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The Influence of Firm Characteristics on the Adoption of Data Analytics in Performance Management

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Dear Editors and Reviewers,

The authors would like to sincerely thank the editors and reviewers for allowing us to revise and resubmit our manuscript. We have carefully addressed the comment and revised our manuscript accordingly. The changes made, and responses to comments were summarized in this document. Our manuscript has greatly benefited from your detailed and constructive remarks.

We look forward to hearing from you soon.

Best regards,

The authors

15 Nov 2023

Responses to Reviewers' Comments

Thank you for your feedback. We appreciate your attention to the numbering of the theoretical framework and research hypotheses. We have ensured that the headings have been numbered correctly in the revised version. We have also taken note of your concerns regarding the length of the content. We have therefore reduced the information to a minimum and summarized it in tables. We now have 10436 words. By presenting the data in a condensed and visual format, we wanted to make it easier for readers to grasp the most important information efficiently. Thank you once again for your valuable suggestions. We have incorporated these improvements into the revised version of the manuscript.

Firm Characteristics and the Adoption of Data Analytics in Performance Management: A Critical Analysis of EU Enterprises

1. Introduction

In today's rapidly evolving business landscape, performance management is significant for managers striving to manage their workforce and achieve organizational goals effectively. With recent technological advancements, particularly in analytics and artificial intelligence applications, how people work and organizations operate has been transformed (Almazmomi et al., 2022; Patil and Mason, 2015; Yu et al., 2021). These technological innovations have opened new possibilities for leveraging data-driven tools, such as data analytics, to enhance decision-making processes, automate recruitment, evaluate performance, improve customer retention, and forecast sales (Barley, 2020; Sharma and Sharma, 2017).

While there is ample evidence supporting the potentially positive impact of data analytics (i.e., people data) for business (Dahlbom et al., 2019; Guenole et al., 2017; Kryscynski et al., 2018; Levenson, 2011), the extent to which organizations have adopted these technologies in practice remains unclear. Furthermore, academic research on the intersection of analytics and performance management has not received the same level of attention as other areas, such as marketing (Palos-Sánchez et al., 2022; Pan et al., 2022). This discrepancy is highlighted by Marler and Boudreau (2017), who identified a shortfall in empirical research examining the impact of analytics on the workforce. While a few studies (only four studies identified: Aral *et al.,* 2012; Falletta, 2014; Lawler *et al.,* 2004; Pape, 2016) have explored this relationship, many lack information about the internal validity, statistical significance, and generalizability of the findings, resulting in a primarily descriptive research landscape (Marler and Boudreau, 2017; Ransbotham et al., 2017; Tambe et al., 2019). Additionally, many research reports have emphasized the scarcity of rigorous quantitative and qualitative studies examining the consequences of data analytics in employee management (e.g., Giermindl et al., 2022; Greasley and Thomas, 2020; van den Heuvel and Bondarouk, 2017).

Within this context, it is intriguing that although analytics have been extensively researched in various business sectors, the academic exploration of analytics related to the performance management context remains relatively underdeveloped. This research gap presents an opportunity to delve deeper into the adoption of analytics in managing employee performance, considering the potential advantages offered by these technologies (Cascio and Montealegre, 2016; Kryscynski et al., 2018; Levenson, 2011; Meijerink et al., 2018; Müller et al., 2020; Pan et al., 2022). Furthermore, a good understanding of the factors influencing data analytics adoption in performance management can provide valuable insights for practitioners and scholars in the field.

The novelty of this study lies in its examination of the factors influencing the adoption of data analytics for monitoring employee performance within the context of performance management. Furthermore, what sets it apart is the utilization of a high-quality dataset generated by Eurofound, in conjunction with the guidance provided by the Technology-Organization-Environment (TOE) framework (Marler and Boudreau, 2017; Pan et al., 2022). This study aims to investigate the relationship between adopting data analytics and organizational characteristics by employing a quantitative research methodology grounded in the TOE framework. In other words, we also propose a novel TOE model with details on sub-criteria pertaining to technology adoption, which is applicable to data analytics in performance management but might also be applicable in the adoption of other technologies such as AI, robotic automation, augmented reality, and virtual reality. The research questions guiding this study include: What factors influence the adoption of data analytics in performance management? *How do organizational and environmental contexts shape the adoption patterns?* To answer these questions, the study will utilize up-to-date, large-scale, cross-national, and cross-sectoral datasets on the usage of data analytics to monitor employee performance in all member states of the European Union (EU). Also, this study will provide both theoretical and practical implications and offer valuable insights in five areas, namely structural alignment, strategic decision-making, resource allocation, performance improvement, and change management.

The main findings of this study indicate that the utilization of data analytics in managing employee performance is relatively low, with only a minority of organizations incorporating performance analytics into their practices. The adoption of data analytics varies across different countries and industries, with countries following liberal market economy systems showing higher adoption rates. The study also highlights the significant role of organizational and environmental factors in shaping adoption patterns. These findings contribute to the existing literature by shedding light on the factors that affect the adoption of data analytics in performance management and emphasize the importance of internal organizational and market-related factors in driving adoption decisions.

In Section 2, we provide an overview of data analytics in performance management and evaluate definitions of performance analytics, the dependent variable in our study. We review the Technology-Organization-Environment (TOE) theory and Rogers' (2003) IDP theory in technology adoption, selecting the most suitable theory. This section presents hypotheses derived from our analysis. Moving to Section 3, we describe the data sources and methods used to test hypotheses, explaining specific data sources and analytical techniques. Section 4 presents and discusses detailed results, including statistical findings and their implications. In Section 5, we discuss obtained results, explore implications, and engage in comprehensive analysis. Section 6 explores theoretical and practical implications, shedding light on broader significance and potential applications. In Section 7, we conclude by highlighting practical and policy implications, discussing benefits of using data analytics to monitor employee performance and addressing challenges organizations may face. Finally, in Section 8, we provide recommendations for future research, identifying areas requiring further investigation and suggesting potential avenues for exploration.

2. Theoretical framework and research hypotheses

Data analytics research has experienced remarkable growth, particularly in people analytics (Giermindl et al., 2022; Qamar and Samad, 2022). However, it is worth noting that the existing literature primarily consists of systematic literature reviews, indicating that the understanding of analytics is still at an early stage (Angrave et al., 2016; Huselid, 2018; Marler and Boudreau, 2017; Margherita, 2022; Minbaeva, 2018; Qamar and Samad, 2022). Most studies focus on the positive implications of analytics for organizational success (e.g., Koohang *et al.,* 2023; McIver et al., 2018; Simón and Ferreiro, 2018), as well as its definition and operational mechanisms (Falletta and Combs, 2020). Additionally, research explores the implementation strategies (Boudreau and Cascio, 2017; Fernandez and Gallardo-Gallardo, 2020) and the value proposition it offers (McCartney and Fu, 2022; Tursunbayeva et al., 2018; Van den Heuvel and Bondarouk, 2017) with a limited number of high-profile case studies (e.g., Google's Project Oxygen, Jetblue, Sysco) (Qamar and Samad, 2022).

For example, Hoffman et al. (2017) conducted a study examining the performance outcomes of employees selected through data analytics-based computer recommendations compared to those chosen solely by managers. The findings revealed that employees selected against the computer's recommendations performed poorly. This suggests that when managers override analytics-based recommendations, it is likely due to bias or error rather than possessing superior private information. These results underscore the value of data-driven decision-making in recruitment processes, highlighting the importance of organizations relying on analytics to support and enhance managerial judgments.

Koohang et al. (2023) investigate the relationships between eight constructs and explore the impact of data analytics in leadership on organizational performance. The study collected data through 188 surveys administered to employees from various organizations in the USA. The findings reveal that data analytics in leadership significantly and positively influences talent performance, which, in turn, impacts security, privacy, and innovation. Additionally, the study demonstrates that innovation significantly and positively impacts a firm's financial performance, market performance, and customer satisfaction. The results emphasize the importance of data management and the adoption of data analytics.

In another study, Wang and Cotton (2018) utilized over 100 years of baseball data to demonstrate a positive correlation between team performance and players' social ties. Drawing on network closure theory and differentiated workforce theory, the authors suggested that companies should form teams based on employees' capabilities, fostering close collaboration and strong relationships, ultimately leading to improved organizational performance. This finding emphasizes the potential of data analytics in optimizing team dynamics and enhancing overall effectiveness.

Moreover, it is essential to remember that performance analytics is a subset of business analytics that uses various methods to analyze data and information about performance-related matters. As a part of the broader field of business analytics, it is a set of techniques that facilitate improved decision-making by providing insights derived from data and information (Camm *et al.,* 2014). Specifically, in terms of the application in organizational performance, business analytics involves collecting, analyzing, and interpreting workforce data to inform decision-making and optimize performance (Bassi, 2011). Leveraging technologies and data science, performance analytics seeks to gain insights into workforce dynamics and optimize human resources practices and processes (Kelleher *et al.,* 2015).

After reviewing various definitions (Table I), this study relies on Bassi's (2011) definition as its foundation for several reasons. Bassi's definition highlights the evidence-based nature of performance analytics. It emphasizes that decisions made using performance analysis are based on empirical data and analysis rather than the subjective opinions of management. This approach improves decision-making processes by ensuring that they are based on objective information. In addition, this definition recognizes the wide range of tools and technologies that performance analysis encompasses. It highlights its versatility in using different methods, from simple reports on employee performance metrics to more advanced techniques such as predictive modelling. This recognition allows for a comprehensive examination of the various approaches and their potential impact on decision-making.

[Insert Table I: Examples of commonly used definitions in the field of business]

2.1 Theoretical backgrounds: Technology adoption perspective

In understanding why some organizations adopt performance analytics while others do not, selecting the most appropriate theoretical framework to support the hypotheses is essential. To achieve this, the following section will explore several relevant theoretical frameworks, i.e., the Technology Acceptance Model (TAM) (Davis, 1989), Rogers' Innovation Decision Process (IDP) (Rogers, 1962), and the Technology-Organization-Environment (TOE) framework by Tornatzky *et al.* (1990). By examining these different frameworks, we can comprehensively understand the contexts that influence decisions around adopting data analytics. Once we have evaluated these frameworks, we will rely on the one best suited to our research question and objectives, ensuring a clear focus and rigorous analysis.

A theoretical model for adopting performance analytics must consider the contextual factors influencing the propensity to adopt and implement the technology innovation. These contextual factors are rooted in the specific beliefs held by managers within an organization. In this context, the TAM suggests that the acceptance and usage of new technology (i.e., data analytics) are influenced by two key factors: perceived usefulness and perceived ease of use (Singh, 2005). Perceived usefulness refers to how much a manager believes technology will improve their job performance. This perception is based on the user's beliefs about the potential benefits of the new technology. For example, managers may perceive data analytics as helpful in providing more objective and data-driven feedback on their workforce performance instead of relying on subjective evaluations from traditional management tools. While the perceived ease of use refers to the degree to which a manager believes the data analytics tool is easy to use. In other words, this perception is based on the manager's beliefs about the technology's simplicity, intuitiveness, and ease of learning (Ku, 2009; Singh, 2005).

Another framework worth evaluating in the later section is the TOE framework. It is widely used as a theoretical foundation in the field of management (Bradford *et al.,* 2014), finance (Kulkarni and Patil, 2020) and information systems research (Kuan and Chau, 2001; Wu and Chen, 2014). The framework was first proposed by Tornatzky and Fleischer in 1990 as a way of understanding the contexts that influence the adoption and implementation of new technology in organizations. It suggests that technology adoption depends not only on the characteristics of the technology itself but also on the characteristics of the organization and its environment (Baker, 2012; Tornatzky *et al.,* 1990).

The TOE framework consists of three primary contexts. The first is the technology, which includes the characteristics of the new technology, such as its complexity, compatibility with existing systems, the relative advantage over other technologies, and trialability (i.e., the ability to test the technology before fully committing to it) (Al-Sharhan *et al.,* 2018). This is relevant to data analytics, as it involves the characteristics of the technology used to collect, store, and analyze data from employees' performance (Lu, 2015; Wastell and McMaster, 2008). For instance, the complexity and compatibility of the data analytics software with the organization's existing systems can affect its adoption and implementation. The trialability of the analytics software can also be necessary, as it allows organizations to test its usefulness and effectiveness before fully committing to it.

The organization: This idea includes the organization's characteristics that may affect technology adoption, such as the size, structure, culture, resources, and strategic goals. Organizational contexts can either facilitate or hinder the adoption of new technologies, depending on how well they match the characteristics of the technology (Lu, 2015; Wastell and McMaster, 2008). For example, the size and structure of the organization may affect the ability to capture and analyze data analytics (e.g., benefiting larger organizations due to economy of scale). In contrast, the organization's culture and resources can impact its willingness and ability to invest in data analytics.

The environment: This component includes the external contexts influencing technology adoption, such as industry trends, market competition, and regulatory requirements (Al-Sharhan *et al.,* 2018). These contexts can create opportunities or barriers to adopting new technology, depending on how well they align with the characteristics of the technology and the organization (Lu, 2015; Wastell and McMaster, 2008). For instance, industry trends and competition can create pressure and "force" organizations to adopt employee performance analytics to remain competitive. Regulatory requirements and legal considerations can also affect the adoption and implementation of the analytics.

Another widely adopted framework is Rogers' IDP, which provides a framework for understanding the stages managers go through when adopting a new technology (i.e., data analytics); it can be used to further deepen our understanding of adopting data analytics in organizations. In adopting data analytics to manage employee performance, this framework might involve the following stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003; Michelini, 2012). For example, a manager may become aware of the data analytics tool through training or communication from other colleagues, become interested in how it could improve their performance, evaluate the tool through trial and error, and ultimately adopt it if they find it useful and effective. In other words, it is a theoretical framework that emphasizes and explains how individuals adopt any innovation. It consists of five phases: i) Knowledge: the organization becomes aware of the innovation (i.e., data analytics) and learns about it. ii)Persuasion: the organization forms an attitude toward the innovation based on its perceived advantages and disadvantages. iii) Decision: the organization makes the decision to accept or reject the innovation. iv) Implementation: the organization begins to use the innovation to varying degrees, depending on their level of engagement. v) Confirmation: the organization evaluates the results of the innovation and decides whether to continue using it.

It is important to note that the whole process might be influenced by several contexts (e.g., the characteristics of the innovation itself, the management style of the individual, and the social system in which the innovation is introduced) (Huang et al., 2003; Marangunic and Granic, 2015; Kamal et al., 2020).

2.2 Comparison of TAM, TOE, and IDP

Adopting data analytics to manage employee performance is a complex process involving multiple contexts. Under this situation, the TAM and IDP provide valuable insights into individual-level contexts influencing technology adoption. However, after comparing these three frameworks, we believe that the TOE framework offers a more comprehensive and nuanced approach to understanding the adoption of data analytics for performance management (see Table II).

[Insert Table II: Framework comparison for the adoption of performance analytics]

Firstly, the TAM model and the IDP offer valuable insights into technology adoption; it captures how individuals think, decide, and process such logic of technology adoption. However, the two models fail to consider other contexts (i.e., organizational and environmental contexts) that can impact the adoption of data analytics. For instance, managers may be willing to adopt data analytics if they perceive it to be useful and easy to use, as per the TAM model. Still, the adoption may not be successful if the organization lacks the necessary infrastructure or resources to support the tool. Similarly, Rogers' IDP can explain an individual's decision-making process in adopting new technology but fails to capture the organizational contexts that can impact the adoption process.

The TOE framework, on the other hand, takes a more comprehensive approach by considering the interplay between technology, organizational, and environmental contexts. In terms of adopting data analytics for performance management, this framework could consider the availability of data infrastructure, the organization structure, and the regulatory environment around data privacy and security of each country. By considering these broader contexts, the TOE framework provides a more realistic and practical approach to understanding organizational characteristics influencing data analytics adoption. Furthermore, the TOE framework recognizes that the adoption of new technology is not a one-time event, but rather an ongoing process that is influenced by a variety of internal and external contexts (Codara and Sgobbi, 2023; Cruz-Jesus *et al.,* 2019). This is important when considering data analytics adoption, as organizations may need to continually update their technology and processes to keep up with changing data needs and trends. Organizations may also face different challenges and opportunities depending on their unique context.

In addition, by relying on TOE, this study can take full advantage of the ECS dataset, which captures many variables that are related to internal organizational (i.e., variable-pay systems, ownership structure, and company size) and environmental contexts (i.e., market competitiveness).

Based on this evaluation process, we posit that companies' adoption of data analytics to monitor employee performance can be better explained by TOE. Three primary contexts influence this. Firstly, the presence of an organizational environment that is equipped with the requisite structural and managerial capacity, such as expertise or knowledge among managers, is crucial in utilizing the data and methods required (Angrave *et al.,* 2016; Huselid *et al.,* 1997; Thompson and Heron, 2005). Secondly, the availability of opportunities, such as regulatory frameworks and managerial prerogatives that permit companies to collect, store, and analyze data, is also essential. Finally, given that the implementation of data analytics is associated with considerable costs, companies must also be motivated to engage in this practice, which may be driven by market forces or pressures (Levenson, 2018). Therefore, by examining and understanding what company characteristics influence the adoption of data analytics, we could deepen our understanding of the TOE concept and answer why some companies use business analytics to monitor employee performance while others do not.

2.3 The determinants of the use of analytics

Figure 1 illustrates the influence of the various hypotheses on the adoption of performance analytics in organizations. The subsequent section details further insights into the development of these hypotheses and their implications for performance analytics adoption. Due to the design of the ECS, this study will concentrate on the remaining two contexts, namely the organizational context and the environmental context. The organizational contexts hypotheses highlight how the variable-pay that is based on the result (H1a), individual performance (H1b), complex company processes (H2), and ownership changes (H3a) might influence the adoption of performance analytics. Additionally, the hypotheses suggest that the organization's size (H4) and age (H5) also play a role in determining the adoption of performance analytics. While the environmental contexts hypotheses focus on the influence of the economic environment, with (H6) indicating that companies located in coordinated market economies (CMEs) may have a lower incidence of using performance analytics compared to companies in liberal market economies (LMEs). Furthermore, (H7) suggests that companies embedded in competitive markets are more likely to adopt performance analytics. Ultimately, the adoption of performance analytics is expected to positively increase the efficiency of performance management and decision-making within organizations (Falletta and Combs, 2020; Marler and Boudreau, 2017; Van den Heuvel and Bondarouk, 2017).

[Insert Figure 1: Organization-Environment model of performance analytics adoption]

Research hypothesis

2.4 Organizational contexts

Variable-pay

Implementing certain managerial strategies can significantly impact the adoption of data analytics within an organization. Specifically, we posit that managers are more inclined to utilize data analytics when a company's variable-pay structure is tied to individual performance or results-based. This preference arises from the understanding that data analytics can provide valuable insights, enabling managers to enhance the accuracy of performance evaluations and foster a greater sense of employee fairness. Numerous studies have demonstrated the positive effects of business practices, such as individual variable-pay systems, on employee performance (Cable and Judge, 1994; Cadsby et al., 2007; Trank et al., 2002) and retention (Harrison et al., 1996; Nyberg, 2010; Salamin and Hom, 2005; Shaw et al., 2009). For instance, Lazear (2000) found that workforce productivity increased by 44% when organizations shifted from fixed salaries to individual variable-pay. Therefore, it would be reasonable to assume that data analytics would be a valuable tool to ensure an appropriate performance appraisal plan for organizations.

Data analytics plays a crucial role in measuring and assessing performance for different types of variable-pay (Tafkov, 2013). When variable-pay is based on result success, data analytics allows managers to gather insights into key performance indicators (KPIs) that drive employee success. By tracking and analyzing data related to production, sales, revenue, profitability, and customer satisfaction, managers can make informed decisions, identify areas for improvement, and align goals with company objectives.

Similarly, for variable-pay based on individual performance, data analytics enhances the accuracy and fairness of performance evaluations. By analyzing quantitative and qualitative data on productivity, quality of work, customer feedback, and project outcomes, managers can make objective assessments, identify high performers, and reward them accordingly. Data analytics also helps identify performance gaps, coaching opportunities, and areas for training and development.

In the case of variable-pay based on team performance, data analytics provides valuable insights into team dynamics and collaboration. Analyzing team-level data, such as project milestones, productivity, and communication patterns, allows managers to identify high-performing teams, areas of synergy, and potential bottlenecks. Data analytics also helps recognize individual contributions within the team context and ensures fair reward allocation based on measurable team outcomes.

Furthermore, when variable-pay is tied to company performance, data analytics is instrumental in measuring and assessing overall organizational achievements. Managers gain insights into factors influencing company performance by leveraging data analytics tools to track and analyze company-wide metrics, financial indicators, market trends, and competition. This data-driven approach enables data-informed decision-making and aligns variable-pay incentives with the organization's overall success. Therefore, we hypothesize that:

Hypothesis:

H1a: The incidence of adopting performance analytics would be higher when organizations have a high proportion of variable-pay measured on the basis of result success (e.g., piece rates, brokerages, or commissions).

H1b: The incidence of adopting performance analytics would be higher when organizations have a high proportion of variable-pay measured on the basis of individual performance.

H1c: The incidence of adopting performance analytics would be higher when organizations have a high proportion of variable-pay measured on the basis of team performance.

H1d: The incidence of adopting performance analytics would be higher when organizations have a high proportion of variable-pay measured on the basis of company performance.

<u>Complexity practice</u>

Another management practice worth mentioning is the idea of complex processes in organizations (e.g., the number of variable-pay systems, training needs assessment, hierarchical structures within organizations, the number of managers, complex coordination between (groups of) employees, and the frequency of implementing various monetary rewards across departments). When an organization has several or more of these complex processes, business practices such as the use of data analytics are thought to be of greater benefit (Batt, 1999; Hauff *et al.,* 2014; Gooderham *et al.,* 2015; Margherita, 2022; Minbaeva, 2018; Parry, 2011; Qamar and Samad, 2022).

It is essential to recognize that companies operating in different environments require different combinations of practices and processes to effectively sustain their day-to-day operations. Relying solely on a fixed set of practices without considering the ever-changing business environment, including political, economic, and legal factors, can pose company risks (Zinecker *et al.,* 2022). Organizations need to incorporate different business practices that adapt to these changing conditions to effectively manage their workforce. Therefore, when business practices and processes become increasingly complex, managers are more likely to utilize business-related technologies such as data analytics to effectively manage their workforce.

Further studies conducted by Maduenyi et al. (2015) and Nahm et al. (2003) have also found a correlation between organizational effectiveness and various structural dimensions. These dimensions include the number of hierarchical levels, the degree of horizontal integration, the locus of decision-making, the type of formalization, and the level of communication (i.e., the complexity of the organization processes). The results indicate that the number of hierarchical levels, the degree of horizontal integration, and the type of formalization directly and significantly influence the locus of decision-making in organizations.

Hypothesis:

H2a: The incidence of performance analytics is higher when a company has more complex variable-pay systems processes.

H2b: The incidence of performance analytics is higher when a company has a more complex employee training structure.

H2c: The incidence of performance analytics is higher when a company has more complex hierarchical structures.

H2d: The incidence of performance analytics is higher when a company has a high proportion of managers.

H2e: The incidence of performance analytics is higher when an employee is working at least in a team.

H2f: The more frequently the company uses monetary rewards in managing employees, the more it needs to use performance analytics.

<u>Ownership and management</u>
Changes in ownership, whether accompanied by changes in management or not, have significant implications for a company's operations and practices. When ownership changes, it often presents an opportunity for strategic realignment and restructuring, fostering the emergence of new ideas (Thompson and Wright, 1995). One such idea that can be explored is the adoption of data analytics for performance evaluations. This potential for value creation through ownership change is particularly prominent in less developed industries, where managers may have more autonomy to implement innovations that were previously unfeasible (Wright et al., 2000; Wright et al., 2001).

Furthermore, research suggests that when ownership changes, management tends to provide employees with increased opportunities, foster better relationships based on trust, and establish improved incentive plans (Bruining et al., 2005; EVCA, 2001; Wright et al., 1992). A change in ownership may also introduce a new business strategy that necessitates changes in business policies. To address the uncertainty associated with the transition, additional investments in tools such as data analytics may be required to build trust between employees and the new owner (Bruining et al., 2005). Consequently, it can be assumed that changes in ownership and management increase the likelihood of implementing new technologies, including data analytics, within the organization.

Moreover, the relationship between employees and management plays a crucial role in the adoption of technology. When there is trust, open communication, and collaboration between employees and management, it creates an environment conducive to the adoption and utilization of data analytics for performance evaluations (Ramos and Castro, 2017). Therefore, fostering a positive employee-management relationship is vital for successful technology adoption and utilization. Consequently, we hypothesize that:

Hypothesis:

H3a: The incidence of performance analytics is higher when companies experience a change in ownership and management.

H3b: The incidence of performance analytics is higher when companies experience a change in ownership, but management remains the same.

H3c: The incidence of performance analytics is higher when the relationship between employees and management is positive.

<u>Company size</u>
Additionally, organizational contexts play an important role in evaluating the use of data analytics. In particular, we believe that structural characteristics of companies, (e.g., size). For example, the number of employees in a company would be one of the contexts influencing the use of different business practices (Florkowski and Olivas-Luján, 2006; Hausdorf and Duncan, 2004). Therefore, it would be reasonable to assume that the size of a company also matters for the use of data analytics. Larger companies may be more inclined to adopt data analytics because larger companies tend to have a more standardized process to collect and analyze data, benefiting from greater bargaining power and economies of scale (Gao *et al.,* 2023; Hirsche, 2016; Pan *et al.,* 2022), while smaller companies may be less equipped with the structural processes to collect and analyze data. It might largely rely on personnel in the sense that data managers are aware of all employee matters (e.g., performance level and work attitude).

Hypothesis:

H4: The smaller a company, the lower the incidence of using performance analytics.

<u>Company age</u>
Next is the idea of company age (i.e., years since its establishment). We believe that the "age" of a company is one of the determinants of why and how certain business practices are used within an organization (Benders *et al.,* 2006; DiMaggio and Powell, 1983; Pan *et al.,* 2022; Scott, 2001). Generally, the longer a company has been in business, the less likely it is to adopt new business practices and tools (i.e., new technology). This is because older companies have a long history and strong traditions already embedded in organizational structures and practices (Kok *et al.,* 2003; Wager, 1998), resulting in a higher resistance rate to new tools than newly established companies. Management might

also consider new business practices that would affect and compromise the current structure and responsibilities of the organization (Haller and Siedschlag, 2008)

Hypothesis:

H5: The younger a company, the higher the incidence of performance analytics.

2.5 Environmental contexts

Legal and political contexts

From an institutional perspective, legal and policy elements may also play an essential role in explaining differences in the use of business analytics across countries (e.g., DeFidelto and Slater, 2001; Goergen *et al.,* 2013). Different countries may have different regulations and policies to protect the analysis and sharing of employee data, which explains differences in the prevalence of data analytics in various countries. For example, many Central and Eastern European Countries (CEECs), including the United Kingdom, have a liberal approach, meaning managers often have more prerogatives in business practices. This ideology of strictness in data protection and privacy regulations across countries is mainly consistent with the classification of capitalist varieties (VoC) developed by Hall and Soskice in 2001 (Hall and Soskice 2001).

Furthermore, the idea of VoC also plays a role concerning data privacy, data collection, and storage regulations (Rothstein *et al.,* 2019). For instance, countries like the Netherlands, Germany, and Belgium would be categorized as coordinated market economies (CMEs), where stricter data protection regulations apply. Liberal market economies (LMEs) such as the United Kingdom, Ireland, and Malta take a more relaxed approach to data privacy, collection, and retention. Therefore, we hypothesize that:

Hypothesis:

H6: The incidence of the usage of performance analytics is lower in companies located in CMEs than in companies that are in SMEs and LMEs.

Market competitiveness

To motivate organizations to adopt a new data analytics tool, it is imperative to establish the necessity for such practices. One effective approach is to consider market competitiveness as a catalyst for management to incorporate data analytics into their operations (Levenson, 2018). Market competitiveness can be defined as the total number of suppliers or retailers in the same market competing to provide comparable goods and services to consumers (Hansen and Mowen, 2014). If a company perceives a need to utilize data analytics to manage its workforce efficiently, and thereby attain a competitive edge over its rivals, it is more likely to adopt data analytics. Therefore, we hypothesize that:

Hypothesis:

H7: There will be a higher incidence of performance analytics when a firm is embedded in a competitive market.

3. Research methodology

The data in this study comes from the 2019 European Company Survey (ECS), which covers 28 European countries with 21,869 company cases, including business practices, skills utilization, skills strategies, and organizational structure. The categorization of organizational size is based on three distinct groups: small establishments with 10–49 employees, medium-sized establishments with 50–249 employees, and large establishments with 250 workers or more. Micro-establishments, which have fewer than 10 employees, were not included in the survey. The sample primarily consists of small establishments, accounting for 83% of the total. The data set further classifies economic operation into six broad categories: industry (22%), construction (10%), commerce and hospitality (31%), transport (6%), financial services (4%), and other services (28%). Moreover, because the survey includes only establishments with 10 employees or more, it does not include many establishments that started operating recently (See Table III).

[Insert Table III: Data source summary]

Furthermore, the utilization of a five-model analysis in this study serves multiple purposes. Firstly, it allows for a systematic exploration of the relationship between the adoption of data analytics and employee performance by gradually introducing additional independent variables. This progressive approach provides a comprehensive framework for evaluating the complex dynamics at play and enables the identification of both basic relationships and more nuanced effects and interactions among variables.

The use of multiple models also enhances the robustness of the analysis. By comparing the results across different models, researchers can assess the consistency and stability of the findings. This approach helps to mitigate potential biases or confounding factors and provides a more reliable basis for drawing conclusions and making inferences.

The selection of Model 3 as the primary model for drawing conclusions and making inferences is based on its significance and relevance to the research questions at hand. Model 3 is likely to represent a balanced combination of explanatory power and parsimony, capturing the essential factors influencing the adoption of data analytics in performance management. By focusing on Model 3, this study can provide a clear and concise understanding of the relationships under investigation without overwhelming the analysis with unnecessary complexity.

For the dependent variable, question 23 has been selected. Specifically, it asked: "Does this establishment use data analytics to monitor employee performance?" and participants will have the option to respond with either "Yes" or "No." In this context, "data analytics" can encompass any of the three types: descriptive, predictive, and prescriptive analytics. Therefore, if the participant's organization utilizes any of these three types of data analytics for monitoring employee performance, they would indicate "Yes" for the question. Moreover, a list of independent variable questions is attached in Appendix 2.

3.1 Modelling strategy

As the dependent variable is dichotomous, it should reflect the predicted probabilities at "0" and "1". If a company is marked as "0", it is not using performance analytics to monitor employee performance. In contrast, if a company is marked as "1, " it uses performance analytics to monitor employee performance. Therefore, the author decided to use a logit specification in the analysis. A summary table of the measurement scales of the dependent and independent variables is present below (see Table IV).

[Insert Table IV: Measurement Scales of Variables]

To test the hypotheses, it estimates the influence of each independent variable, adjusted for other variables. Furthermore, due to the ECS response being gathered from 28 EU countries, it cannot be assumed that the errors can be distributed independently. Since the dependent variable is a dichotomy, the effect should reflect the predicted probability (bounded by 0 and 1). Therefore, it appreciates a multi-level (logit) model that contains country-specific random sections, the estimate of a *multilevel logistic model* which includes a country-specific random intercept that follows the form of:

$$\ln (p/1\text{-}\ p) = \gamma 00 + \gamma 10 X1ij \ldots + \gamma k0 Xkij + \gamma 01 W1j \ldots + \gamma 0k Wkj + u0j$$

Where p is the probability that companies use performance analytics; $\gamma 00$ is the conditional grand mean; $\gamma 10,\ldots,k0$ is the set of coefficients that consider company-level variables $X1ij,\ldots,Xkij$; while $\gamma 01,\ldots,\gamma 0k$ is the set of coefficients that consider a wider range of variables, for example, at a macro-level $W1j,\ldots,Wkj$. The coefficients can be evaluated as linear effects on the "log-odds" of using performance analytics. $u0j$ represents the country-specific error for which the variance $\sigma u02$ is estimated, and is assumed to be zero-mean normally distributed. The company-level variance is implied by the binomial distribution. Moreover, based on the data set provided by the ECS, we noticed that ECS uses a stratified sample based on company size and industry, creating unequal probabilities of sample inclusion according to the value of these variables. We solve this problem by including sector and size as covariates in all estimated models to ensure that the errors are conditionally independent.

4. Results

The findings of this study provide valuable insights into adopting data analytics for managing employees' performance in companies. The results indicate that using data analytics in performance management is not widely prevalent, with only 32% of the surveyed companies adopting this approach. Out of the 21,869 sample companies, 20,047 provided answers to this question. Among them, 6,499 (32%) companies employed performance analytics, while 13,548 (68%) did not.

Interestingly, a distinct pattern emerged when examining data analytics adoption across the 28 European Union (EU) countries. Countries following the liberal market economy (LME) systems were more likely to adopt data analytics than countries following the coordinated market economy (CME) systems. Notably, countries such as Romania (53%), Croatia (50%), and Spain (47%) exhibited relatively high percentages of companies using data analytics for performance management, while Germany (14%), Sweden (18%), Denmark (25%), and Finland (39%) showed lower adoption rates (See Figure 2).

The results also shed light on the industries where data analytics is more prevalent. The study found that the finance (38%), manufacturing (37%), and mining and quarrying (35%) sectors had relatively high usage rates of data analytics for performance management. On the other hand, the real estate (17%), art, entertainment, and recreation (16%), and construction (22%) sectors had lower adoption rates.

[Insert Figure 2: The use of Performance Analytics by Country]

The findings from the literature on the relationship between variable-pay systems and the adoption rate of technology in business reveal some interesting insights. According to the results presented in (Table V), there is a high significance level between organizations using the results-based pay method and data analytics. This suggests that companies offering results-based pay can easily evaluate employee performance, making them more inclined to adopt data analytics. The ability to measure and track employee performance in real-time provides managers with valuable insights for identifying areas of improvement and driving business results.

Surprisingly, the results for "pay linked to individual performance" do not show a strong significant correlation with the adoption of technology. Several factors may influence this relationship, such as the complexity of the organization, the nature of the work performed, and the availability of resources for investing in analytics.

Analyzing the various models, it can be observed that models 1, 2, 3, and 4 demonstrate some levels of significance between "pay linked to individual performance" and the use of data analytics. However, it is essential to consider contextual factors influencing this relationship. The adoption of data analytics may be driven by reasons beyond the variable-pay system, such as the organization's complexity, work dynamics, and resource availability.

Furthermore, the analysis indicates that there is no conclusive evidence supporting the idea that variable-pay based on team or company performance measurements significantly influences the adoption of analytics. This outcome can be attributed to the emphasis on collaborative efforts rather than individual contributions in team and company performance measurements, which may minimize the perceived benefits of adopting performance analytics.

[Insert Table V: Types of variable-pay system]

The findings related to the complexity dimension (H2a) indicate that the number of hierarchy levels in organizations influences the adoption of data analytics. Hierarchical levels 2, 3, 4, and 5 show significant coefficients, with higher coefficients associated with higher hierarchical levels. For example, the coefficient for level 2 is 0.396, level 3 is 0.630, level 4 is 0.845, and level 5 is 0.836, all with a p-value < 0.001. This suggests that as the hierarchical level increases, the adoption and effective use of analytics also increase.

Regarding the relationship between teamwork and the adoption of data analytics, the results indicate that employees working in more than one team have a higher adoption rate. The coefficient for this relationship is 0.541, with a p-value < 0.001, compared to employees who do not work in a team (model 3). This suggests that teamwork facilitates the adoption of data analytics, possibly due to enhanced collaboration and information sharing among team members.

The results also support the hypothesis that training complexity is positively associated with adopting data analytics. The coefficient values increase with each additional training level, indicating a stronger association. For example, the coefficients for training complexity levels "less than 20%," "20% to 39%," "40% to 59%," "60% to 79%," and "80% or more" are 0.301, 0.329, 0.518, 0.809, respectively, for Model 4 (p < 0.001). This finding suggests that organizations and departments that require complex training routines are more likely to adopt data analytics. Integrating data analytics into routine training enhances the understanding and utilization of data-driven insights.

However, there is no correlation between the number of managers and the adoption of data analytics (H2d). It is important to note that the estimates for the levels of "40% to 59%," "60% to 79%," and "80% to 100%" should be interpreted with caution due to the relatively small number of observations in these categories.

Regarding the complexity of the influence of variable-pay systems on adopting data analytics, the results suggest that companies using multiple variable-pay systems are more likely to incorporate data analytics in performance management. This pattern holds true across all five models and becomes stronger with each additional system. For example, in Model 3, the coefficients associated with companies employing two variable-pay systems, three variable-pay systems, and four variable-pay systems are 0.140 (p-value < 0.05), 0.310, and 0.413 (p-value < 0.001), respectively. This indicates that each additional level of variable-pay systems is crucial for effectively using data analytics.

[Insert Table VI: Reward frequency offered by an organization]

The findings related to the frequency of use of monetary rewards (H2b) indicate a positive association with the adoption of data analytics. In Model 3, the coefficient values for companies that use monetary rewards "very often," "fairly often," and "not very often" are 0.571, 0.403, and 0.208, respectively, with p-values < 0.001 compared to companies that never use performance analytics. These results suggest that the frequency of using monetary rewards positively influences the adoption of data analytics.

Regarding business ownership structure (H3a), the results indicate that there is a high level of significance when companies experience a "change in ownership" and a "change in management" (0.255, $p < 0.001$). However, there is no evidence to suggest that the level of data analytics adoption is higher when the company's ownership changes while the management remains the same (H3b). This suggests that management change is a more significant determinant of the increase in data analytics adoption. When management changes, employees are more likely to receive better incentives, training, and development plans, which can contribute to the adoption of data analytics (Bruining et al., 2005; EVCA, 2001; Wright et al., 1992).

Furthermore, the analysis results reveal that a positive relationship between employees and management (H3c) does not have a significant influence on the adoption of performance analytics. Because the positive relationship between employees and management does not directly impact the strategic decision-making process but rather focuses on business objectives.

[Insert Table VII: The number of people working in the organization]

The results support the hypothesis that larger companies are more likely to adopt performance analytics (H4). In Model 3, the coefficient for the largest companies is 0.554 ($p < 0.001$), while for companies with 20 to 49 employees, the coefficient is 0.0562 ($p > 0.05$). This trend is consistent across all five models, with significant coefficient values being higher for companies with more than 500 employees.

The findings also support the hypothesis that older companies are more hesitant to adopt performance analytics (H5). Although the effect size is still significant, its magnitude is relatively small. In each model, the coefficients associated with the age of the company are negative but close to zero: (model 1 = -0.0016, $p < 0.01$), (model 2 = -0.0013, $p < 0.05$), (model 3 = -0.0013, $p < 0.05$), (model 4 = -0.0013, $p < 0.05$), and (model 5 = -0.0015, $p < 0.01$). These results suggest that older companies tend to adopt performance analytics at a slightly lower rate than younger companies.

Regarding country contexts (H6), the results suggest that the institutional context, particularly the legal-political system, plays a role in the adoption of data analytics. Countries following the Liberal Market Economy (LME) systems are more likely to adopt data analytics than those following Coordinated Market Economy (CME) systems. However, the pattern does not hold when compared with Social Market Economy (SME) systems. The results indicate a coefficient value of 0.399 ($p < 0.05$) for LME systems, suggesting a higher likelihood of data analytics adoption in these contexts. This finding highlights the influence of the institutional environment on organizational practices and the adoption of data analytics.

Furthermore, the results support the hypothesis that the degree of competition in which companies are embedded influences the adoption of data analytics (H7). Companies operating in "very competitive" and "fairly competitive" markets are more likely to adopt performance analytics compared to those operating in "not very competitive" and "not at all competitive" markets. The specific coefficient values and p-values associated with these market conditions suggest that higher levels of competition drive the adoption of performance analytics as organizations seek to gain a competitive edge and make data-driven decisions.

Overall, this study offers valuable insights into using data analytics for managing employee performance within companies. The findings reveal that a mere 32% of the surveyed companies employ data analytics in performance management. The adoption of data analytics is not uniform across all countries and industries, with higher adoption rates observed in countries with liberal market economy systems and in industries such as finance, manufacturing, mining and quarrying.

The analysis also uncovers that the type of variable-pay can impact the adoption of data analytics. Furthermore, the study identifies a positive correlation between the adoption of data analytics and factors such as organizational complexity, teamwork level, and training complexity. Larger companies and those that have undergone changes in ownership or management are more inclined to adopt data analytics. Conversely, older companies are less likely to do so. This study also highlights the influence of the institutional context, specifically the legal-political system, and the degree of market competition in adopting data analytics.

5. Discussion

Variable-pay system

Variable-pay systems can significantly influence the rate of technology adoption (i.e., in decision-making) within organizations. Implementing variable-pay systems ties directly to their performance, incentivizing them to achieve specific goals and objectives (Trank et al., 2002). One interesting finding is the strong significance between organizations utilizing results-based pay and adopting data analytics. The rationale behind this connection is that results-based pay enables organizations to effectively evaluate employee performance, providing the necessary data to leverage analytics for decision-making. Real-time measurement and tracking of employee performance offer managers valuable insights into areas of improvement, ultimately driving business results. Moreover, variable-pay systems often require establishing measurable performance metrics and goals. This necessitates the use of data analytics to evaluate results-based pay performance accurately. As a result, organizations with variable-pay systems that are result-based focus are more likely to prioritize the adoption of data analytics.

However, it is surprising that pay linked to individual performance does not exhibit a solid significant correlation with technology adoption. This discrepancy raises questions and prompts further exploration into the underlying factors influencing this relationship. It is plausible that several factors come into play, such as the complexity of the organization, the nature of the work performed, and the availability of resources for investing in analytics.

Firm size

Numerous studies, including our research analysis, have explored the connection between company size and adopting technological innovations and information systems. These studies shed light on the relationship and provide valuable insights. Eder and Igbaria (2001) discovered a positive correlation between company size and the diffusion of intranets, indicating that larger companies are more inclined to adopt technological innovations. Similarly, Giunta and Trivieri (2007) emphasized the positive association between firm size and the adoption of information technology, attributing it to creating economies of scale that facilitate the adoption and benefits of new technologies. Thong (1999) further supported these findings by identifying company size as the most influential organizational characteristic affecting the adoption of information systems. Smaller companies were found to adopt fewer systems due to their specific needs and resource constraints.

When considering these studies in conjunction with the results of our own analysis, a consistent pattern emerges, highlighting the greater propensity of larger companies to adopt data analytics for performance management. This relationship can be attributed to several factors. Firstly, larger companies often have greater resource availability regarding finances and personnel, enabling them to invest in and implement data analytics technologies. Secondly, economies of scale come into play, as larger organizations can spread the costs of technology adoption over a broader customer base or operational scale. Lastly, the complexity of operations in larger companies may necessitate using data analytics to manage and optimize performance effectively.

These findings underscore the significance of considering company size when devising strategies for technology adoption. Organizations of different sizes have distinct needs, capabilities, and resource constraints. Therefore, tailoring technology adoption strategies to accommodate these variations is crucial for maximizing the potential benefits derived from new technologies.

Firm age

Our analysis indicates a notable difference in the adoption between older and younger companies. Older companies tend to adopt more slowly than their younger counterparts. Several factors contribute to this phenomenon. One is organizational inertia, where established companies may resist change due to ingrained practices and processes. The presence of well-established systems that do not prioritize data analytics can also hinder the adoption in older companies.

However, when we compare the results with other research, it is suggested that there are conflicting findings regarding the relationship between company age and technology adoption. The relationship is rather complex. For example, Haller and Siedschlag (2008) found a positive influence of company age on adopting innovative technologies, contrasting our findings. Their research suggests that older companies may be more likely to adopt new technologies.

Whereas Ben-Youssef et al. (2010) found no significant difference in the relationship between firm age and the adoption of information and communication technologies (ICT). Their findings align with our analysis, where we observed that the coefficients associated with company age and performance analytics adoption were close to zero. Similar result found in Bayo-Moriones and Lera-Lopez (2007), Bocquet and Brossard (2007), and Choi et al. (2011).

These discrepancies highlight the importance of considering other factors when examining the relationship between company age and technology adoption. These factors are the specific technologies being considered, the industry context in which companies operate, and regional variations can all influence the adoption patterns. In conclusion, a more nuanced understanding is required to determine the effects of company age.

Business ownership

The findings from our study suggest that management change significantly influences data analytics adoption in organizations. This aligns with the comprehensive review conducted by the European Private Equity and Venture Capital Association (EVCA, 2001), which emphasizes the pivotal role of management in organizational performance and strategic changes, including business policies. Although the review may not explicitly mention data analytics adoption, its emphasis on the importance of management implies that management changes have a profound impact on various aspects of HR practices, including the integration of data analytics.

Additionally, the research by Bruining et al. (2005) further supports this idea by exploring the relationship between business practices and firm performance. Their findings also suggest that when new management takes charge of an organization, they possess a heightened ability to bring about positive changes in employee incentives, such as using data analytics. This implies that management change, regardless of ownership, can act as a catalyst for adopting data analytics within HR practices.

It is important to note that while ownership change may indirectly influence data analytics adoption through its impact on management dynamics, the primary driver appears to be the changes in management itself. When new management assumes leadership, they have the opportunity to introduce new strategies, policies, and incentives that promote and foster the integration of data analytics into performance management practices. This suggests that the new management team's mindset, vision, and expertise are crucial factors in driving the adoption of data analytics within an organization.

Firm complexity process

The analysis results revealed that the complexity of an organization's process (i.e., frequency of monetary rewards, hierarchical level, and training frequency) can positively impact the need for data analytics adoption. Complex organizational processes often involve extensive data exchange between departments and intricate business processes, which can be better managed and understood with the help of analytics tools. By combining various data sources, data analytics provides a comprehensive view of an organization's performance, enabling better decision-making and strategic planning.

However, it is essential to note that the influence of complexity on data analytics adoption may not hold uniformly across all aspects of organizational structure (Maduenyi *et al.,* 2015; Nahm *et al.,* 2003). For example, when organizations with more than five hierarchical levels, the results of the analysis did not support the initial hypothesis. This could be due to the smaller sample size and less precise statistical estimates, which may require further investigation.

Moreover, we believe the complexity of organizational processes can significantly impact the adoption of data analytics. For instance, complex processes often generate a large volume of data from various sources, making data analytics a valuable tool for effective data management. By leveraging analytics tools, organizations can gain insights from this vast amount of data and make informed decisions. Additionally, data analytics can help address decision-making challenges inherent in complex processes by extracting patterns, trends, and correlations from the data. This enables organizations to make data-driven decisions that consider the intricacies of their processes, leading to improved outcomes. By analyzing data from different stages of the process, organizations can optimize their operations and enhance overall efficiency.

Market competitiveness

The importance of market competitiveness in encouraging organizations to adopt data analytics is essential. When organizations perceive a need to gain a competitive advantage over their competitors, they are more likely to implement analytics to manage their workforce effectively (Levenson, 2018). Therefore, when a company operates in a highly competitive market, there is a greater incentive to adopt new technology to gain a competitive edge and outperform competitors (Levenson, 2018). This suggests that market pressure can be a driving force behind the adoption of data analytics.

The results support the hypothesis stating the degree of competition influences the adoption of data analytics. Specifically, companies operating in very competitive and fairly competitive markets are more likely to adopt performance analytics than those operating in not very competitive and not at all competitive markets (Hansen and Mowen, 2014). The coefficient values and p-values associated with these market conditions further indicate that higher levels of competition drive the adoption of performance analytics. This is because organizations seek to leverage data-driven insights to make informed decisions and gain a competitive advantage.

Legal and political factors

From an institutional perspective, legal and policy elements play a significant role in explaining variations in HRM practices across countries (DeFidelto and Slater, 2001; Goergen et al., 2013). Our results broadly agree with their studies that the institutional context matters, where countries that follow the LME system, like the United Kingdom, Ireland, and Malta, are more likely to adopt data analytics than countries that follow the CME system: Netherlands, Germany, and Belgium, with stricter data protection regulations. Different countries have distinct regulations and policies to safeguard the analysis and sharing of employee data, which contributes to differences in the prevalence of data analytics adoption. For instance, Central and Eastern European Countries (CEECs) and the United Kingdom tend to adopt a more liberal approach, granting managers greater discretion in utilizing HR practices (Ellmer and Reichel, 2021). This aligns with the classification of VoC proposed by Hall and Soskice (2001). This classification supports the idea that institutional factors, including legal-political systems and data protection regulations, influence adopting of data analytics practices (H6) (Ellmer and Reichel, 2021).

Our study also agrees with Ellmer and Reichel (2021) study that utilizing data analytics in Germany might face challenges and difficulties due to the need to follow the regulations such as justify their data usage and data protection laws. As a result, they might have limited access to data, impeding their ability to effectively conduct and develop analytics outputs. This example underscores how stringent data protection regulations can hinder the practical implementation and outcomes of Data analytics initiatives. The interplay of legal and policy elements within the institutional context shapes the adoption and utilization of data analytics across countries.

6. Study implication

Theoretical Implications:

This study's theoretical implications contribute to the existing knowledge in performance management and data analytics adoption. By investigating the relationship between the adoption of data analytics in monitoring employee performance and various organizational and environmental factors, this study expands our understanding of the factors influencing data-driven decision-making processes in performance management. The findings provide theoretical insights into the mechanisms underlying the adoption and utilization of data analytics in organizations. Furthermore, by examining different factors within the TOE framework, this study adds depth to our understanding of how and what TOE factors shape the adoption of performance management practices. The processes and characteristics of a firm will influence their decision to adopt performance analytics. Identifying specific processes and structural characteristics within organizations provides valuable insights into their impact on adopting analytics in performance management. These insights can inform future research and theory development by enhancing our understanding of the distinct roles played by different types of data analytics in performance management.

Practical Implications:

The processes and characteristics of a firm play a significant role in their decision to adopt performance analytics, which has practical implications for organizations aiming to enhance their performance management practices by adopting data analytics. Identifying specific processes and structural characteristics within organizations provides valuable insights into their impact on adopting analytics in performance management, informing future research and theory development. The findings of this study can guide practitioners in making informed decisions and implementing effective strategies to leverage data analytics for monitoring employee performance, suggesting optimizing processes, aligning structures, managing change effectively, and allocating resources strategically to improve performance management practices and maximize the benefits of adopting analytics. Some practical implications include structural alignment, strategic decision-making, resource allocation, performance improvement and change management (Table VIII).

[Insert Table VIII: Key practical implications on adopting Data Analytics in Performance Management]

6. Conclusions

In conclusion, using data to manage performance is at an exploring stage, but has recently gained momentum. The digitization of business processes has led to the emergence of data, allowing companies to use data analytics to manage employee performance. This study examines the use of data analytics in organizations from the perspective of TOE, using a cross-national multi-level analysis of over 21,869 companies in the European Union.

Within the organizational context, this analysis reveals that adopting performance analytics is contingent upon various company characteristics. Our findings align with previous research (Florkowski and Olivas-Luján, 2006; Hausdorf and Duncan, 2004) and indicate that larger companies employing a results-based pay methodology and possessing complex processes are more inclined to leverage data analytics for employee performance management (Batt, 1999; Hauff *et al.,* 2014; Gooderham *et al.,* 2015; Parry, 2011). This propensity can be attributed to their ample resources and the likelihood of having dedicated teams to facilitate the integration of these tools. Moreover, we concur that such complex organizations may exhibit a greater propensity to adopt data analytics (Batt, 1999; Hauff *et al.,* 2014; Gooderham *et al.,* 2015; Maduenyi *et al.,* 2015; Nahm *et al.,* 2003; Parry, 2011) due to its ability to offer a comprehensive view of organizational performance by consolidating data from various sources.

Environmental context, e.g., industry competition, also influences the adoption of data analytics. Our analysis found that companies in more competitive industries are more likely to use data analytics to gain a competitive edge (Hansen and Mowen, 2014; Levenson, 2018). Regarding country contexts, our results broadly agree with DeFidelto and Slater (2001) and Goergen *et al.* (2013) studies that the institutional (e.g., legal-political) context matters to some extent. Countries that follow the LME systems are more likely to adopt data analytics than countries that follow the CME systems. Interestingly, a distinct pattern emerged when examining data analytics adoption across the 28 European Union (EU) countries. Countries following the liberal market economy (LME) systems were more likely to adopt data analytics than countries following the coordinated market economy (CME) systems.

Our findings reaffirm that the TOE framework helps to explain the contexts that influence an organization's adoption and implementation of new technologies. Many organizations may not be aware of the usefulness of data analytics or may not fully understand how to apply it to their specific data challenges (Stone *et al.,* 2020). This lack of awareness can lead to a reluctance to invest in it, as organizations may not perceive it as a priority. Another reason for the limited adoption is the lack of skills or resources to collect and analyze performance data. Data analytics requires specialized skills and expertise in data collection, management, analysis, and access to relevant performance data sources (Dahlbom *et al.,* 2020).

Furthermore, a lack of top management support or strategic alignment with organizational goals can also hinder the adoption and implementation of data analytics (Dahlbom *et al.,* 2020), if top management does not see the value or prioritize it as a strategic initiative. It may not receive the necessary resources or attention from the organization (Ku, 2009; Singh, 2005). Companies with higher IT capabilities and access to more advanced technologies are likelier to adopt data analytics. This suggests that technological readiness is essential for successfully adoption (Lu, 2015; Wastell and McMaster, 2008)). The ease of use and compatibility of data analytics tools with existing systems are important considerations.

8. Limitations and future directions

There are some limitations embedded in this study. Despite using a reliable dataset from ECS, this quantitative data analysis did not adequately address how the technology influences the adoption of data analytics in organizations in the TOE framework. Future research should explore this context in greater depth and examine the specific mechanisms of the influence of technology.

Caution should be exercised in interpreting the impact of the country context, as the survey included only European countries. To gain a more comprehensive understanding, it is recommended that future studies be expanded to include organizations from different regions. This would allow researchers to explore potential differences and influences of organization characteristics and culture-specific contexts, such as collectivism and individualism. Other research opportunities lie in examining the long-term benefits of performance analytics. Conducting longitudinal studies would help determine whether performance analytics can act as a catalyst for improving organizational function over time.

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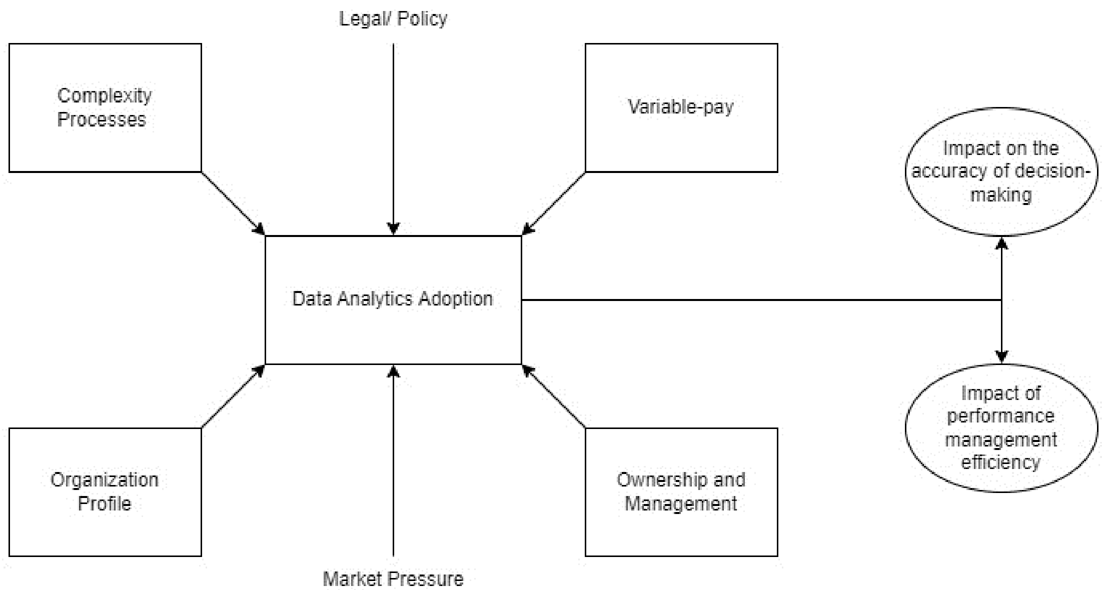
The Influence of Firm Characteristics of the Adoption of Data Analytics in Performance Management



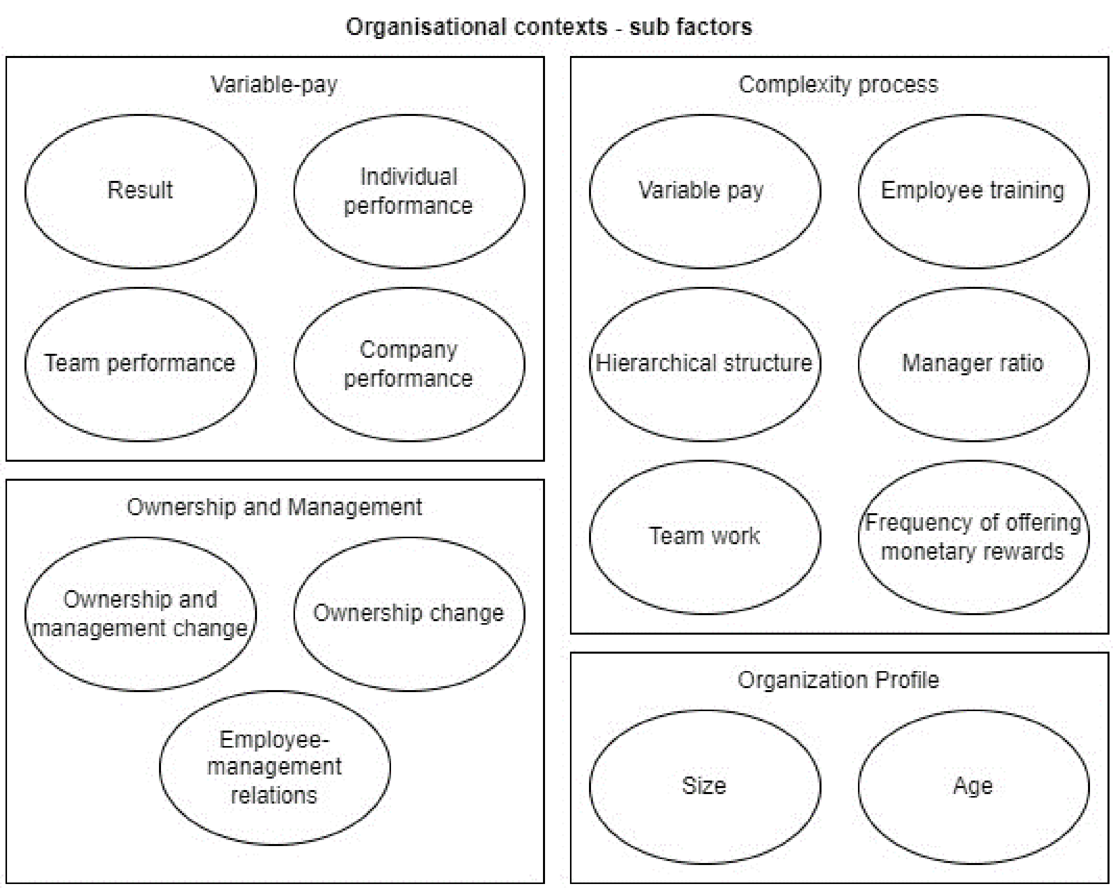


Figure 1: Organisation-Environment Model of Performance Analytics Adoption

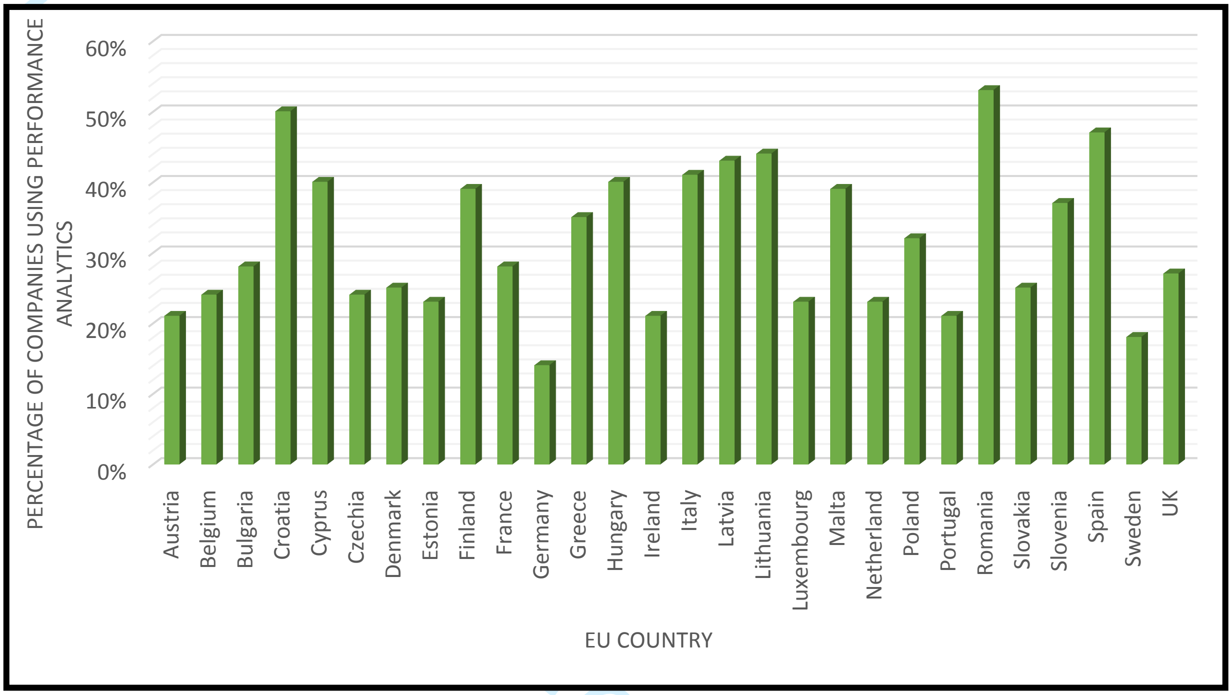


Figure 2: The use of Performance Analytics by Country

The Influence of Firm Characteristics on the Adoption of Data Analytics in Performance Management

Table I: Examples of Definitions of Performance Analytics

Bassi, 2011, p.16	Performance analytics refers to "an evidence-based approach for making better decisions on the people side of the business, it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modelling"
Van den Heuvel and Bondarouk, 2017, p.4	Performance analytics as "the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions".
Marler and Boudreau, 2017, p.15	Performance analytics is a business "practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to…, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making"
Falletta and Combs, 2020, p.53	Performance analytics is "a proactive and systematic process for ethically gathering, analysing, communicating and using evidence-based… analytical insights to help organisations achieve their strategic objectives"
Walsh, 2021, p.2	Performance analytics is "the use of data collected on or about people within an organisation to make better business decisions".

Table II: Comparison of Adoption Frameworks for Performance Analytics

Framework	Key concept	Similarities	Differences	Advantages	Limitations
TAM	How individual mindset might influence technology adoption: manager's perception of technology's usefulness in improving job performance and ease of use (Davis, 1989).	Both TAM and TOE frameworks consider the importance of perceived ease of use in data analytics adoption (Bryan and Zuva, 2021; Saeed *et al.,* 2019)	TAM focuses specifically on perceived usefulness and perceived ease of use (Themistocleous and Morabito, 2022)	Provides insights into individual perceptions towards technology adoption, which are crucial factors for data analytics adoption.	Does not consider elements outside the individual level.
TOE	Contextual contexts influencing organisational level of innovation adoption: Technology, Organisational, and Environmental.	See Above	TOE considers a broader range of contexts beyond individual perceptions (Yamamoto 2014).	Recognises that data analytics adoption is an ongoing process influenced by various internal and external contexts (Baker, 2012; Tornatzky *et al.,* 1990).	Does not offer specific guidelines or recommendations for organisations. It does not address the unique characteristics and requirements of industries.
IDP	Individual-level stages of technology adoption: awareness of innovation, attitude development, decision-making, implementation, and evaluation (Rogers, 1962).	IDP and TAM frameworks focus on individual-level contexts influencing technology adoption (Ordóñez 2015).	IDP focuses on the sequential stages of the individual adoption process (Michelini, 2012).	Provides a structured framework to understand the sequential stages of the individual adoption process (Rogers 2015).	Does not consider elements outside individual level. Assumes a linear progression of adoption stages, which may not always reflect the complex reality of technology adoption.

Table III: Data source summary

Characteristic	Description
Data Source	2019 European Company Survey (ECS)
Focus	Aspect of organization practices: workforce planning, compensation policies, organizational structure
Coverage	28 European countries
Number of Cases	21,869
Organizational Size	Small establishments (10-49 employees) – (83%)
	Medium-sized establishments (50-249 employees) – (15%)
	Large establishments (250+ employees) – (2%)
Sectors	Industry – (22%)
	Construction – (10%)
	Commerce and hospitality – (31%)
	Transport – (6%)
	Financial services – (4%)
	Other services – (28%)
Establishment Duration	Less than 10 years – (13%)
	11-20 years – (22%)
	21-30 years – (25%)

Source: Eurofound. 2019. European Company Survey

Table: IV: Measurement Scales of Variables

Variable	Measurement Scale	Definition
Dependent Variable: The use of Data analytics to monitor employee performance	Nominal (Categorical)	The process of using data analysis methods to gain insights and make data-driven decisions in the field of human resources
Independent Variables		
Variable-pay systems (H1)	Ordinal (Categorical)	Systems that link employee compensation to performance
Complexity processes (H2)	Ordinal (Categorical)	The degree of complexity involved in organizational processes
Ownership and Management (H3)	Nominal (Categorical)	The ownership structure and management status of the company
Company size (H4)	Ordinal (Categorical)	The total number of employees in the company
Company age (H5)	Interval (Numeric scale)	The number of years since the company's establishment
Legal and Political (H6)	Nominal (Categorical)	The legal and political environment in which the company operates
Market competitiveness (H7)	Ordinal (Categorical)	The level of competition in the market where the company operates

Table V: Types of Variable-pay System

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Pay by results	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.027	0.011	0.050
Pay by individual performance	0.022	0.011	0.050	0.024	0.011	0.050	0.022	0.011	0.05	0.022	0.011	0.050	0.021	0.011	> 0.050
Pay by team performance	0.009	0.012	> 0.050	0.003	0.012	> 0.050	0.004	0.012	> 0.050	0.003	0.012	> 0.050	-0.000	0.012	> 0.050
Pay by company performance	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.009	0.009	> 0.050

Table VI: Reward Frequency offered by an Organisation

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Very often	0.675	0.086	0.001	0.580	0.087	0.001	0.571	0.087	0.001	0.561	0.088	0.001	0.538	0.089	0.001
Fairly often	0.496	0.070	0.001	0.426	0.071	0.001	0.403	0.071	0.001	0.399	0.072	0.001	0.385	0.073	0.001
Not very often	0.281	0.067	0.001	0.225	0.068	0.001	0.208	0.068	0.010	0.206	0.068	0.010	0.197	0.069	0.010

Table VII: The number of People Working in the Organisation

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
20-49 employees	0.174	0.044	0.001	0.128	0.045	0.010	0.056	0.046	> 0.050	0.061	0.046	> 0.050	0.042	0.047	> 0.050

50-249 employees	0.595	0.046	0.001	0.502	0.047	0.001	0.345	0.051	0.001	0.355	0.051	0.001	0.316	0.054	0.001
250-499 employees	0.725	0.078	0.001	0.584	0.08	0.001	0.384	0.085	0.001	0.396	0.085	0.001	0.317	0.087	0.001
500 or more employees	0.892	0.091	0.001	0.754	0.093	0.001	0.554	0.100	0.001	0.563	0.100	0.001	0.488	0.102	0.001

Table VIII: Key practical implications on adopting Data Analytics in Performance Management

Topic	Key Insights
Structural Alignment	- Organizational structure influences the adoption of analytics
	- Organizations should align their structures to support effective implementation
	- Adjusting reporting lines, creating cross-functional teams, and defining roles and responsibilities can facilitate adoption
Strategic Decision-Making	- Consider organizational and environmental factors when adopting data analytics in performance management
	- Align strategies and resources to ensure adoption aligns with organizational goals and contextual requirements
Resource Allocation	- Understanding factors driving adoption helps allocate resources effectively
	- Identify critical factors influencing adoption to prioritize investments in infrastructure, training, and talent
Performance Improvement	- Design and implement data-driven approaches to improve performance
	- Leverage data analytics to effectively monitor employee performance
Change Management	- Implementing data analytics may require organizational changes and a mindset shift

	- Identify barriers and facilitators to adoption for targeted change management strategies
	- Foster a culture of data-driven decision-making

The Influence of Firm Characteristics on the Adoption of Data Analytics in Performance Management

Appendices

Appendix 1: Result Table

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Independent variables															
Organisational contexts															
Company size															
10-19 employees (Ref)															
20-49 employees	0.174	0.044	0.001	0.128	0.045	0.010	0.056	0.046	> 0.050	0.061	0.046	> 0.050	0.042	0.047	> 0.050
50-249 employees	0.595	0.046	0.001	0.502	0.047	0.001	0.345	0.051	0.001	0.355	0.051	0.001	0.316	0.054	0.001
250-499 employees	0.725	0.078	0.001	0.584	0.080	0.001	0.384	0.085	0.001	0.396	0.085	0.001	0.317	0.087	0.001
500 or more employees	0.892	0.091	0.001	0.754	0.093	0.001	0.554	0.100	0.001	0.563	0.100	0.001	0.488	0.102	0.001
Company age	-0.002	0.001	0.010	-0.001	0.001	0.050	-0.001	0.001	0.050	-0.001	0.001	0.050	-0.002	0.001	0.010
Rewards practices: Monetary rewards															
Never (Ref)															
Very often	0.675	0.086	0.001	0.580	0.087	0.001	0.571	0.087	0.001	0.561	0.088	0.001	0.538	0.089	0.001
Fairly often	0.496	0.070	0.001	0.426	0.071	0.001	0.403	0.071	0.001	0.399	0.072	0.001	0.385	0.073	0.001
Not very often	0.281	0.067	0.001	0.225	0.068	0.001	0.208	0.068	0.010	0.206	0.068	0.010	0.197	0.069	0.010
Type of variable pay systems															
Pay by results	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.027	0.011	0.050
Pay by individual performance	0.022	0.011	0.050	0.024	0.011	0.050	0.022	0.011	0.050	0.022	0.011	0.050	0.021	0.011	> 0.050
Pay by team performance	0.009	0.012	> 0.050	0.003	0.012	> 0.050	0.004	0.012	> 0.050	0.003	0.012	> 0.050	-0.000	0.012	> 0.050
Pay by company performance	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.009	0.009	> 0.050
Number of pay system a company use															
None at all (Ref)															

Single pay system	0.091	0.092	> 0.050	0.078	0.093	> 0.050	0.079	0.093	> 0.050	0.079	0.093	> 0.050	0.061	0.094	> 0.050
Two pay systems	0.162	0.061	0.010	0.145	0.061	0.050	0.140	0.061	0.050	0.142	0.062	0.050	0.141	0.062	0.050
Three pay systems	0.365	0.056	0.001	0.326	0.056	0.001	0.310	0.056	0.001	0.313	0.057	0.001	0.308	0.057	0.001
Four pay systems	0.468	0.061	0.001	0.417	0.061	0.001	0.413	0.061	0.001	0.417	0.061	0.001	0.403	0.062	0.001
Change in the ownership															
No (Ref)															
Yes, and it involved a change of management				0.258	0.054	0.001	0.255	0.054	0.001	0.253	0.055	0.001	0.256	0.055	0.001
Yes, but management remained the same				0.109	0.055	0.050	0.104	0.055	> 0.050	0.105	0.055	> 0.050	0.108	0.056	> 0.050
Team works between employees															
No team (Ref)															
Single team				0.464	0.045	0.001	0.427	0.045	0.001	0.421	0.045	0.001	0.397	0.046	0.001
More than a team				0.579	0.050	0.001	0.541	0.050	0.001	0.537	0.050	0.001	0.496	0.050	0.001
Complexity of hierarchical levels															
No hierarchical levels (Ref)															
Two hierarchical levels							0.396	0.113	0.001	0.392	0.114	0.001	0.384	0.115	0.001
Three hierarchical levels							0.630	0.107	0.001	0.627	0.107	0.001	0.614	0.109	0.001
Four hierarchical levels							0.845	0.113	0.001	0.840	0.113	0.001	0.816	0.115	0.001
Five hierarchical levels							0.836	0.143	0.001	0.822	0.143	0.001	0.788	0.145	0.001
Six hierarchical levels							0.305	0.222	> 0.050	0.302	0.222	> 0.050	0.281	0.224	> 0.050
Relationship with manager															
Very bad (Ref)															
Very good										0.032	0.436	> 0.050	-0.001	0.439	> 0.050
Good										-0.004	0.435	> 0.050	-0.020	0.438	> 0.050
Neither good nor bad										-0.013	0.437	> 0.050	-0.025	0.440	> 0.050
bad										-0.039	0.466	> 0.050	-0.054	0.469	> 0.050
Number of managers															
None at all (Ref)															
less than 20%													0.178	0.092	> 0.050
20% to 39%													0.061	0.105	> 0.050

40% to 59%													-0.089	0.219	> 0.050
60% to 79%													-0.377	0.332	> 0.050
80% or more													-0.049	0.331	> 0.050
Require continuous training															
None at all (Ref)															
less than 20%													0.301	0.064	0.001
20% to 39%													0.329	0.069	0.001
40% to 59%													0.518	0.076	0.001
60% to 79%													0.632	0.080	0.001
80% or more													0.809	0.072	0.001
Environmental contexts															
Competitiveness															
Not at all competitive (Ref)															
Very competitive				0.737	0.125	0.001	0.745	0.125	0.001	0.739	0.126	0.001	0.696	0.126	0.001
Fairly competitive				0.534	0.124	0.001	0.548	0.124	0.001	0.546	0.125	0.001	0.519	0.125	0.001
Not very competitive				0.227	0.132	> 0.050	0.241	0.133	> 0.050	0.242	0.133	> 0.050	0.228	0.133	> 0.050
Company sector															
Art, entertainment and recreation (Ref)															
Mining and quarrying	0.734	0.272	0.010	0.752	0.279	0.010	0.745	0.280	0.010	0.771	0.281	0.010	0.867	0.281	0.010
Manufacturing	0.849	0.124	0.001	0.789	0.126	0.001	0.778	0.126	0.001	0.805	0.127	0.001	0.853	0.128	0.001
Electricity, gas and steam supply	0.142	0.232	> 0.050	0.192	0.234	> 0.050	0.166	0.234	> 0.050	0.200	0.235	> 0.050	0.159	0.236	> 0.050
Water, Sewerage activities	0.344	0.184	> 0.050	0.464	0.187	0.050	0.452	0.187	0.050	0.478	0.188	0.050	0.469	0.188	0.050
Construction	0.248	0.133	> 0.050	0.152	0.135	> 0.050	0.145	0.135	> 0.050	0.171	0.136	> 0.050	0.186	0.137	> 0.050
Wholesale, retail trade, repair of motor and motorcycles	0.954	0.126	0.001	0.843	0.128	0.001	0.846	0.128	0.001	0.873	0.129	0.001	0.880	0.130	0.001
Transportation and Storage	1.067	0.136	0.001	1.037	0.138	0.001	1.075	0.138	0.001	1.103	0.139	0.001	1.053	0.140	0.001
Accommodation and food service	0.493	0.140	0.001	0.384	0.142	0.010	0.373	0.142	0.010	0.395	0.143	0.010	0.444	0.144	0.010
Information and communication	0.917	0.144	0.001	0.766	0.146	0.001	0.797	0.146	0.001	0.821	0.147	0.001	0.724	0.149	0.001
Financial and insurance	1.217	0.165	0.001	1.085	0.167	0.001	1.091	0.167	0.001	1.117	0.168	0.001	0.978	0.169	0.001

Real estate services	0.064	0.214	> 0.050	0.055	0.216	> 0.050	0.050	0.216	> 0.050	0.077	0.217	> 0.050	0.057	0.218	> 0.050
Professional, scientific and technical services	0.967	0.135	0.001	0.846	0.136	0.001	0.857	0.137	0.001	0.881	0.138	0.001	0.777	0.139	0.001
Administrative and support services	0.761	0.153	0.001	0.681	0.155	0.001	0.697	0.155	0.001	0.723	0.156	0.001	0.684	0.157	0.001
Other service activities	0.614	0.131	0.001	0.556	0.132	0.001	0.568	0.132	0.001	0.592	0.133	0.001	0.568	0.134	0.001
Country contexts															
Cultural contexts															
CME (Ref)															
SME							0.376	0.254	> 0.050	0.379	0.255	> 0.050	0.387	0.263	> 0.050
LME							0.399	0.197	0.050	0.400	0.198	0.050	0.435	0.204	0.050
Constant	-2.555	0.166	0.001	-3.329	0.204	0.001	-4.093	0.257	0.001	-4.118	0.498	0.001	-4.530	0.509	0.001
Country variance constant	0.225	0.063	0.001	0.233	0.065	0.001	0.200	0.056	0.001	0.201	0.056	0.001	0.215	0.060	0.001
Log likelihood	-107925.925			-10629.371			-10581.18			-10564.729			-10423.075		
Wald X^2 (df)	1076.03(30)		0.001	1294.97(37)		0.001	1365.42(44)		0.001	1365.32(48)		0.001	1483.53(58)		0.001
N	18838			18809			18809			18787			18690		

Appendix 2

Independent variable

Variable pay systems (H1)

We used the answer to the question 46: "How many employees at this establishment received the following types of variable pay?", (1) Payment by results, for example, piece rates, provisions, brokerages or commissions. (2) Variable extra pay linked to individual performance following management appraisal. (3) Variable extra pay linked to the performance of the team, working group or department. (4) Variable extra pay linked to the results of the company or establishment (profit-sharing scheme).

And, participants would be able to answer from one of the three following: "None at all", "Less than 20%", "20% to 39%", "40% to 59%", "60% to 79%", "80% to 99%" and "All".

Complexity processes (H2)

For variable pay, we have grouped all answers together (apart from "None at all") to evaluate how the number of variable pay system that use in organisations would influence the performance analytics adoption.

Second, we included question 34 about: "How many employees in this establishment are in jobs that require continuous training?" Participants would be able to select one of the following: "None at all", "Less than 20%", "20% to 39%", "40% to 59%", "60% to 79%", "80% to 99%" and "All".

Third, we selected four questions that are expressed in a different dimension of company complexity. Firstly, we included question 25 about: "How many hierarchical levels do you have in this establishment?" and participants would be able to indicate the number of hierarchical levels within their organisation.

Next, we used question 13 about: “How many people that work in this establishment are managers?” to evaluate the relationships between variables. Participants would be able to select one of the following: "None at all", "Less than 20%", "20% to 39%", "40% to 59%", "60% to 79%", "80% to 99%" and "All".

Next, we included question 17 about: "With regard to the employee’s doing teamwork, do most of them work in a single team or do most of them work in more than one team?" Participants would be able to answer either "No teams", "Most of them work in a single team" and "Most of them work in more than one team"

<u>Ownership and Management (H3)</u>

We used the answer to the question 8: "Since the beginning of 2016, has there been any change in the ownership of the company to which this establishment belongs?" and participants would be able to answer from one of the three following: "Yes, and it involved a change of management", "Yes, but management remained the same" or "No".

We used the answer to the question 63" "How would you describe the relations between management and employees in this establishment in general?" And participants would be able to answer from one of the five following: "Very bad", "Bad", "Neither good nor bad", "Good" and "Very good".

Last but not last "How often are the following practices used to motivate and retain employees at this establishment (monetary rewards)?" And participants would be able to answer from one the four following: "Very often", "fairly often", "not very often" and "never".

Company size (H4)

We used the answer to the question 1: "Approximately how many people work in this establishment?" which were grouped into 5 categories, being 10-19 employees; 20-49 employees; 50-249 employees; 250-499 employees and more than 500 employees.

Company age (H5)

We used the answer to the question 3: We calculated the year of operation using the answers to the question "Since what year has this establishment been carrying out this activity?".

Legal and Political (H6)

As regards the role of institutional, juridico-political context express the ability of companies to make use of performance analytics. We used the VoC classification developed by Hall and Soskice (2001). There is a continuous debate on which EU countries should be considered as CME or LME or something else. For the test of (H6), it was primarily comparing the classical CME countries by referring to Hall and Soskice (2001) and European Commission (2008). Therefore, we have put Austria, Belgium, Denmark, Finland, Germany, Slovenia, Luxembourg, Netherlands, and Sweden in the category of CME. Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Romania, Slovakia, Slovenia, UK, Ireland, Czech Republic (Czechia), Malta, and Cyprus are in the category of LME, while Greece, Spain, France, Italy, and Portugal are under SME (European Commission, 2008).

Market competitiveness (H7)

We used the answer to the question 66: "How competitive would you say the market for the main products or services provided by this establishment is?", and participants would be able to select one of the following: "Not at all competitive", "Not very competitive", "Fairly competitive", and "Very competitive".