li, Y. (2023), "Exploring how big data analytics management capability fuel market performance: evidence from a mediated moderation model", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 9080-9093, doi: 10.1109/tem.2023.3312774.

Spector, P.E. (2006), "Method variance in organizational research: truth or urban legend?", *Organizational Research Methods*, Vol. 9 No. 2, pp. 221-232, doi: 10.1177/1094428105284955.

Stekelorum, R., Gupta, S., Laguir, I., Kumar, S. and Kumar, S. (2022), "Pouring cement down one of your oil wells: relationship between the supply chain disruption orientation and performance", *Production and Operations Management*, Vol. 31 No. 5, pp. 2084-2106, doi: 10.1111/poms.13708.

Sullivan, Y. and Wamba, S.F. (2024), "Artificial intelligence and adaptive response to market changes: a strategy to enhance firm performance and innovation", *Journal of Business Research*, Vol. 174, 114500, doi: 10.1016/j.jbusres.2024.114500.

Tong, X., Linderman, K. and Zhu, Q. (2023), "Managing a portfolio of environmental projects: focus, balance, and environmental management capabilities", *Journal of Operations Management*, Vol. 69 No. 1, pp. 127-158, doi: 10.1002/joom.1201.

Trist, E. and Bamforth, K. (1951), "Some social and psychological consequences of the long wall method of coal-getting", *Human Relations*, Vol. 1, pp. 3-38, doi: 10.1177/001872675100400101.

Tucker, A.L., Edmondson, A.C. and Spear, S. (2002), "When problem solving prevents organizational learning", *Journal of Organizational Change Management*, Vol. 15 No. 2, pp. 122-137, doi: 10.1108/09534810210423008.

Tumbas, S., Berente, N. and vom Brocke, J. (2017), "Three types of chief digital officers and the reasons organizations adopt the role", *MIS Quarterly Executive*, Vol. 16 No. 2, pp. 121-134.

Van Dun, D.H. and Kumar, M. (2023), "Social enablers of Industry 4.0 technology adoption: transformational leadership and emotional intelligence", *International Journal of Operations and Production Management*, Vol. 43 No. 13, pp. 152-182, doi: 10.1108/IJOPM-06-2022-0370.

Vidgen, R., Shaw, S. and Grant, D.B. (2017), "Management challenges in creating value from business analytics", *European Journal of Operational Research*, Vol. 261 No. 2, pp. 626-639, doi: 10.1016/j.ejor.2017.02.023.

Wamba, S.F., Dubey, R., Gunasekaran, A. and Akter, S. (2020), "The performance effects of big data analytics and supply chain ambidexterity: the moderating effect of environmental dynamism", *International Journal of Production Economics*, Vol. 222, 107498, doi: 10.1016/j.ijpe.2019.09.019.

Wang, Y., Kung, L., Wang, W.Y.C. and Cegielski, C.G. (2018), "An integrated big data analytics-enabled transformation model: application to health care", *Information and Management*, Vol. 55 No. 1, pp. 64-79, doi: 10.1016/j.im.2017.04.001.

Wu, L., Hitt, L. and Lou, B. (2020), "Data analytics, innovation, and firm productivity", *Management Science*, Vol. 66 No. 5, pp. 2017-2039, doi: 10.1287/mnsc.2018.3281.

Wu, D., Lin, X., Gupta, S. and Kar, A.K. (2024), "Big data analytics capability, dynamic capability, and firm performance: the moderating effect of IT–Business strategic alignment", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 11638-11651, doi: 10.1109/tem.2024.3429648.

Wu, L., Lou, B. and Hitt, L. (2019), "Data analytics supports decentralized innovation", *Management Science*, Vol. 65 No. 10, pp. 4863-4877.

Xue, L., Ray, G. and Sambamurthy, V. (2012), “Efficiency or innovation: how do industry environments moderate the effects of firms’ IT asset portfolios?”, *MIS Quarterly*, Vol. 36 No. 2, pp. 509-528, doi: 10.2307/41703465.

Yasmin, M., Tatoglu, E., Kilic, H.S., Zaim, S. and Delen, D. (2020), “Big data analytics capabilities and firm performance: an integrated MCDM approach”, *Journal of Business Research*, Vol. 114, pp. 1-15, doi: 10.1016/j.jbusres.2020.03.028.

Zhu, S., Dong, T. and Luo, X.R. (2021), “A longitudinal study of the actual value of big data and analytics: the role of industry environment”, *International Journal of Information Management*, Vol. 60, 102389, doi: 10.1016/j.ijinfomgt.2021.102389.

Zu, X., Fredendall, L.D. and Douglas, T.J. (2008), “The evolving theory of quality management: the role of six sigma”, *Journal of Operations Management*, Vol. 26 No. 5, pp. 630-650, doi: 10.1016/j.jom.2008.02.001.

**Corresponding author**
Bart Alex Lameijer can be contacted at: b.a.lameijer@uva.nl