What Explains the Use of HR Analytics to Monitor Employee Performance? An Analysis of the Role of the Organizational, Market, and Country Context

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Abstract: The digitalization 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 analysis and an up-to-date dataset that covers more than 20,000 firms in all member states of the European Union we investigate which firms make use of HR analytics and which 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, i.e. juridico-political, and cultural environment in which firms are embedded influences firms' opportunities to use HR analytics.

Keywords: HR analytics, Europe, Comparative HRM, Contextual HRM factors

INTRODUCTION

The digitalisation and technological advancements of the recent past has increasingly enabled many firms to collect and store information and quantitative data of and about their work force (*e.g.,* Davenport, 2014; Fitz-enz, 1984; Parry *et al*., 2007). Methodological developments, which went along with these improvements, also provided firms with the analytical methods, i.e. tools, to take a more evidence-based approach to management and to analyse the information and quantitative data more systematically (*e.g.,* Angrave *et al*., 2016; Edwards, 2019; Pfeffer & Sutton, 2006). These developments not only led to the accumulation of (often big) data in firms, but also entailed the advance of Human Resource (HR) analytics.

Since many Human Resource Management (HRM) problems can be traced to a lack of information and/or information asymmetries between the management and employees (*e.g.,* Campbell *et al*., 2012), the availability of more information and data and the use of methods that process this data appears to be particularly welcome in the area of HRM. Consequently, one might expect strong incentives for firms to make use of both the data and HR analytics in order to effectively manage their workforce and ultimately gain a comparative advantage over competing firms (*e.g.,* Minbaeva, 2018).

However, even though the use of HR analytics and the effective "exploitation" of the available information and data appears to be a self-evident advantage for firms and given the evidence that analytical approaches in HRM are paying off (*e.g.,* Guenole *et al*., 2017; Kryscynski *et al*., 2018; Levenson, 2011), comparatively few firms make use of it. Recent literature argues that many firms hesitate to make use of HR analytics because there are a number of factors that hinder or even prevent its use (Schiemann *et al*., 2018). Most notably, it needs to be embedded in an environment that has the *structural and managerial capability*, e.g.

expertise or knowledge of (HR) managers to make use of the data and methods (*e.g.*, Angrave *et al*., 2016; Huselid & Jackson, 1997; Stone & Lukaszewski, 2009; Thompson & Heron, 2005; Vargas *et al*., 2018), and the *opportunity,* e.g. the (legal) regulations and managerial prerogatives that allow firms to collect, store and analyse data accordingly. Furthermore, since the implementation of HR analytics is costly, firms also need the *motivation* to use HR analytics, e.g. the market factors or market pressures that motivate or even "force" firms to do so (Levenson, 2018).

Consequently, there are various firm specific and contextual factors that encourage as well as restrain firms from making use of HR analytics but little is known about their role and relevance. On the basis of an up-to-date, large scale, cross-national and cross-sectoral data set on the incidence of use of HR analytics in 20,411 firms in all member states of the EU (Eurofound, 2019), we investigate the role and relevance of a comprehensive list of factors that potentially explain why some firms make use of HR analytics while others refrain from its use. Against the background that the dataset covers firms within a wide range of countries and therefore within different institutional juridico-political systems and within different cultural traditions which were shown to be decisive for the use of distinct management practices such as HR analytics (*e.g.,* Aycan, 2005; Goergen *et al.*, 2006, 2013), we systematically analyse the role and relevance of firm specific, i.e. organizational, market specific, and country factors on the incidence of HR analytics in firms using a multi-level framework. More specifically, this paper tests hypotheses on the relationship between different kinds of factors at different analytical levels and their interplay on the incidence of *HR analytics to monitor employee performance* in firms.

Thus, in this paper we provide a comprehensive, multi-layered and multi-faceted analysis of the relationship between firm, market and country level factors and the use of HR analytics in firms using up-to-date cross-European firm data at the establishment level. The structure of the paper is as follows. First we give an overview of different HR analytics areas followed by a literature review on 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, i.e. tools, for the analysis of HR related data and information (*e.g.,* Edwards, 2019; Marler & Boudreau, 2017; Van der Laken, 2018). More specifically, as HR analytics is a sub area of business analytics, it can be defined in accordance with common business analytics definitions (*e.g.,* Camm *et al*., 2019) as a set of methods that aid HR decision making by providing insights from data and information. Use of these analytics therefore allows (HR) managers to better address HR problems as it helps to improve planning, evaluates and even quantifies risk, and offers better and further alternatives for decision making.

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" (*e.g.,* Hoffman *et al.*, 2017), 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". Analytics could also include the analysis of qualitative information which can often be combined with quantitative data in order to understand HR problems better. 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, e.g. 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 (*e.g*., Aral *et al*., 2012, Asano *et al*., 2015; Autor & Scarborough, 2008; Chalfin *et al*., 2016; Hoffman *et al*., 2017; Horton, 2017; 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, i.e. monitor, employee performance while others refrain from its use.

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

Methodologically, we base our analysis on the firm level and investigate the question of why some firms make use of HR analytics to monitor employee performance while others do not. Thus, the theoretical framework on which we will formulate and test our hypotheses is the firm level. However, 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, i.e. the sectoral, and country level (Bondarouk & Brewster, 2016; MacDuffie, 1995; Paauwe & Boselie, 2005), we augment our firm level perspective by a multi-level analysis which integrates the market as well as country context.

Therefore we will refer to different kind of factors at different levels as well as different strands in the literature accordingly. First, since HR analytics is a management practice (Strohmeier, 2009), we will refer to factors and relevant literature explaining the adoption of HR analytics in organisations (*e.g.,* Burbach & Royle, 2013; Marler & Parry, 2016; Parry, 2011). Second, to explain differences in the management and operation of HR analytics by different organisations we will refer to literature on contextual factors, particularly the role of markets and sectors and especially literature on differences in market pressures and exposures to competitiveness (*e.g.,* Strohmeier & Kabst, 2009; Farndale & Paauwe, 2007). Third, 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 (*e.g.*, Bondarouk & Brewster, 2016; Brewster, 2006; Gooderham *et al*., 2015, 2018). As regards the latter, we will differentiate between the role of juridico-political and cultural differences.

In the following we will derive hypotheses on the determinants of the use of HR analytics on the basis of these different factors and relevant streams of research starting with, first, organizational, i.e. firm, factors including both structural and managerial factors of firms, second, market contextual factors, and third, country contextual factors.

Organizational factors

Academic literature points towards the relevance of a number of organizational factors including the *structural characteristics* of firms, i.e. the size, traditions, and the general climate, i.e. the "quality" of relationship between management and employees, as well as *managerial characteristics and the complexity of firm processes* including the role and form of rewards practices, hierarchies, team work and management responsibilities, regarding the incidence of different HRM practices.

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 (*e.g.*, Florkowski & Olivas-Luján, 2006; Hausdorf & Duncan, 2004). We can therefore expect that firm size also matters for the use of HR analytics. This is because larger firms tend to take more advantage of formalized and standardized HRM practices and processes which are also accompanied by standardized information and data collection (*e.g.*, Brewster & Suutari, 2005; Paauwe & Boselie, 2003; Parry & Tyson, 2011). Standardized and formalized 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 computerized 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 formalized: 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 specialized HR that has the capacity to specialize in HR analytics in order to exploit the potential that HR analytics offers. Hence we formulate our first hypothesis:

> *H1a: The larger a firm, the higher the incidence of HR analytics as larger firms tend to be equipped with the structural prerequisites (e.g. data is collected and stored anyway) and have the capacity (e.g. are able to employ specialized HR analytics managers) to use HR analytics*.

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 (*e.g.,* Benders *et al*., 2006; DiMaggio & Powell, 1983; Scott, 2001). 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 organizational 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. Resistance to the implementation of HR analytics in firms with longer traditions can also be explained by the fact that a change might also lead to organizational change and shifts in formal as well as informal responsibilities, roles of employees and even to changes in "traditional" power relationships. According to this reasoning we formulate our next hypothesis:

> *H1b: The older a firm, the lower the incidence of HR analytics, 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 the management and employees matters for the use of HR analytics. Specifically, we expect that the quality of the relationship matters, i.e. 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 the management and employees facilitates the implementation of HRM practices as employees trust that new practices introduced by management are mutually beneficial (*e.g.,* Bissola & Imperatori, 2014; Parry & Strohmeier, 2014; Parry & Tyson, 2011). In analogy we hypothesize:

> *H1c: The better the climate between the management and employees, the higher the incidence of HR analytics 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 in firms. As regards managerial practices, we expect that the use of HR analytics 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 (*e.g.,* Brown & Medoff, 1989, 2003; Frey *et al*., 2013; Hendry *et al*., 2000). Against the background that HR analytics 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 "computerized" 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 a positive relationship 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 in firms.*

Literature shows that the complexity of firm processes and practices influences the use of distinct HRM practices (*e.g.,* Delery & Doty, 1996; Martin-Alcazar & Romero-Fernandez, 2005; Stavrou & Brewster, 2005). Basically, we expect that the higher the degree of complexity within a firm, i.e. 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 (*e.g.,* Batt, 1999; Hauff *et al*., 2014; Gooderham *et al*., 2015; Parry, 2011). Accordingly we formulate our next hypothesis:

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

Market factors

One important reason why firms make use (or not) of HR analytics 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 in order to make use of the potential of HR analytics (*e.g.,* Angrave *et al*., 2016). Furthermore, new HRM practices might also lead to significant organizational and procedural changes within firms which can lead to disruptions and potentially organizational change costs.

Therefore, firms might need incentives, i.e. the motivation, to make use of HR analytics (*e.g*., Levenson, 2011). Such incentives can originate from market pressures which motivate or even "force" firms to make use of effective HR analytics (*e.g*., 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 (*e.g.,* 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 in order to compete, the motivation to make use of HR analytics 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, as the stronger the competition, the higher the incentive to make use of HR analytics.

National factors

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 (*e.g.,* 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 (*e.g.,* 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 (Hostede, 1980), on why distinct HRM practices and tools are (more often) used in some countries than in others (*e.g.,* Bondarouk & Brewster, 2016; 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) of which “uncertainty avoidance” and “collectivism” are most relevant for the use of HRM practices and tools in general and for HR analytics specifically (*e.g.*, 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 traditions, or social norms, and well-known bureaucratic practices to mitigate the uncertainty that comes along with changes. Since the use of HR analytics is largely based on new developments and changes in technology, it causes risks and uncertainties for both employees and managers in firms. Hence we can formulate our hypothesis:

H3a: The higher the degree of uncertainty avoidance in a country, the lower the incidence of HR analytics in firms, as HR analytics increases uncertainty.

Also, the use of HR analytics might fundamentally change how the performance of employees is organized, monitored, and even rewarded. For example, the use of HR analytics might lead to a change from face-to-face interactions, e.g. individual performance management and appraisal meetings with line managers, to a more "anonymous", e.g. computerized and "algorithmic driven" performance management approach. Thus, the use of HR analytics might even change relations and ties between individuals in firms. Therefore, differences in the degree of collectivism, defined as by how close and valued strong relations and ties between individuals and groups are (Hofstede, 1980), might matter for the use of HR analytics. Hence we can formulate our next hypothesis:

H3b: The higher the degree of collectivism in a country, the lower the incidence of HR analytics in firms, as HR analytics can be expected to suppress personal ties and relationships with others by anonymous (e.g. algorithmic and computer based) mechanisms of interactions.

Institutional context: juridico-political factors

Besides cultural differences between countries, also institutional, i.e. juridico-political, factors can be expected to matter in explaining differences in the use of HRM practices and tools in different countries (*e.g.*, DeFidelto & Slater, 2001; Goergen *et al*., 2013). Differences between countries in how the use of HR analytics are legally regulated and potentially constrained by differences in juridico-political privacy considerations can be expected to be of special importance in explaining differences in the incidence of HR analytics in different countries as it determines the extent of HR management prerogatives (HR). Given that significant differences between countries exist with respect to privacy regulations, data protection and the collection and storage of (personalized) data of the workforce and the ability to analyse these data (Custers *et al.*, 2018), country differences in the use of HR analytics are highly likely since these legal differences often prevent and disable the use of HR analytics.

In fact differences in the juridico-political context between countries, i.e. 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 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 harmonize 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 harmonize 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, i.e. there are differences in the ability to use HR analytics.

Literature (*e.g.*, Custers *et al*., 2018) argues that countries such as in particular Austria and Germany are characterized by relatively strict data protection and privacy regulations while countries like the UK or many Central and Easter European Countries (CEECs) are characterized by a more liberal approach and management is vested with more extensive prerogatives over the use of HRM practices. In fact the juridico-political context and management prerogatives with respect to the degree of strictness of data protection and privacy regulations in different countries corresponds widely with the Varieties of Capitalism (VoC) categorization developed by Hall & Soskice (2001). We will therefore base our analysis of the role of differences between countries in the organizational capacity of firms in using HR analytics 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). Consequently, we can expect that firms which are embedded in a CME face more restrictions on the effective use of HR analytics than firms which are embedded in a LME. From this expectation we form the hypothesis:

H3c: The incidence of the usage of HR analytics is higher in firms embedded in LMEs than firms which are placed in CMEs.

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 which is not commonly included in other datasets, most notably the CRANET dataset, 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 dataset. The ECS collect establishment-level, i.e. 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 is representative for businesses and organizations 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 variables

Our dependent variable is based on the answer “Yes” or “No” to the question in the ECS “Does this establishment use data analytics to monitor employee performance?” As regards the operationalization of variables for *organizational factors* we use data from the ECS. More specifically, for H1a on the role of the size of the company, we used answers to the question “Approximately how many people work in this establishment?” which were grouped into 5 categories (10-19; 20-49; 50-249; 250-499; and 500 and more employees). For H1b on the age of the firms, we used the logarithm of the answers to the question “Since what year has this establishment been carrying out this activity?” For the role of the climate between management and employees, i.e. H1c, we used answers to the question “How would you describe the relations between management and employees in this establishment in general?” by differentiating between “Very good”, “Good”, “Neither good nor bad”, and “Bad or very bad”.

In order to test H1d on the use of monetary rewards we used answers “Never”, “Not very often”, “Fairly often”, and “Very often” to the question on how often monetary rewards are offered. As regards the test of H1e on the role of the complexity of firm processes and management, we refer to three variables which all express different dimension of complexity. First, we use answers to the question on “How many hierarchical levels do you have in this establishment?” by capping the number at 7 because of limited observations for the higher number of levels. Second, for the role of team work, we created the categories “No teams”, “Most of them work in a single team” and “Most of them work in more than one team”, based on the questions “A team is a group of people working together with a shared responsibility for the execution of allocated tasks. Team members can come from the same unit or from different units across the establishment. Do you have any teams fitting this definition in this establishment?” and “With regard to the employees doing teamwork, do most of them work in a single team or do most of them work in more than one team?”. Third, for the share of managers in the firm, we used answers to the question “How many people that work in this establishment are managers?” which were categorized in “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, “80% or more”.

In order to test H2 on the role of *market factors*, we used the NACE categorizations B, C, D, E, F, G, H, I, J, K, L, M, N, R, S which were provided by the ECS. As regards the role of the degree of competitiveness of the market firms are embedded in, we used answers “Not at all competitive”, “Not very competitive”, “Fairly competitive”, and “Very competitive” to the question “How competitive would you say the market for the main products or services provided by this establishment is?”. Even though both variables express differences in the market and the degree of competitiveness between markets, i.e. sectors, the latter variable is certainly preferable as it expresses more directly the competitiveness the firm faces. Nevertheless we include also the sector variables, not least because it provides us with additional information on sector differences which we know are important for the implementation of HRM practices (*e.g.*, Laursen, 2002; Strohmeier & Kabst, 2009).

Finally, as regards *country factors* and the country context, 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 “collectivism”. Even though literature provides further cultural dimensions, most notably House *et al*. (2004), we used the Hofstede (1980) concept and data as these dimensions are widely used in the academic literature and data is provided for all our countries which is not the case for alternatives. As regards the role of institutional, juridico-political factors, that express the ability of firms to make use of HR analytics we use the VoC classification developed by Hall & 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 & Soskice (2001) and European Commission (2008), i.e. Austria, Belgium, Denmark, Finland, Germany, Netherlands, Sweden, and classical LME, i.e. 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”, i.e. Greece, Spain, France, Italy, and Portugal, and into a group of CEECs, i.e. 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

In order 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 opt for a logit specification. Moreover, because we use samples of firms from 28 different countries, we cannot assume the errors to be independently distributed. We therefore estimate *multilevel (logit) models,* which include a country-specific random intercept. In general, our models thus take the form:

$$\ln\left(\frac{p}{1-p}\right) = \gamma_{00} + \gamma_{10}X1_{ij} \dots + \gamma_{k0}Xk_{ij} + \gamma_{01}W1_j \dots + \gamma_{0k}Wk_j + u0_j$$

Where p is the probability that firms use HR analytics; γ_{00} is the conditional grand mean; $\gamma_{10}, \dots, \gamma_{k0}$ is the set of coefficients for the included firm-level variables $X1_{ij}, \dots, Xk_{ij}$; while $\gamma_{01}, \dots, \gamma_{0k}$ is the set of coefficients for the included macro-level variables $W1_j, \dots, Wk_j$. The coefficients can be interpreted as linear effects on the "log-odds" of using HR analytics. $u0_j$ represents the country-specific error for which the variance σ^2_{u0} is estimated, and is assumed to be zero-mean normally distributed. The firm-level variance is implied by the binomial distribution.

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 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 maximizes the use of available information.

RESULTS: THE DETERMINANTS OF HR ANALYTICS

The descriptive statistics of the variables included in the analysis are presented in Table 2 in the appendix. Across the entire sample, we find that about 27% of firms use HR analytics. 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 across all countries in our sample. Here, we see that HR analytics use 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 economies in general seem less inclined to use HR analytics than their counterparts in CEEC.

- INSERT FIGURE 1 ABOUT HERE -

However, our multilevel estimates indicate that the variance between countries is limited and most of the variation in HR analytics-use is within, not between countries. The estimated unconditional intraclass correlation is only about 7%. Although this is relatively small, we do find evidence of systematic differences between countries (LR $\chi^2 = 977.74$).

In Table 1, we present the estimates for three multilevel logit 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 vary in the inclusion of macro-level 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"; and Model 3 includes all the macro 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).

- INSERT TABLE 1 ABOUT HERE –

- INSERT FIGURE 2 ABOUT HERE -

The estimates for the firm-level variables are virtually identical in all three models. Overall, we find 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 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 the management and employees, the higher the use of HR analytics. This does not necessarily imply the total absence of an effect. This is, because the relationship might be more complex and multi-dimensional. For example the use of HR analytics might be different to other HRM practices and tools as it curtails the relationship and therefore might potentially disrupt a good relationship and therefore firms do not make use of it. However, given that we can reasonably assume quite high statistical power due to the sample size, it is suggestive that whatever average effect there exists, will be negligible. In sum, some structural characteristics of firms, in particular size, can be assumed to impact on analytics-use.

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 (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 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 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. 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 hypothesized association between the degree of competition in which firms are embedded and the use of HR analytics (H2) is however quite clearly supported: we find that 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-factors, our results would, by and large, indicate that the institutional, i.e. juridico-political, 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 in LMEs is significantly higher than in CMEs. However, we do find indirect support for the role of the juridico-political context as we find evidence that the use of HR analytics is significantly higher in CEECs in which firms are also embedded in a liberal environment in which data and privacy protection is relatively more liberal and management prerogatives are high.

However, when interpreting the results, the usual advantages and disadvantages of questionnaire survey data and the estimation of multivariate models with cross-sectional data apply. In particular, the variable measuring the quality of the relationship between the management and the employees may be affected by social-desirability bias. Re-estimating the models without this variable suggests that the other estimates are robust to this issue. Furthermore, in particular effects of relationship between the management and employees as well as regarding reward practices may suffer from some degree of simultaneity. Also, the effects of the country-factor should be interpreted with some caution. The relatively small number of observations at the country level, the small interclass correlation, and regarding the cultural factors, the limited variation across our country sample limit statistical power and our ability to correct for country-specific confounders. Finally, estimates based on random-intercept models assume independence of the country-level error term and the firm-level variables. However, this does not appear to be problematic for our estimates: re-estimation with country-fixed effects produces virtually identical results.

CONCLUSION

In this paper we provided a comprehensive, multi-level and multi-faceted analysis of the role of *organizational*, *market*, and *country* (i.e. cultural and juridico-political) *factors* in order to explain why some firms make use of the potential of HR analytics for monitoring the performance of employees while others do not. Methodologically we based our analysis at the firm level and argued that the use of HR analytics is determined by *firms' structural and managerial capability*, *motivation* and the *opportunity* to make use of HR analytics.

More specifically, on the basis of recent literature (*e.g.*, Angrave *et al*., 2016), we argued that the use of HR analytics is very much dependent upon the structural and managerial capability of firms to make use of them and analysed the impact of organizational factors accordingly. Furthermore, since the literature also points towards the key role of contextual factors (*e.g.,* Bondarouk & Brewster, 2016; Levenson, 2018; MacDuffie, 1995; Paauwe & Boselie, 2005) in explaining the use of HRM practices, we argued 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, and that the cultural and juridico-political country context in which firms are embedded is able to explain differences in the opportunity to use HR analytics.

The analysis in the paper 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. *Methodologically*, we developed a multi-level approach which integrates the firm, 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 in firms in all member states of the EU which allowed us to present generalizable results.

The results of our analysis showed that organizational, i.e. 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 because of a tendency to rely rather more on "traditional" HRM practices and tools was supported.

As regards 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. In fact we found that the degree of competitiveness is 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 the country context, our results show that while cultural differences between countries are unable to explain differences in the use of HR analytics, juridico-political differences, i.e. differences in the legal ability and opportunity of firms to collect and store data and therefore make efficient use of HR analytics are able to explain some differences. More precisely, our results showed that firms embedded in countries with more liberal 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 HR analytics, particularly if the trend of an increasing digitalization of firms and of the economy as well as the availability of (big) data increases and therefore the use of HR analytics becomes increasingly attractive and important as a method for managing the 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 matter more. While the motivation to make use of HR analytics is a completely variable parameter of any strategic HRM, some organizational factors do matter and therefore limit the options of HRM to make use of HR analytics. For example, we showed that it is more challenging for smaller and older firms to make use of HR analytics.

However, for firms that have a relative disadvantage in potentially making use of HR analytics 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. For example, our results show that firms can draw on support on the implementation and use of HR analytics from employers' and business organizations that usually provide support. Also, since some constraints in the opportunity of firms to make use of HR analytics 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 and that their use is mostly determined by firms' own capabilities, motivations and opportunities.

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TABLE 1 Logit estimates of the impact of organizational, market, and country factors on the use of HR analytics

	Model 1			**Model 2**			**Model 3**		
Independent variables	*γ*	s.e.	*p*	*γ*	s.e.	*p*	*γ*	s.e.	*p*
Organizational factors									
Structural characteristics									
Size									
10-19 employees (Ref)									
20-49 employees	0.110	0.043	0.011	0.114	0.043	0.009	0.114	0.043	0.008
50-249 employees	0.401	0.049	<0.001	0.402	0.049	<0.001	0.403	0.049	<0.001
250-499 employees	0.564	0.085	<0.001	0.565	0.085	<0.001	0.565	0.085	<0.001
500 or more employees	0.485	0.094	<0.001	0.485	0.094	<0.001	0.485	0.094	<0.001
Age (log)	-0.088	0.021	<0.001	-0.089	0.021	<0.001	-0.087	0.021	<0.001
Management – employee relations									
Very good (Ref)									
Good	-0.014	0.040	0.732	-0.010	0.040	0.813	0.011	0.040	0.782
Neither good nor bad	-0.037	0.055	0.507	-0.030	0.056	0.587	-0.033	0.056	0.552
Bad or very bad	-0.041	0.154	0.792	-0.041	0.155	0.793	-0.043	0.155	0.780
Managerial characteristics & complexity									
Rewards practices: monetary rewards									
Never (Ref)									
Not very often	0.310	0.065	<0.001	0.318	0.065	<0.001	0.316	0.065	<0.001
Fairly often	0.611	0.066	<0.001	0.619	0.067	<0.001	0.616	0.067	<0.001
Very often	0.847	0.081	<0.001	0.848	0.082	<0.001	0.845	0.082	<0.001
Hierarchical levels									
1 (Ref)									
2	0.330	0.108	0.002	0.322	0.108	0.003	0.323	0.108	0.003
3	0.595	0.101	<0.001	0.591	0.101	<0.001	0.591	0.101	<0.001
4	0.842	0.106	<0.001	0.840	0.107	<0.001	0.841	0.107	<0.001
5	0.864	0.134	<0.001	0.865	0.136	<0.001	0.866	0.136	<0.001
6	0.456	0.211	0.030	0.452	0.211	0.032	0.455	0.211	0.031
7 or more	0.893	0.244	0.001	0.887	0.244	<0.001	0.893	0.244	<0.001
Teamwork									
No teams(Ref)									
Most in single team	0.475	0.043	<0.001	0.473	0043	<0.001	0.475	0.043	<0.001
Most in more than one team	0.616	0.047	<0.001	0.614	0.047	<0.001	0.616	0.047	<0.001
Share of managers									
None at all (Ref)									
Less than 20%	0.252	0.108	0.002	0.249	0.087	0.004	0.249	0.087	0.004
20% to 39%	0.168	0.099	0.090	0.169	0.099	0.088	0.169	0.099	0.088
40% to 59%	-0.167	0.206	0.419	-0.169	0.206	0.414	-0.169	0.206	0.412
60% to 79%	-0.331	0.313	0.290	-0.333	0.313	0.288	-0.335	0.313	0.284
80% or more	-0.023	0.308	0.939	-0.026	0.308	0.933	-0.028	0.308	0.928
Market factors									
Competition									
Not at all competitive(Ref)									
Not very competitive	0.227	0.123	0.065	0.215	0.123	0.080	0.216	0.123	0.079
Fairly competitive	0.536	0.114	<0.001	0.528	0.114	<0.001	0.530	0.114	<0.001
Very competitive	0.721	0.115	<0.001	0.712	0.115	<0.001	0.715	0.115	<0.001
Country factors									
Cultural factors									
Uncertainty avoidance				0.005	0.005	0.310	0.002	0.005	0.669
Individualism				-0.002	0.007	0.793	0.004	0.006	0.472
Institutional factors									
Varieties of Capitalism									
CME (Ref)									
LME	0.168	0.268	0.531				-0.006	0.290	0.982
CEE	0.624	0.197	0.002				0.660	0.218	0.002
Statist	0.446	0.240	0.063				0.441	0.281	0.116
Constant	-3.159			-3.063			-3.572		
Country-level variance	0.170			0.226			0.163		
Log likelihood	-11617.102			-11546.766			-11542.442		
Wald X^2 (df)	1323.25(44)		<0.001	1309.67(43)		<0.001	1319.19(45)		<0.001
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. *γ* = logit coefficient, s.e. = standard error, *p* = two sided *p*-value of the null-hypothesis of no effect.
Source: European Company Survey 2019.

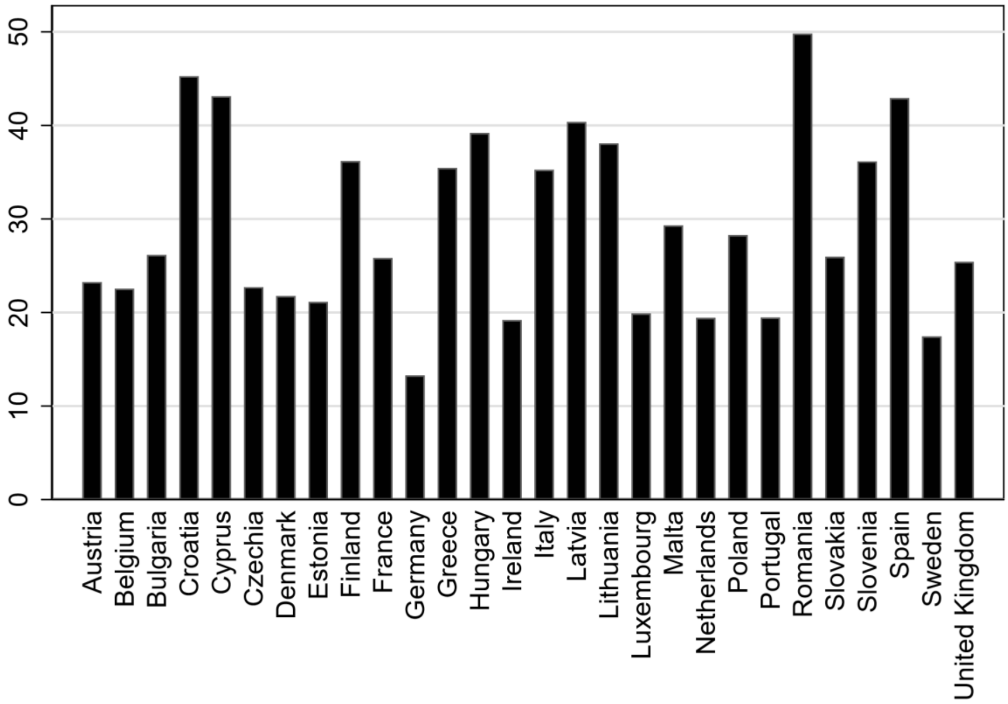

FIGURE 1 Percentage shares of HR analytics use across countries

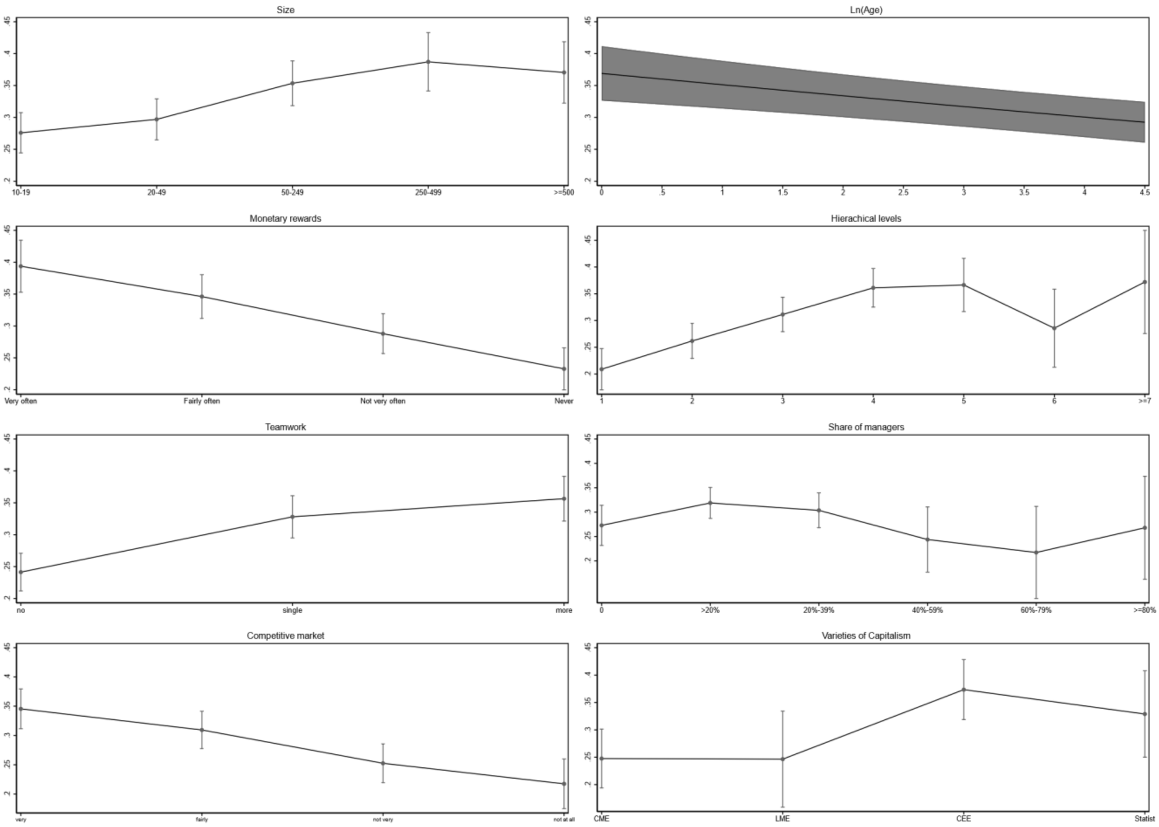

FIGURE 2 Average predicted probabilities and associated 95 percent confidence intervals across covariate values (based on Model 3)

APPENDIX

TABLE 2 Descriptive statistics

	Valid *N*	Mean/%	s.d.
Dependent variable			
Use of HR analytics	21,772	26.72	
Covariates			
Organizational 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 & 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	
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% to 39%		16.81	
40% to 59%		1.41	
60% to 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		67.26	16.01
Institutional factors			
Varieties of Capitalism	21,869		
CME		31.02	
LME		17.32	
CEE		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.