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RESEARCH ARTICLE

The role of the capability, opportunity, and motivation of firms for using human resource analytics to monitor employee performance: A multi-level analysis of the organisational, market, and country context

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Abstract

The digitalisation of business processes has led to the availability of (big) data which increasingly allows firms to analyse their workforce using HR analytics. On the basis of a cross-national multi-level analysis and a data set that covers more than 20,000 firms in all member states of the European Union we investigate the reasons why some firms make use of human resource (HR) analytics to monitor employee performance while others refrain from doing so. We show that the use of HR analytics depends upon firm characteristics as well as contextual factors. In terms of firm characteristics, we find that firms require the structural and managerial capability to make use of HR analytics. For contextual factors, our findings show that some market factors motivate firms to make use of HR analytics while the institutional, that is, juridico-political, and cultural environment in which firms are embedded influences firms' opportunities to use HR analytics.

KEYWORDS

comparative HRM, contextual factors, Europe, HR analytics

INTRODUCTION

The digitalisation of business and management processes and activities as well as technological advancements of the recent past has increasingly enabled many firms to collect and store information and data about their work force (Davenport, 2014; Parry et al., 2007). Methodological developments, which went along with these improvements, also provided firms with the analytical methods, that is tools, to take a more evidence-based approach to management and to analyse the information and quantitative data more systematically (Angrave et al., 2016; Edwards, 2019). These developments not only led to the accumulation of (often big) data in firms, but also promoted the use of human resource (HR) analytics as a strategic organisational capability (Margherita, 2021).

From a firm as well as from a wider societal perspective this accumulation of data and the possibility for management to analyse HR-related data with new and sophisticated analytical methods is ambiguous. Especially when it is about monitoring employees and when using the data and analyses for performance management (Ball & Margulis, 2011; Carter et al., 2011). This is because on the one hand, literature regularly emphasises the negative consequences the use of data-driven HR practices and tools can have on work autonomy and control (McGovern et al., 2007; Moore et al., 2018). More specifically research has shown that the use HR analytics as a central mechanism to manage employee behaviour and control their performance more closely (Taylor & Bain, 1999) can have severe negative implications on well-being and health of safety of employees (Carter et al., 2013; Taylor & Connelly, 2009). On the other hand, literature has also shown that applying HR analytics can help increasing face validity and even objectivity and consistency, positively affecting occupational health and safety as well as employees' perceived fairness and satisfaction in management processes (Sharma & Sharma, 2017). In this sense, HR analytics can support management and promote evidence-based organisational decision-making if (and only if) its benefits are balanced and contextualised.

Although the context for the use of HR analytics matters a lot, the availability of more information and data on HR and the use of methods that process this data can help to address some fundamental problems in the area of human resource management (HRM). Most notably problems caused by the lack of information and/or information asymmetries between management and employees (Campbell et al., 2012). Consequently, one might expect incentives for firms to make use of both the data and HR analytics. Especially management can be expected to be interested in the use of HR analytics because it potentially allows management to gain a comparative advantage over competing firms (Minbaeva, 2018).

Against this background, it is puzzling that even though the use of HR analytics and the effective ‘exploitation’ of the available information and data appears to offer advantage for management, more arguably even for employees, and despite evidence supporting the benefits of analytical approaches in HRM are paying off (Guenole et al., 2017; Kryscynski et al., 2018; Levenson, 2011), its use is by no means universal and many firms are not making use of its potential. Recent literature shows that many firms hesitate to make use of HR analytics because there are a number of contextual and firm-specific factors that hinder or even prevent its use (Schiemann et al., 2018). This study contributes to our understanding of why some firms make use of HR analytics for monitoring employees while others do not and is novel in three main ways.

First, the study proposes a theoretical framework that moves beyond the focus on predominantly organisation-specific factors by studying the role of market- and contextual factors. In this way, it augments the range of the analysis by embedding it into a cross-country comparative perspective which includes the analysis of the role of the market and country context. As regards the latter, this further includes the investigation of the role of institutional and cultural factors which are found highly important for the use of HR-practices and tools (Aycan, 2005; Goergen et al., 2013; Mayrhofer et al., 2019) such as HR analytics. Hence, we also aim to understand in the paper if and why the use of HR analytics might also be explained by factors including the wider cultural and institutional context in which firms are embedded.

Second, it synthesises and clarifies different firm-specific and contextual mechanisms leading to the use of HR analytics. This means that the paper also allows for a theoretical and empirical comparison of multiple mechanisms that have until now been studied in isolation.

Third, the paper tests these mechanisms using up-to-date, large scale, cross-national and cross-sectoral data on the incidence of use of *HR analytics to monitor employee performance* in 20,411 business establishments (i.e., firms) in all member states of the EU (Eurofound, 2019). These data hence cover a large number of firms within a wide range of institutional system and cultural traditions. This allows us to better address issues of generalisability than previous case-study oriented research, as well as to better compare the effects implied by different mechanisms. Thus, by focusing on one key domain of HR analytics, that is, performance monitoring, we provide a comprehensive, multi-leveled and multi-faceted analysis of the relationship between firm, market and country-level factors and the use of HR analytics.

The structure of the paper is as follows. First, we give an overview of different HR analytics areas and thereby critically discuss the use of HR analytics for monitoring employee performance which is the dependent variable in our paper. Then we derive and explain our theoretical model which is followed by a discussion of the determinants of the use of HR analytics in firms from which we derive and present our hypotheses. We then describe the data and methods we use and then present and discuss in detail the results of our analysis. Finally, we draw conclusions on the practical and policy implications of our findings.

THE VARIETY OF HR ANALYTICS

HR analytics is an umbrella term that includes a number of methods, that is, tools, for the analysis of HR-related data and information (Edwards, 2019). More specifically, as HR analytics is a subarea of business analytics, it can be defined in accordance with common business analytics definitions (Camm et al., 2014) as a set of methods that aid HR decision making by providing insights from data and information.

While HR analytics very often refer to the analysis of quantitative data and recently more often to the analysis of 'big data' by the use of 'sophisticated algorithms', 'data mining', and 'artificial intelligence', essentially, in a wide definition and as exemplified in the wider area of business analytics (Kelleher et al., 2015), data does not necessarily have to be 'big', and methods and tools do not need to be 'too sophisticated'. Against this background, HR analytics can also be defined by the use of any evidence-based approach for making better HR decisions (Bassi, 2011) and thus can also be designated in practical terms as a set of tools that includes both traditional relational methods, for example, database and spreadsheet-based analysis, as well as new and sophisticated forms of database and analysis software that allow the handling of very large quantities of data (Angrave et al., 2016).

In any case, as exemplified in the literature (Marler et al., 2017), nowadays HR analytics is used in many different parts of HRM including workforce planning and employment (i.e., recruitment and selection), HR development (i.e., training and development), rewards (i.e., compensation and benefits), talent management, and performance management (i.e., performance monitoring). In the following analysis, we focus on the latter. More specifically, we will investigate the reasons why some firms make use of HR analytics to manage, that is, monitor, employee performance while others refrain from its use. In doing so, we will address the question not only from an employer/management perspective but also from an employee perspective (Jeske & Calvard, 2020).

THEORETICAL FRAMEWORK

Even though HR analytics consists of a variety of different methodologies and tools as well as different epistemological perspectives can be taken on their nature (Greasley & Thomas, 2020; Jeske & Santuzzi, 2015), there are three main factors that appear crucial in understanding why some firms use of HR analytics to monitor employee performance while others do not. First, it needs to be embedded in an environment that has the *structural and managerial capability*, for example, expertise or knowledge of (HR) managers to make use of the data and methods (Angrave et al., 2016; Huselid et al., 1997; Thompson & Heron, 2005). Second, it requires the *opportunity*, for example, the (legal) regulations and managerial prerogatives that allow firms to collect, store and analyse data accordingly. Third, since the implementation of HR analytics is costly, firms also need the *motivation* to use HR analytics, for example, the market factors or market pressures that motivate or even 'force' firms to do so (Levenson, 2018).

On the one hand, it is clear that our framework that is based on the structural and managerial capability, opportunity, and motivation is similar in its broad terminology to the well-known ability, motivation, opportunity (AMO) framework, which is widely used in HRM in context of performance (Boxall & Purcell, 2003) but also with respect to the implementation of HRM practices (Bos-Nehles et al., 2013). On the other hand, our framework differs to most studies using the AMO framework (Marin-Garcia & Martinez Tomas, 2016) significantly for two main reasons. First, the components ability, motivation and opportunity in the AMO framework are usually referring to the identification and use of HRM practices to develop the performance of employees. All these three components are largely covered by capability in our framework. Hence, the components are in the two frameworks are different. Second, in the AMO framework motivation and opportunity are largely conceptualised by internal/endogeneous factors and not by external/exogeneous factors as in our framework. In the AMO framework, external/exogeneous factors are usually considered and discussed within the organisational context. For example, in the AMO framework motivation is conceptualised by organisational or employee-specific, factors including extrinsic and intrinsic motivators. In our conceptualisation, the motivation component is defined by external factors such as in particular market competition which is given to organisations. The same for opportunity which in AMO framework refers to internal, that is, organisational, factors such as employee involvement and job design. Again, this is different to our concept in which opportunity is defined by external factors that such as (legal) regulations that are determined by the institutional and socioeconomic environment in which firms are embedded.

Hence, the components that constitute the well-known AMO framework differ to the components in our framework and in the following section, we apply these three main factors to the explanation of why some firms make use of HR analytics to monitor employee performance while others do not and formulate hypotheses. These hypotheses cover the potential effects of two main classes of determinants: those which vary across individual firms (organisational level), and those that vary across the countries within which these firms are situated (national level). Since HR analytics is a management practice (Strohmeier, 2009), we will first refer to factors and relevant literature explaining the adoption of HR analytics in organisations (Marler & Parry, 2016; Vargas et al., 2018). Furthermore, to explain differences in the management and operation of HR analytics by different organisations, we will refer to the role of markets and especially literature on differences in market pressures and exposures to competitiveness (Farndale & Paauwe, 2007; Strohmeier & Kabst, 2009).

Against the background that the literature in international and comparative HRM increasingly points towards the key role of contextual factors on higher levels including the market, that is, the sectoral, and country level (Bondarouk & Brewster, 2016; Lloyd & Payne, 2019; Paauwe & Boselie, 2005), we augment our firm level perspective by a multi-level analysis which integrates the market as well as country context. We consider the market and country context not least because recent literature has shown that cultural and institutional factors can matter a lot in explaining differences in the use of different HRM practices and tools (Mayrhofer et al., 2019). More specifically, since country contextual differences are found to be key in the literature for HRM, we will refer to economic institutional theory and relevant literature in comparative and international HRM (Bondarouk & Brewster, 2016; Brewster, 2006; Gooderham et al., 2015, 2018). As regards the latter, we will differentiate between the role of institutional and cultural differences.

THE DETERMINANTS OF THE USE OF HR ANALYTICS TO MONITOR EMPLOYEE PERFORMANCE

Organisational factors and the capability of firms to use HR analytics

Structural characteristics of firms

As regards the role of *firm size* as a structural characteristic of firms, there is a substantial amount of literature that clearly shows that the size of a firm, in terms of its workforce, matters for the use of different HRM practices (Hausdorf & Duncan, 2004). We can therefore expect that firm size also matters for the use of HR analytics to monitor employee performance, as we assume large firms to have a higher *capability* to make use of analytical methods. This is because larger firms tend to take more advantage of formalised and standardised HRM practices and processes which are also accompanied by standardised information and data collection (Paauwe & Boselie, 2003; Parry & Tyson, 2011). Standardised and formalised practices and processes arise from the larger quantities of data larger firms deal with. For example, larger firms with thousands of employees can clearly reduce costs by automated HRM practices that range from computerised recruitment to performance management. Also, while HRM can be largely personal in the sense that HR managers know employees and vice versa in small firms, in large firms much HRM practice needs to be formalised: data needs to be collected and stored for many HRM practices and therefore can be easily used for further analyses by using analytics. Furthermore, larger firms are able to afford specialised HR that has the capability to specialise on the potentials that analytical methods offer. Hence, we formulate our first hypothesis:

> *H1a: The larger a firm, the higher the incidence of HR analytics to monitor employee performance as larger firms tend to be equipped with the structural prerequisites (e.g.*

data is collected and stored anyway) and have the capability (e.g. are able to employ specialised HR analytics managers) to use HR analytics to monitor employee performance.

Literature also points towards the role of the 'history' of firms and firm traditions. In fact, there is evidence of path dependency in firms on why and how certain HRM practices are used or not (Benders et al., 2006; DiMaggio & Powell, 1983). Usually, this literature suggests that the older a firm, the more accentuated the role of distinct HRM practices and the more difficult it is to make use of new HRM practices and tools. In firms with a long history and strong traditions as well as deeply engraved organisational structures and practices, the resistance to change practices can also be expected to be higher than in (more) recently founded firms in which management finds it easier to make use of the newest technologies and methods (Shulzhenko & Holmgren, 2020). Although the recent increase in data collection and analysis that is (or can be) used for the control of employees can expected to lead to resistance among employees in general (Moore et al., 2018), resistance to the implementation of HR analytics in firms with longer traditions which also reduce uncertainty within firms can also be explained by the fact that a change might also lead to organisational change and shifts in formal as well as informal responsibilities, roles of employees and even to changes in 'traditional' power relationships. Hence, long traditions are assumed to decrease the motivation for adoption. According to this reasoning, we formulate our next hypothesis:

H1b: The older a firm, the lower the incidence of HR analytics to monitor employee performance, as older firms tend to monitor employee performance on the basis of previously existent HRM practices rather than on recently available practices such as HR analytics.

As another factor, we expect that the 'climate' between management and employees matters for the use of HR analytics to monitor employee performance. Specifically, we expect that the quality of the relationship matters, that is, it matters if there is a good relationship between management and employees or not. There is evidence in the literature that a good relationship between management and employees facilitates the capability for firms to implement and use HRM practices as employees trust that new practices introduced by management are mutually beneficial (Parry & Tyson, 2011). In analogy, we hypothesise:

H1c: The better the climate between management and employees, the higher the incidence of HR analytics to monitor employee performance as its implementation is facilitated.

Managerial characteristics and complexity of firm processes

In addition to structural factors of firms, we also expect managerial practices and the complexity of firm processes to matter for the use of HR analytics to monitor employee performance in firms. As regards managerial practices, we expect that the use of HR analytics to monitor employee performance is influenced by the role of monetary rewards. More specifically, we expect that the more intensively a firm makes use of monetary rewards for performance management, the more important the use of accurate and comprehensive methods and tools for performance management (Hendry et al., 2000). Against the background that HR analytics to monitor employee performance can increase the accuracy of performance management, the likelihood of its use can be expected to be higher the more often monetary rewards are used in firms. In addition, the use of automated or 'computerised' forms in HR analytics for monitoring employee performance might be encouraged in firms making increased use of monetary rewards as such methods are simply more cost effective than traditional forms of performance management. Either way, we expect the use of monetary rewards increases motivation for adoption, and therefore formulate our next hypothesis accordingly:

H1d: The more often firms make use of monetary rewards in managing their employees, the more need to make use of any HR method that provides accurate information and therefore the higher the incidence of HR analytics to monitor employee performance in firms.

Literature shows that the complexity of firm processes and practices influences the use of distinct HRM practices (Stavrou & Brewster, 2005). Basically, we expect that the higher the degree of complexity within a firm, that is, the more hierarchical levels needed, the more coordination of (groups of) employees and team work, and the more management positions required to run the business, the more advantageous the use of analytical methods are and the more motivated forms are to make use of it. Accordingly, we formulate our next hypothesis:

H1e: The more complex firm processes and organisational structures are, the higher the incidence of HR analytics to monitor employee performance, as HR analytics help to manage and understand the complexity of the firms' processes.

Market factors and the motivation of firms to use HR analytics

One important reason why firms are motivated to make use (or not) of HR analytics in general can be found in the costs of its implementation. For some firms, implementation costs might be considerably higher depending upon the qualifications of (HR) management and the need for training to make use of the potential of HR analytics (Angrave et al., 2016). Furthermore, new HRM practices might also lead to significant organisational and procedural changes within firms which can lead to disruptions and potentially organisational change costs.

Therefore, firms might need incentives, that is, the motivation, to make use of HR analytics (Levenson, 2011). Such incentives can originate from market pressures which motivate or even 'force' firms to make use of effective HR analytics (Levenson, 2018). Against the background that there is evidence that HR analytics can be effective, in the sense that it allows firms to manage their workforce more effectively (Guenole et al., 2017; Kryscynski et al., 2018; Levenson, 2011) and therefore allows firms to gain a comparative advantage over competing firms (e.g., Minbaeva, 2018), we expect that firms that are embedded in a market that is very competitive and therefore need to make use of any possible advantage to compete, the motivation to make use of HR analytics to monitor employee performance is high. Hence, we can formulate our next hypothesis accordingly:

H2: The more competitive the market in which firms are embedded, the higher the incidence of HR analytics to monitor employee performance, as the stronger the competition, the higher the incentive to make use of HR analytics to monitor employee performance.

National factors and the opportunity of firms to use HR analytics

There is a vast amount of research pointing towards substantial differences regarding the use of different HRM practices in firms in different countries (Aycan, 2005; Brewster et al., 2004; Ruta, 2005). It is usually argued in the literature that there may not necessarily be differences between firms in different countries regarding the question of if a HRM practice is useful or not, but the actual use of the practice and how it is implemented differs across countries because of different contextual factors (Panayotopoulou et al., 2010; Tayeb, 1995). This means that whilst the importance and need for the practice of monitoring employee performance is universal across countries, the degree of use of HR analytics to monitor employee performance, compared with other HRM practices, is strongly influenced by the national context. As regards the latter, literature differentiates between two kinds of factors, namely cultural and institutional factors (Brewster, 2006). Even though both kinds of factors are not independent of each other, as they refer to distinct dimensions with respect to the use of HR analytics, we will differentiate between the two in our analysis.

Cultural context

Research in comparative and international HRM provides evidence of the important role of national culture, defined as a distinct set of collective beliefs and values within countries (Hofstede, 1980), on why distinct HRM practices and tools are (more often) used in some countries than in others (Bondarouk & Brewster, 2016; Panayotopoulou et al., 2010; Papalexandris & Panayotopoulou, 2000; Ramamoorthy & Carroll, 1998; Ruël et al., 2004; Strohmeier, 2007). Conceptually and empirically, many studies on the role of cultural differences are based on the cultural dimensions outlined by Hofstede (1980), that is, on differences in the dimensions 'power distance', 'individualism/collectivism', 'uncertainty avoidance', 'masculinity/femininity', 'long-term orientation/short-term orientation', and 'indulgence/restraint'. Although not only the conceptualisation of these dimensions, but also the data collection is critically debated in literature (Hofstede, 2002; McSweeney, 2002), these dimensions are still frequently used in academic literature. Even though the validity and reliability of the cultural dimensions developed by Hofstede (1980) are not perfect and an analysis of sub-dimensions on some main dimensions are often preferable (Ramamoorthy & Carroll, 1998), among those cultural dimensions differences 'uncertainty avoidance' and 'individualism/collectivism' are considered in literature to be most relevant for the adoption and use of innovative HRM practices such as analytical methods (Jackson & Harris, 2003; Panayotopoulou et al., 2010; Shane et al., 1995).

More specifically, *uncertainty avoidance* refers to the degree to which individuals strive to avoid uncertainty by reliance on religion, traditions, social norms, and well-known bureaucratic practices to mitigate the uncertainty that comes along with changes. In this sense, in countries with a high degree of uncertainty avoidance any changes in HRM, such as the introduction of new HR practices, including HR analytics, can be expected to lead to resistance among individuals, because this would cause a deviation from HRM norms, traditions, and well-known bureaucratic practices which are important to individuals to avoid uncertainty (Panayotopoulou et al., 2010).

But apart from the fact that the introduction of analytical methods in hindered by a high degree of uncertainty avoidance, the collection, use and analysis of as much data as possible can also increase transparency and therefore be a means to reduce uncertainty (Straub, 1994). Hence, as argued by Aycan et al. (1999), in countries with a high degree of uncertainty avoidance, both management and employees might want to reduce uncertainty by a transparent and in this sense more visible (Newton & Findlay, 1996), for example, data driven and analytical, strategy which includes a close monitoring of employees and their performance. The crucial question, however, is whether HR analytics is able to reduce uncertainty. On the one hand, recent literature shows that the technology, methodology and 'algorithms' behind HR analytics are a 'black box' for employees and often also for the management (Cheng & Hackett, 2021; Leicht-Deobald et al., 2019). On the other hand, there is also evidence that suggests that predictive HRM strategies and practices, as HR analytics certainly are making performance management more transparent and efficient (Fitz-enz, 2010, pp. 85–93) and therefore reduce uncertainty.

Hence, differences in uncertainty avoidance between countries can have different possible effects on the incidence of HR analytics to monitor employee performance in firms in different countries and therefore it is an empirical question which relationship is stronger. However, since we are concentrating on the use of HR analytics in the context of performance management and not on HR analytics in general, we expect the positive relationship because of increased performance measurement accuracy to be of higher importance and therefore formulate our hypothesis:

> *H3a: The higher the degree of uncertainty avoidance in a country, the higher the incidence of HR analytics to monitor employee performance in firms, as HR analytics decreases uncertainty by increasing the efficacy of performance management.*

Also, differences in the degree of *individualism/collectivism* between countries might explain differences in the use HR analytics to monitor employee performance. This dichotomous differentiation between individualism and collectivism by Hofstede (1980) is, of course, very coarse and was refined by subsequent literature. Most notably by differentiating between institutional collectivism (or societal collectivism) on the one hand, which refers to the role of institutions in influencing collective behaviour such as in particular how resources should be distributed or allocated, and on the other hand, in-group collectivism, which refers to the role factors such pride, loyalty, and cohesiveness in and to the organisation (Bullough et al., 2017; House et al., 2004).

In countries in which employees' behaviour is characterised by a high degree of (both types of) collectivism, they can be expected to act (more) in the interests of the group (or firm/ organisation), while in individualist countries employees are acting (more) in their own interests and on their own initiative. Hence, because of the higher importance of own initiatives in individualistic countries it can be argued that less direction on how the work has to be done and therefore also less control and monitoring of employee performance is needed (Milliman et al., 1998). In this sense, HRM on basis of HR analytics changes the way how the performance of employees is organised, monitored, and even rewarded, that is, how performance is recognised. It also changes the role of esteem factors in performance management and any social factors such as pride, loyalty, and cohesiveness that matter for the evaluation of employees (Dejours, 2007). Hence, it affects in-group collectivism (Bullough et al., 2017; House et al., 2004). For example, the use of HR analytics to monitor employee performance might lead to a change from face-to-face interactions, for example, individual performance management and appraisal meetings with line managers, to a more 'anonymous', for example, computerised and 'algorithmic driven' performance management approach. This means that the 'group' interaction is (increasingly) replaced by an anonymous interaction which can be expected to affect pride and cohesiveness to the organisation and therefore affects the degree of group collectivism. In fact, the intensive use of HR analytics might even lead away from the idea that performance is a common good for the entire organisation, since it leads towards performance monitoring and an increased emphasise on the benefits of individuals. This would undermine collectivistic values in general and specifically it would undermine institutional collectivism since the latter involves the common good for the entire organisation rather than the benefit of individuals Galanaki et al. (2020). Therefore HR analytics could be expected to be welcomed in countries with a high degree of individualism but not in countries in which institutional collectivistic values are characteristic for organisational behaviour and values.

Finally, as outlined earlier, HR analytics makes performance management more visible in the sense of Newton and Findlay (1996) and enables a more transparent and individualised monitoring of employees and their performance (Aycan et al., 1999). Hence, it's use could be expected to be more welcomed in countries in which employees are characterised by a high degree of individualistic behaviour and values. This is different in collectivist countries in which it is not that important that individualised performance monitoring is improved. Against this background we, therefore, formulate our next hypothesis:

> *H3b: The higher the degree of individualism in comparison to collectivism in a country, the higher the incidence of HR analytics to monitor employee performance in firms, as HR analytics is in line with individual performance management and monitoring.*

Institutional context: Juridico-political factors and management prerogatives

Besides cultural differences between countries, also institutional, that is, juridico-political and employment relations, factors can be expected to matter in explaining differences in the use of HRM practices and tools in different countries (DeFidelto & Slater, 2001; Goergen et al., 2013). Even though these institutional factors and the former cultural factors are not independent from each other, differences between countries in how management can make use (or not) of HR analytics, that is, differences in management prerogatives, can be separated as another contextual factor that needs to be considered explicitly. More specifically, countries differ with respect to the juridico-political framework that defines privacy regulations, data protection and the collection and storage of (personalised) data of the workforce and therefore the ability for management to analyse these data (Custers et al., 2018). Furthermore, there is clear evidence from literature (Aycan, 2005; Brewster, 2006; Brewster et al., 2004; Farndale & Paauwe, 2007; Farndale & Paauwe, 2007; Gooderham et al., 2018; Goergen et al., 2013; Paauwe & Boselie, 2003; 2005; Panayotopoulou et al., 2010; Papalexandris & Panayotopoulou, 2000; Tayeb, 1995; Thompson & Heron, 2005) that countries also differ with respect to the wider institutional framework including the role of employment relations that restricts (or not) management to implement an.

As regards the latter, differences between countries exist because employment relations are different which give different actors in the employment relationship different roles and competences regarding the use and implementation of HR practices and tools (European Commission, 2008). While in some 'liberal' countries employment relations actors such as workplace representatives and trade unions have relatively little say on the use of HR practices and tools, in other ‘coordinated’ countries they do and management prerogatives are constraint. In addition to that there are also differences in the juridico-political context between countries, that is, differences in the regulations and interpretations on the strictness of data protection which are based on different traditions in the role of data protection and the privacy of citizens and employees, can be expected to matter for differences in the incidence of HR analytics to monitor employee performance in different countries. Juridico-political differences between countries in the EU member states became clearly visible during the implementation phase of the general data protection regulation (GDPR) which regulates data protection and privacy in the EU. However, recent research shows that even though the GDPR aims to harmonise data protection and privacy regulations throughout the EU, there are still significant differences in the manner and intensity in which EU member states implement the protection of privacy and personal data in national laws, policies, and practices (Tikkinen-Piri et al., 2018). Thus, even though the GDPR aimed to harmonise data collection and storage within the EU, firms in different countries in the EU still differ in how they collect, store and analyse workforce data, that is, there are differences in the ability to use HR analytics for different purposes. Literature (Custers et al., 2018) argues that countries such as in particular Austria and Germany are characterised by relatively strict data protection and privacy regulations while countries like the United Kingdom or many Central and Easter European Countries (CEECs) are characterised by a more liberal approach and management is vested with more extensive prerogatives over the use of HRM practices.

In fact, the juridico-political degree of strictness of data protection and privacy regulations as well as the wider employment relations context reflect widely the same differences between groups of countries based on the varieties of capitalism (VoC) categorisation developed by Hall and Soskice (2001). We will therefore base our analysis of the role of differences between countries in the organisational capability of firms in using HR analytics to monitor employee performance on the VoC approach and classification, as the VoC classification differentiates in the juridico-political context between countries with respect to the use of HR analytics. The VoC classification not only differentiates between different degrees of management prerogatives per se in the use of HRM practices and tools, but as Rothstein et al. (2019) have recently shown, also with respect to privacy, data collection and storage regulations. More specifically, liberal market economies (LMEs) offer weaker protection, including privacy, data collection and storage, for employees than coordinated market economies (CMEs). Furthermore, management in LMEs is usually less constraint by the employment relations system than in CMEs. Consequently, we can expect that firms which are embedded in a CME face more restrictions on the effective use of HR analytics to monitor employee performance than firms which are embedded in a LME. From this expectation we form the hypothesis:

> *H3c: The incidence of the usage of HR analytics to monitor employee performance is higher in firms embedded in LMEs than firms which are placed in CMEs because of differences in management prerogatives.*

RESEARCH METHODOLOGY

The data we use for the analysis come from the 2019 wave of the European company survey (ECS), see Eurofound (2019). The ECS has the advantage that it includes a question on the use of HR analytics to monitor employee performance. More specifically, the ECS includes the question ‘Does this establishment use data analytics to monitor employee performance?’, with the answer categories 'Yes' or 'No' which is used as dependent variable in this study. The ECS includes further questions on the use of analytical methods in firms in general, that is, on the use of any data analytics methods or tools to improve the processes of production or service delivery. This means that all other questions in the ECS are referring to the use of data analytics in an encompassing and broad way that includes areas such as for example marketing, logistics and supply chain optimisation. Hence, the use of all other variables on data analytics goes far beyond HR, work, and employment-related discussions and debates and would need a different theoretical and methodological approach. Although the variable used in our analysis is narrow and focuses on the use of HR analytics to monitor employee performance exclusively and not on all analytical methods and areas in HRM its analysis is very interesting to analyse for two reasons. First, the dependent variable on HR analytics to monitor employee performance is not too narrow so that it focuses on a niche area in the field of HR, work, and employment but also not broad so that it is beyond the field. Against the background that there is a long-standing literature looking at performance management, and management rationales and motives, work which examines the use of HR analytics to achieve this remains limited, the analysis of this particular variable is also interesting because, second, the used dependent variable focuses exactly on that area and there is no large-scale data is available in other international and comparative datasets. For example, there is no variable on HR analytics in the CRANET data set, which is frequently used in the field of international and comparative HRM. See for example Farndale et al. (2017), for an overview of related studies using the CRANET data set. The ECS collect establishment-level, that is, firm-level, data based on interviews with managers, usually HR managers, in firms. The ECS data was collected in the first half of 2019 across all current 28 EU member states. The ECS data are representative for businesses and organisations with 10 or more employees throughout the EU and thus enables us to test our hypothesis on a large sample of countries with different institutional and market contexts. The minimum sample size for our estimations is 20,411 firms.

Operationalization of market and country factor variables

All firm-level variables are based on the ECS (Eurofound, 2019). To test the role of *market factors*, which influence the *motivation* of firms to use HR analytics to monitor employee performance, we also use a direct measurement of the degree of competitiveness that the individual firms face, as measured in the ECS. While competitiveness of course also varies between markets, that is, sectors, which is likely relevant for the implementation of HRM practices (e.g., Laursen, 2002; Strohmeier & Kabst, 2009), this direct measurement of competitiveness is preferable as it expresses the firm-level variation in experienced competitiveness, which may be substantial within sectors.

Finally, as regards *country factors* and the country context, which define the *opportunity* for firms to make use of HR analytics to monitor employee performance, we use the dimensions by Hofstede (1980) for the test of H3a on the role of country differences. More specifically we use the relevant cultural dimensions, 'uncertainty avoidance' and 'individualism/collectivism'. Even though literature, most notably within the GLOBE approach by House et al. (2004), provides further operationalisations and data of cultural differences between countries on several dimensions, we used the Hofstede (1980) concept and data because data are available for all our countries within our sample. For example, the GLOBE data set includes only data for a very limited number of countries. As regards the role of institutional, juridico-political and employment relations factors, that express the ability of firms to make use of HR analytics to monitor employee performance we use the VoC classification developed by Hall and Soskice (2001). Given that there is a continuous debate with respect to which EU countries can be considered as CME or LME or something else, for our test of H3b we will primarily compare the classical CME countries by referring to Hall and Soskice (2001) and European Commission (2008), that is, Austria, Belgium, Denmark, Finland, Germany, Netherlands, Sweden, and classical LME, that is, UK, Ireland, Malta, and Cyprus. Countries which are often argued to be in between LME and CME are divided into two groups including 'statist market economies', that is, Greece, Spain, France, Italy, and Portugal, and into a group of CEECs, that is Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Romania, Slovakia, Slovenia. However, the latter group might even be considered to be within the group of LME (European Commission, 2008).

Modelling strategy

To test our hypotheses, we estimate the effects of each independent variable, adjusted for other variables. As our dependent variable is dichotomous, the effects should reflect predicted probabilities, which are bounded at 0 and 1. We, therefore, estimate logistic regression models. Moreover, because we use samples of firms from 28 different countries, we cannot *assume* the errors to be independently distributed. Indeed, there is clear evidence against the null-hypothesis that the intraclass correlation is zero (LR $\chi^2 \approx 977.74$). We, therefore, estimate *multilevel (logistic regression) models*, which include a country-specific random intercept. For details on the multi-level approach, see Rabe-Hesketh and Skrondal (2008). We present the exponentiated estimated coefficients, which can be interpreted as multiplicative effects on the odds of using HR analytics to monitor employee performance, that is, the effects expressed as odds ratios.

The ECS uses stratified sampling by firm size and sector, leading to unequal probabilities of sample inclusion according to the value of these variables. We address this issue by including sector and size as covariates in all estimated models to ensure that the errors are conditionally independent. For the country-level factors, our sample size is effectively limited to the number of countries. Therefore, the estimates need to be based on parsimonious models. We therefore first include the institutional and cultural country factors separately in our models, before estimating their effects jointly. As the cultural factors are not available for one country (Cyprus), this strategy also maximises the use of available information.

RESULTS: THE DETERMINANTS OF HR ANALYTICS TO MONITOR EMPLOYEE PERFORMANCE

The descriptive statistics of the variables included in the analysis are presented in Table A2. Across the entire sample, we find that about 27% of firms use HR analytics to monitor employee performance. We do however find that there exist differences across countries. This is illustrated in Figure 1, which shows the estimated share of firms which make use of HR analytics to monitor employee performance across all countries in our sample. Here, we see that the use of HR analytics to monitor employee performance is, for instance, relatively high in Romania (50%), Croatia (45%), and Spain (43%), but low in Germany (13%), Sweden (17%) and Ireland (19%). An overall pattern is that firms in Nordic countries and coordinated market

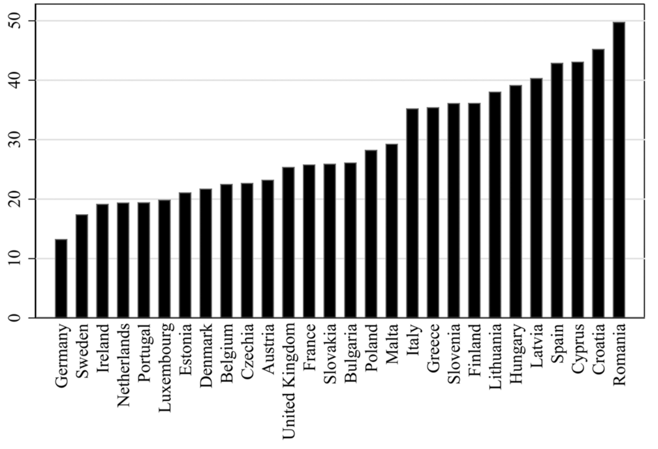

FIGURE 1 The percentage share of firms within countries using HR analytics to monitor employee performance (weighted by design-, and response-based differences)

economies in general seem less inclined to use HR analytics to monitor employee performance than their counterparts in CEEC.

Even though descriptive statistics show differences between groups of countries, our multilevel estimates which are shown in the following indicate that the variance between countries is rather limited and most of the variation in the use of HR analytics to monitor employee performance is within and not between countries. Specifically, the estimated unconditional intraclass correlation is only about 7%. Although this is relatively small, this still suggests that differences between countries should not be neglected totally. However, this result also indicates that other factors including the market context and firm-specific factors are more important in explaining why firms make use of HR analytics to monitor employee performance and others do not. Hence, these findings also indicate that the country context is not always essential and necessary when it comes to analyses of all HR practices.

In Table 1, we present the estimates for three multilevel models. The full set of firm-level variables is included in all three models (with the coefficients for the NACE sector dummies omitted from the table for reasons of space), but the three models vary with respect to the inclusion of macro-level contextual variables. Model 1 includes only the dummy variables indicating the VoC classification of the countries; Model 2 only includes the two cultural factors 'Uncertainty Avoidance' and 'Individualism/Collectivism'; and Model 3 includes all the macro-level variables. For ease of interpretation, we graphed the average predicted probability (APP) across values of the covariates for those variables that we consider to provide at least some evidence against the null-hypothesis of no effect in Figure 2 (based on Model 3).

As can be seen, the estimates for the firm-level variables are virtually identical in all three models which can be considered as a solid support for the robustness of these estimates. Specifically, we find robust and strong support for the hypothesis that larger firms are more likely to use analytics (H1a), although this effect appears to taper off for the largest firms. The increase in APP from the smallest to the largest firms is about 9%-points. We also find support for the hypothesis that older firms are more reluctant to implement analytics, though the magnitude of this effect is limited. For instance, the APP of analytics-use for firms that have

TABLE 1 Estimates of the impact of organisational, market, and country factors on the use of HR analytics to monitor employee performance

Independent variables	Model 1		Model 2		Model 3	
	Odds ratio	S.E.	Odds ratio	S.E.	Odds ratio	S.E.
Organisational factors						
Structural characteristics						
Size						
10–19 employees (Ref)						
20-49 employees	1.116*	(0.048)	1.120**	(0.049)	1.121**	(0.049)
50–249 employees	1.493***	(0.073)	1.494***	(0.074)	1.496***	(0.074)
250–499 employees	1.757***	(0.149)	1.759***	(0.149)	1.759***	(0.149)
500 or more employees	1.624***	(0.153)	1.624***	(0.153)	1.624***	(0.153)
Age (log)	0.916***	(0.019)	0.915***	(0.019)	0.916***	(0.019)
Management—employee relations						
Very good (Ref)						
Good	0.986	(0.040)	0.991	(0.040)	0.989	(0.040)
Neither good nor bad	0.964	(0.053)	0.970	(0.054)	0.968	(0.054)
Bad or very bad	0.960	(0.148)	0.960	(0.149)	0.958	(0.148)
Managerial characteristics & complexity						
Rewards practices: monetary rewards						
Never (Ref)						
Not very often	1.363***	(0.088)	1.374***	(0.089)	1.372***	(0.089)
Fairly often	1.841***	(0.122)	1.858***	(0.067)	1.851***	(0.123)
Very often	2.333***	(0.190)	2.336***	(0.191)	2.327***	(0.190)
Hierarchical levels						
1 (Ref)						
2	1.391**	(0.150)	1.380**	(0.149)	1.381**	(0.149)
3	1.813***	(0.183)	1.807***	(0.183)	1.807***	(0.183)
4	2.323***	(0.247)	2.316***	(0.247)	2.318***	(0.248)
5	2.373***	(0.323)	2.374***	(0.323)	2.378***	(0.324)
6	1.578*	(0.332)	1.571*	(0.331)	1.577*	(0.332)
7 or more	2.443***	(0.596)	2.429***	(0.593)	2.443***	(0.596)
Teamwork						
No teams(Ref)						
Most in single team	1.609***	(0.069)	1.605***	(0.069)	1.608***	(0.069)
Most in more than one team	1.851***	(0.087)	1.848***	(0.088)	1.852***	(0.088)

TABLE 1 (Continued)

Independent variables	Model 1		Model 2		Model 3	
	Odds ratio	S.E.	Odds ratio	S.E.	Odds ratio	S.E.
Share of managers						
None at all (Ref)						
Less than 20%	1.287**	(0.112)	1.283**	(0.111)	1.283**	(0.111)
20%–39%	1.182	(0.117)	1.184	(0.117)	1.184	(0.117)
40%–59%	0.846	(0.175)	0.845	(0.174)	0.844	(0.174)
60%–79%	0.718	(0.225)	0.717	(0.225)	0.715	(0.224)
80% or more	0.977	(0.301)	0.974	(0.300)	0.973	(0.299)
Market factors						
Competition						
Not at all competitive(Ref)						
Not very competitive	1.254	(0.154)	1.240	(0.152)	1.241	(0.152)
Fairly competitive	1.709***	(0.196)	1.696***	(0.194)	1.700***	(0.194)
Very competitive	2.057***	(0.237)	2.038***	(0.235)	2.043***	(0.236)
Country factors						
Cultural factors						
Uncertainty avoidance			1.005	(0.005)	1.002	(0.005)
Individualism/ Collectivism			0.998	(0.007)	1.004	(0.006)
Institutional factors						
Varieties of Capitalism						
CME (Ref)						
LME	1.182	(0.317)			0.0994	(0.288)
CEEC	1.867**	(0.368)			1.935**	(0.422)
Statist	1.562	(0.375)			1.555	(0.437)
Constant	0.042		0.047		0.281	
Country-level variance	0.170		0.226		0.163	
Log likelihood	−11617.102		−11546.766		−11542.442	
Wald X^2 (df)	1323.25 (44)		1309.67 (43)		1319.19 (46)	
N	20.522		20.411		20.411	
N (country)	28		27		27	

Note: The full set of NACE sector dummies is included in all three models, but their coefficients are omitted from the table for reasons of space. Ref, reference category; s.e., standard error [delta method: Exp(b) * $s.e._b$],
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed z-test of H_0: $b = 0$). *Source*: European Company Survey 2019.

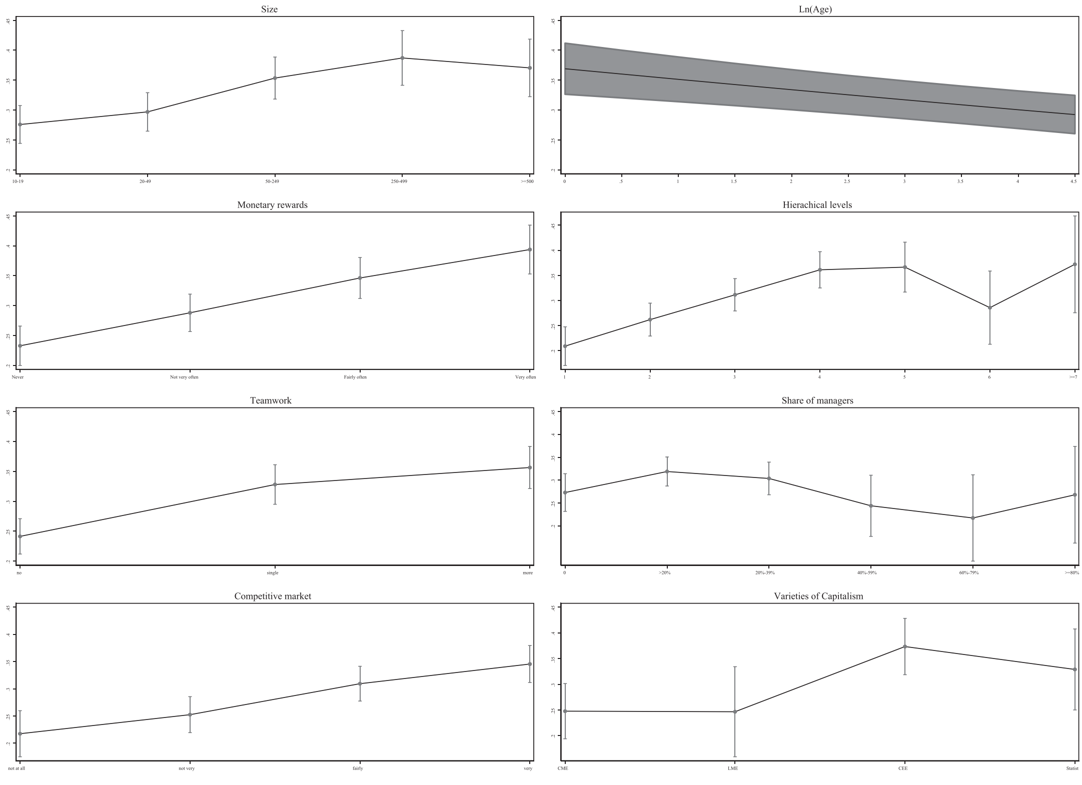

FIGURE 2 Average predicted probabilities of the use of HR analytics to monitor employee performance (*y*-axis) and associated 95% confidence intervals across covariate values (based on Model 3)

been operating for 100 years is only about 8%-points lower than it is for firms that have been operating for 1 year.

However, we find no evidence in favour of the hypothesis (H1c) that the better the quality of the relationship between management and employees, the higher the use of HR analytics to monitor employee performance. This does not necessarily imply that the quality of the relationship can be considered as completely obsolete. This is because the relationship might be more complex and multi-dimensional than investigated in this analysis in which we are only able to identify an average effect. For example, we cannot rule out that the use of HR analytics to monitor employee performance curtails the relationship and therefore might potentially disrupt a good relationship and therefore firms do not make use of it. Hence, we may not be able to model the whole complexity of the relationship and all its details with the available data.

Turning to the managerial characteristic and complexity dimension, the evidence in favour of the hypothesis that the use of monetary rewards is positively associated with the use of HR analytics to monitor employee performance (H1d) is very strong. To illustrate, firms that use monetary rewards very often have an APP of about 0.39, whereas for those that never use such rewards, this is only about 0.23.

Overall, and as predicted under H1e, the use of HR analytics to monitor employee performance also increases with the number of hierarchical levels, on average by roughly 5%-points for each additional level. This pattern does not appear to hold for firms with six hierarchical levels however, but it should be noted that the number of firms with six or seven levels is rather small, making the estimates more imprecise. Firms in which employees mostly work in more than one team are also more likely (APP ≈ 0.36) to use HR analytics to monitor employee performance than those in which employees mostly work in single teams (APP ≈ 0.33); with those with no teamwork least likely (APP ≈ 0.24). Regarding the impact of the share of managers, we find only very weak evidence of an association with the use of HR analytics to monitor employee performance. Firms without managers are less likely to use analytics than those with less than 20% managers, but clearly there is no overall monotonic relationship. Again, it should be noted that the number of observations with 40% managers or more is small and hence these estimates are more uncertain.

The hypothesised association between the degree of competition in which firms are embedded and the use of HR analytics to monitor employee performance (H2) is quite clearly supported. This is because the APP of analytics use among firms that indicate they operate in very competitive markets is on average about 13%-points higher than among firms that indicate they operate in uncompetitive markets.

Regarding the country-level factors, our results would, by and large, indicate that the institutional, that is, juridico-political and employment relations, context matters to a certain degree, but the cultural context does not. Both cultural dimensions have no discernible effect and therefore we are unable to accept H3a and H3b. Also, we do not find direct support for H3c that the use of HR analytics to monitor employee performance in LMEs is significantly higher than in CMEs because LMEs and CMEs differ in terms of management prerogatives as well as data protection and privacy regulations. Although we are not able to accept H3c we do find some support that differences between countries in management prerogatives as well as data protection and privacy regulations play a role for the use of HR analytics to monitor employee performance. This is because in CEECs, in which firms are embedded in an environment with less-developed data and privacy protection regulations, the incidence of HR analytics to monitor employee performance is relatively high. Hence, this result, provides some evidence that country-level factors cannot be considered to be completely irrelevant. Instead, the reason why country-level factors were found to have little or no empirical relevance might be based on two methodological reasons. First, because it is difficult to distinguish the impact and role of different country-specific factors. For example, the role of institutional factors and cultural factors overlap. Second, the relatively small number of observations at the country-level limits statistical power and our ability to correct for country-level specific confounders. Because only European countries are analysed, there is also a limited amount of variation present the cultural variables, as shown in the Table A2.

The implication of these methodological issues is that the result on the insignificance of variables such as the institutional framework as well as the cultural context used here does not imply that institutional and cultural factors do not matter at all, but either suggest that country differences within Europe are potentially too small but might matter when looking at differences at a global level. Hence, our results on the very moderate role of the country context in explaining the use of HR analytics to monitor employee performance should not be interpreted in a way that the country context does not matter as emphasised in recent literature for various other HR practices. This is because first of all our analysis only investigates one distinct practice and secondly, since we are only investigating European countries, country-level differences at a global level can be highly important.

CONCLUSION

Against the background that literature discusses the role and importance of firm as well as contextual factors regarding the question why firms make use of HR practices and tools in general and in this paper HR analytics in particular, we provided in this paper a comprehensive, multi-level and multi-faceted analysis of the role of *organisational*, *market*, and *country factors* to explain why some firms make use of HR analytics for monitoring the performance of employees while others do not. In this sense, we outlined in the paper that the use of HR analytics to monitor employee performance can be explained by *firms' structural and managerial capability*, as well as by their *motivation* and by the *opportunity* to be able to make use of it.

More specifically, on the basis of recent literature (Angrave et al., 2016), we considered that the use of HR analytics to monitor employee performance depends upon the structural and managerial capability of firms to make use of them and analysed the impact of organisational factors accordingly. Furthermore, since the literature also points towards the key role of contextual factors (Bondarouk & Brewster, 2016; Levenson, 2018; Paauwe & Boselie, 2005) in explaining the use of HRM practices, we considered that differences in the market context in which firms are embedded is able to explain differences in the motivation of firms to use HR analytics to monitor employee performance, and that the cultural and institutional country context in which firms are embedded is able to explain differences in the opportunity to use HR analytics to monitor employee performance.

The analysis in the study is novel in many ways. Against the background that literature points towards the importance of integrating the role of contextual factors, *theoretically*, we provided an integrative and multi-faceted analysis on the basis of the firm level. Although our theoretical framework that differentiates between the capability, motivation, and opportunity to use HR analytics to monitor employee performance in firms shares similar elements and terms with the well-known AMO framework (Boxall & Purcell, 2003) both frameworks differ significantly. Most notably because in the traditional AMO framework all factors are largely firm-specific determined while in our framework motivation and opportunity are externally determined by the market and country context. Hence, our framework integrates internal and external factors and differs also *methodologically*. Therefore, we also developed a novel multi-level approach which integrates the firm (internal) level with the (external) market and country level. *Empirically*, our analysis made use of a unique, comprehensive and up-to-date data set on the use of HR analytics to monitor employee performance in firms in all member states of the EU which allowed us to present generalisable results.

The results of our analysis showed that organisational, that is, firm-specific, factors are most important in explaining why firms make use of HR analytics to monitor the performance of employees or not. Among various firm-specific factors that matter, most notably firm size and the firm age was found to be decisive. Our hypothesis that larger firms are equipped with the structural and managerial capability to make use of the potentials of HR analytics was supported. Also, our hypothesis that older firms tend to refrain from the use of HR analytics to monitor employee performance because of a tendency to rely rather more on 'traditional' HRM practices and tools was supported. Against the background that literature points towards the importance of contextual factors these results are of special relevance. The reason for this is that HR analytics to monitor employee performance might be a different HR practice and tool compared to other practices for which contextual factors are of relatively less importance. However, the results of our study certainly do not mean that market and country contextual factors are completely irrelevant but only show that organisational factors are relatively more important in explaining why firms make use of HR analytics to monitor employee performance.

As regards market contextual factors, our results showed that the degree of market competitiveness to which firms are exposed does matter. More precisely, the more competitive the market for firms' products and services, the more these firms make use of HR analytics to monitor employee performance. In fact, we found that the degree of competitiveness can be a strong motivator for firms to gain an advantage over competitors and make use of HR analytics to monitor the performance of employees. As regards country contextual factors our results our results provide a mixed picture. While, on the one hand, cultural differences between countries were found to be unable to explain differences in the use of HR analytics to monitor employee performance, on the other hand, differences in the institutional ability and opportunity of firms to collect and store data and therefore make efficient use of HR analytics can explain some differences among firms in different countries. More precisely, our results provide some evidence that firms embedded in countries with less strict and developed regulations on data and privacy protection, which widen (HR) management prerogatives and opportunities to make use of HR analytics to monitor the performance of employees, make more use of HR analytics than firms in countries in which HRM is faced with more regulatory constraints.

Our results have *practical and policy implications* as they show that it is mainly in firms' own HRM hands to make use of the benefits of analytical methods to monitor the performance of employees, particularly if the trend of an increasing digitalisation of firms and of the economy as well as the availability of (big) data increases and therefore the use of analytics becomes increasingly attractive and important as a method for managing and monitoring the performance of their workforce effectively. This is because our analysis showed that contextual factors are less of a constraint for the majority of firms: firms' capabilities and in particular firms' motivation to make use of HR analytics to monitor employee performance matter more. While the motivation to make use of HR analytics to monitor employee performance is a completely variable parameter of any strategic HRM, some organisational factors do matter and therefore limit the options of HRM to make use of HR analytics to monitor employee performance. For example, we showed that it is more challenging for smaller and older firms to make use of HR analytics to monitor employee performance.

However, for firms that have a relative disadvantage in potentially making use of HR analytics to monitor employee performance because of their structural and managerial capabilities and constraints in their opportunities, our results also indicate that such disadvantages can be mitigated or even eliminated if they receive support. For example, if they are supported by state authorities or business interest organisations. Also, since some constraints in the opportunity of firms to make use of HR analytics to monitor employee performance are due to laws and regulations at the country level, governments may act to change regulations accordingly to mitigate any competitive disadvantages of their firms.

In sum, the strength of our methodological approach and analysis lies in the fact that it integrates firm and contextual factors, demonstrating the relative importance of these different factors for the use of HR analytics to monitor employee performance and that their use is mostly determined by firms' own capabilities, motivations and opportunities.

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APPENDIX

(Dummy Tables A1, A2)

TABLE A1 Descriptive statistics

Dependent variable	Valid (*N*)	Mean (%)	S.D.
Use of HR analytics to monitor employee performance	21,772	26.72	
Covariates			
Organisational factors			
Structural characteristics			
Size	21,869		
10–19 employees	41.84		
20–49 employees	40.54		
50–249 employees	14.00		
250–499 employees	1.30		
500 or more employees	2.32		
Age (log)	21,566	3.24	0.82
Management—employee relations	21,741		
Very good		25.96	
Good		58.90	
Neither good nor bad		14.16	
Bad or very bad		0.98	
Managerial characteristics and complexity			
Rewards practices: monetary rewards	21,721		
Never		11.91	
Not very often		44.81	
Fairly often		35.11	
Very often		8.17	
Hierarchical levels	21,281		
1		4.21	
2		18.86	
3		59.40	
4		15.04	
5		1.81	
6		0.46	
7 or more		0.02	

TABLE A1 (Continued)

Dependent variable	Valid (*N*)	Mean (%)	S.D.
Teamwork	21,786		
No teams		29.37	
Most in single team		46.35	
Most in more than one team		24.28	
Share of managers	21,869		
None at all		5.87	
Less than 20%		74.38	
20%–39%		16.81	
40%–59%		1.41	
60%–79%		0.78	
80% or more		0.75	
Market factors			
Competition	21,593		
Not at all competitive		3.02	
Not very competitive		10.57	
Fairly competitive		50.46	
Very competitive		35.94	
Country factors			
Cultural factors	21,747		
Uncertainty avoidance		68.53	21.84
Individualism/Collectivism		67.26	16.01
Institutional factors			
Varieties of Capitalism	21,869		
CME		31.02	
LME		17.32	
CEEC		17.56	
Statist		34.10	

Note: Mean & S.D.: estimated mean and & standard deviation, weighted by design-, and response-based differences; reported for continuous variables only.

%: estimated percentage, weighted by design-, and response-based differences.

Source: European Company Survey 2019.

TABLE A2 Country-level distributions of cultural variables worldwide and restricted EU sample

	Mean	Standard deviation	Minimum	Maximum
Full country sample ($N = 78$)				
Uncertainty avoidance	67.64	22.99	8	112
Individualism/Collectivism	45.167	23.97	6	91
Analysed country sample ($N = 27$)				
Uncertainty avoidance	71.22	22.97	23	112
Individualism/Collectivism	58.63	17.84	27	89

Note: The maximum values can exceed 100 because the original raw scores on the variables are used, rather than the scores normalised to fall within the 0–100 range.