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REGIONAL COMPETITIVENESS, HRM PRACTICES AND FIRM INNOVATION AT EUROPEAN LEVEL

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Prefazione

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"Il fatto è che, nel momento in cui ci si impegna in modo definitivo a qualcosa,
anche la provvidenza si muove" (L'Esploratore)

Foreword

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"That the moment one definitely commits oneself, then providence moves, too" (The Explorer)

Abstract

English Version

Competitiveness is a complex concept, which is influenced by a multiplicity of factors. At macro level (i.e. regions) the determinants are the socio-economic territorial characteristics, while at company level one of the factors is the capability of the firm to sustain and enhance its innovative capacity through which it can stay competitive on the market. The aim of the current study is on the one hand, the analysis of territorial competitiveness and specifically of regional competitiveness in Europe; on the other hand, it goes deeper by considering at European level, the antecedents of firm innovation, in particular human resource management practices, collaborative research and development as well as digital technologies and employee empowerment in the workplace. The European framework is chosen as a common background to address these topics in three different chapters.

The first chapter, by using data coming from the EU Regional Competitiveness Index (RCI) 2019, makes a comparative assessment of regional competitiveness at European level through a Multiple Criteria Decision Making (MCDM) method, which offers a new perspective on complex concepts such as regional competitiveness, which are difficult to determine and measure. The current analysis on the one hand, integrates and extends the current literature on the methods that are relevant for measuring regional competitiveness; on the other hand, through a comparative approach it offers a fresh perspective on regional competitiveness at European level that could be useful for policy-makers addressing territorial disparities.

The second chapter, by using data coming from the European Company Survey (ECS) 2019, analyses though a mediation model, how human resource management practices may enhance collaborative research and development between firms and how this in turs, influences (and enhances) the probability to make innovations by the companies involved in the process. This part offers some interesting implications for managers on how increasing the innovative capacity of companies by investing in those practices that promote collaborative innovations. At the same time, the study tries to provide empirical answer to the relationship between practices and collaborative innovation, a topic which is currently debated but has been mainly addressed by qualitative studies so far.

The third chapter, by using the ECS dataset and by using a moderation model, drives the attention on how human resource management practices have different effects on different kinds of radical innovations (i.e. product and process innovation), by also taking into account the level of technological context complexity and employee empowerment in the workplace. This study extends the current literature on the effects of human resource practices on radical innovation, which is currently a gap in the literature. Moreover, it considers a "hot" and debated topic, which is how digital technologies shape and influence the determinants in the workplace toward greater radical innovation, also thanks to the interactive effect of the centralization of the decision making process.

Keywords: competitiveness, human resources, innovation, Europe, practices

Italian version

Il tema della competitività è un concetto complesso, il quale è influenzato da una molteplicità di fattori. A livello macro (i.e regioni) le determinanti risultano essere le caratteristiche socio-economiche territoriali, mentre a livello d'impresa uno dei fattori risulta essere la capacità sostenere ed aumentare la propria capacità innovativa, tramite la quale l'organizzazione riesce a permanere sul mercato. Il presente studio ha come obiettivo da una parte, analizzare la competitività territoriale ed in particolare la competitività regionale in Europa; dall'altra si concentra più nel dettaglio, analizzando sempre a livello Europeo, gli antecedenti dell'innovazione d'impresa, in particolare considerando le pratiche per la gestione delle risorse umane, la ricerca e sviluppo collaborativa e l'utilizzo di tecnologie digitali e employee empowerment. In quadro Europeo è alla base della presente tesi, la quale mira ad affrontare queste tematiche attraverso in tre capitoli differenti.

Il primo capitolo, tramite dati provenienti dall' EU Regional Competitiveness Index 2019, mira ad offrire un'analisi comparata della competitività regionale a livello Europeo, attraverso l'utilizzo di un metodo decisionale multi-criterio, volta a fornire una prospettiva nuova su concetti complessi e di difficile misurazione come la competitività regionale. L'analisi da una parte integra ed estende la letteratura esistente sulle metodologie di misurazione della competitività territoriale, dall'altra fornisce un quadro efficace della competitività regionale in Europa, tramite un approccio comparato, il quale può essere utile per decisori politici volti ad affrontare disparità regionali nel contesto Europeo.

Il secondo capitolo, utilizzando il database dell'European Company Survey (ECS) 2019, analizza tramite un modello di mediazione, come determinate pratiche per la gestione delle risorse umane possano promuovere la ricerca e sviluppo collaborativa tra le imprese e come quest'ultima, a sua volta influenza (ed incrementa) la probabilità di innovazione delle organizzazioni coinvolte in questo processo. Questa parte offre spunti di riflessione su come i managers possano aumentare la capacità di innovazione dell'impresa implementando quelle pratiche che promuovono l'innovazione collaborativa. Allo stesso tempo, cerca di dare risposta a livello empirico, ad una tematica attualmente dibattuta in letteratura, quella tra pratiche e innovazione collaborativa, su cui però sono presenti studi principalmente qualitativi.

Il terzo capitolo, sempre utilizzando i dati dell'ECS 2019, sposta l'attenzione, attraverso un modello di moderazione, su come le pratiche della gestione delle risorse umane possano avere un effetto differente rispetto a diverse tipologie di innovazioni radicali (prodotto, processo), anche tenendo in considerazione il livello di tecnologie digitali presenti nel contesto aziendale. Questa parte estende la letteratura esistente nell'analisi della relazione diretta tra pratiche a innovazioni radicali, oggi poco affrontata dagli studiosi. Allo stesso tempo considera un tema 'caldo' e molto dibattuto, su come le tecnologie digitali sul posto di lavoro possano influenzare le determinanti lavorative verso un maggiore innovazione radicale, anche grazie alla centralizzazione del potere decisionale.

Parole chiave: competitività, risorse umane, innovazione, Europa, pratiche

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Introduction and summary of the chapters

This PhD thesis is the product of a broad learning process, both from a methodological and theoretical point of view, the result of months of sacrifices and intense research, whose outcome reflects the characteristic that is the basis of our PhD course in Labour, Development and Innovation, that is interdisciplinarity. Starting from a reduced initial knowledge of both the data analysis techniques as well as the theoretical concepts addressed, the current work is able to develop a fairly discrete result concerning the issue of competitiveness, which is analyzed directly and indirectly, on two different levels. The first level concerns competitiveness at the macro level, that is territorial competitiveness, specifically how regional competitiveness can be analyzed and evaluated. The second level is at a meso level, concerning the antecedents of business competitiveness. In particular it analyzes how business innovation can be favored by human resource management (HRM) practices and how the latter can be influenced by different organizational determinants.

Europe is chosen as the basis for the empirical and theoretical analysis, both for objective matters (availability of datasets at European level), and for personal reasons (personal training and experiences abroad), as well as to give continuity to what was my Master's thesis.

Europe is going through a profound transformation and transition, and it is currently at the center of a heated debate also in view of significant economic and territorial reforms. In particular, from the competitiveness point of view, Europe is a very diversified territory whose development is not uniform, since there are "different levels of development" within the individual member states. In this aspect, regional competitiveness is essential to support and promote growth within each member states. Therefore, the measurement and assessment of regional competitiveness is determinant for promoting regional development and implementing good policy programs by decision makers. A highly competitive territory, whose development is evaluated and promoted, becomes attractive for companies that live there, which can become the driving force for the competitive growth of the region itself, by developing a synergistic process.

At the same time, it is also true that the ability of companies to compete and remain on the market (also regional) largely depends on their ability to attract and catalyze new demand through the development and introduction of new products (and services) and processes through which increase their market shares. Business innovation is a complex concept, which is influenced not only by exogenous factors (interaction with external actors), but also by endogenous ones (i.e. human capital). In particular, human resources and how they are managed is an essential determinant of this process since the ability of an organization to innovate lies in the ability of its human capital to generate ideas and fostering creativity. The higher the ability and motivation of employees to create this process, the greater is the probability of the company to introduce a certain type of innovation. In this sense, human resource management practices are those facilitating actions that influence and optimize the capacity and skills of employees in the generation, sharing and implementation of new ideas for the development of new products and business processes. HRM practices thus, become the main tool for achieving business objectives, which are also conditioned by the context's determinants in which they operate (i.e. technology), which, can increase or inhibit the organizational effectiveness of the practices themselves.

In this context, this PhD thesis aims, on the one hand, to present a comparative assessment of regional competitiveness at European level, and on the other to analyze the antecedents of firm innovation, focusing in particular on the practices of human resource management and on some organizational determinants.

These issues are addressed in three different chapters listed below.

Contribution 1: ***A TOPSIS analysis of regional competitiveness at European level***

Contribution 2: ***AMO-enhancing practices, open innovation and organizations' innovation in the European context: testing a mediation model***

Contribution 3: ***HRM and the moderating role of digital technologies and employee empowerment on different kinds on radical innovations. Evidence from Europe***

The literature is very wide and varied, since the three contributions deals with topics that are partly different from both the theoretical and methodological point of view. Taking extracts from the three different chapters, the literature gaps, the objectives and the contributions of each chapter are summarized in the following paragraphs.

Contribution 1

A TOPSIS analysis of regional competitiveness at European level

Background and literature gaps

The measurement of regional competitiveness is becoming essential for policy-makers. In Europe the economic growth of regions is highly uneven (Borsekova, Korony, & Nijkamp, 2021b; Ertur, Le Gallo, and Baumont 2006; European Union, 2011; European Union, 2017a; Rizzi, Graziano, & Dallara, 2018). Some capital regions are experiencing major growth while outermost ones are challenging to improve their level of development (Annoni & Dijkstra, 2019). In this framework, the measurement of regional competitiveness is becoming essential for policy-makers, since it is crucial to assess the competitiveness of regions to address territorial disparities. Among the different approaches adopted by scholars, the construction of composite indices is the predominant method adopted by researchers (Annoni, Dijkstra & Gargano, 2016; Borsekova, Koróny, & Nijkamp, 2021a;

Bristow, 2010a; Huggins, Izushi & Thompson, 2013). However, these kinds of measurements suffer from significant criticalities. On the one hand, some authors affirms that regions' rankings are not very informative because they do not provide a clear picture of the competitivenss level of a region since they rely only on a single output measure. Hence, failing to provide a clear guide for policy-makers how to adress possble policy interventions (Bristow, 2010b; Fattore & Maggino, 2014; 2021; Fattore, Maggino, & Colombo, 2012). For example, Arcagni, Fattore, & Maggino (2021) highlight how an aggregated indicators as the RCI are hard to interpret since they dilute information though their method of aggregation, hence they do not convey useful evidence for policy making. The same advice is given by Bristow (2010a) who highlights the weaknesses arising from relying on a single measure of competitiveness derived from an index: saying for instance that one region is 1.6 points more competitive than another may not tell us much about the real level of competitiveness of those regions. Therefore, "translating a composite index into concrete policy messages and actions has proven to be a complex task in practice for regional policy makers" (Arcagni, Fattore, & Maggino 2021, 2) since precision do not mean faithful representation of complex concepts (i.e. regional competitiveness) (Fattore & Maggino, 2014). In addition, composite indices are totally compensatory since negative values of some attributes can be compensated with positive values of others attributes although weights are applied (Fernandez, Navarro, Duarte, & Ibarra, 2013; Pérez-Moreno, Rodríguez, & Luque, 2016; Wang & Wang, 2014).

Hence, the literature addressed this problem: *How is it possible to improve such lack of information with a method which is easy and adaptable to measure regional competitiveness and at the same time is able to deliver a compelling policy message*?

Objectives

The measurement of competitiveness is intended as a multiple criterial decision-making problem (Bilbao-Terol, Arenas-Parra, and Onopko-Onopko 2019, Fernandez et al., 2013; Pérez-Moreno, Rodríguez, & Luque, 2016, Wang & Wang, 2014), since the evaluation of competitiveness is the optimization of different criteria. As a result, we decided to measure regional competitiveness at European level, by revisiting the EU Regional Competitiveness Index 2019 (RCI) following a comparative approach by means of a MCDM called *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) (Hwang & Yoon, 1981). We do this by applying three different distance measures, namely the Manhattan, Euclidean and Mahalanobis distance measures. The results are three different rankings which are compared with the RCI on two dimensions: rankings and clusters of competitiveness.

With this approach we can overcome to some criticalities and answer to our research questions. Firstly, we resolve the problem of compensations among criteria derived from a weighted mean since it ranks alternatives on the basis of ratio based on the distance from a positive ideal solution and the distance from a negative ideal solution. At the same time, the application of different distance measures makes possible a comparative assessment of regional competitiveness with a reference, which is rarely done in the literature. The comparative approach permits to identify those regions that maintain membership of the same cluster of competitiveness (top, medium or low) across the overall analysis and those that do not, being more sensitive to the distance measure used. The kind of analysis offers a more comprehensive picture of regional competitiveness that may help to provide insights that were not evident through the use of a single ranking, which inevitably provides only a single take on such a complex matter, in order to identify possible actions to address territorial disparities.

Results

Implications for theory and practice

Firstly, we find that the TOPSIS method can replicate the RCI ranking with the use of the Manhattan distance measure. Hence, we are able not only to overcome to the criticalities derived from a composite index, but also confirming the suitability of the RCI as the reference of the study and providing a bridge between the two approaches. Moreover, from this result we suggest that decision makers should use the TOPSIS method in the measurement of regional competitiveness since it provides reliable evaluations of the performance of territories without great efforts and without the need of complex softwares or high computational power. Second, we find that the TOPSIS ranking based on the Mahalanobis distance measure is the ranking that presents the greatest dissimilarity in the final ranking of regions compared to the RCI. Therefore, this result confirms the insights from previous studies, namely that regional competitiveness is driven by interrelated factors (Aiginger & Firgo, 2017; Pike, Rodríguez-Pose, & Tomaney, 2016).

Third, by the comparative analysis of the results of the three different rankings we are able to identify those regions that maintain membership of the same cluster of competitiveness across the overall analysis and those that do not. Specifically, there are a few leading regions which can be unambiguously categorized as highly competitive. Hence, they have achieved a sort of high development equilibrium and a stable steady high level of development (Annoni & Dijkstra, 2019; Bartkowska & Riedl, 2012; Iammarino & Rodríguez-Pose, 2017). Therefore, they should continue in this path of high development and should be used as possible benchmark for other under competitive regions.

Moreover, we find that most European regions belong to the medium level of competitiveness which cannot be clearly categorized within a specific level of competitiveness throughout the analysis. Hence, they seem in transition from a lower or higher cluster of competitiveness, and this result highlights how the process of convergence in Europe needs further work (Bartkowska & Riedl, 2012;

Borsekova et al., 2021b; Corrado et al., 2005; Iammarino & Rodríguez-Pose, 2017). Thus, medium competitive regions should be accompanied in their transition path with tailored policy actions in order to lead them toward a more clear level of competitiveness.

Finally,there is a great number of low competitive regions which maintain a low level of competitiveness in the whole analysis. Hence, most of these territories are trapped in a sort of low level of competitiveness which may further detach them from other more competitive regions. Therefore, urgent policy actions should be taken for these regions in order to tackle this sort of stagnancy which may accentuate regional differences in the EU.

Contribution 2

AMO-enhancing practices, open innovation and organizations' innovation in the European context: testing a mediation model

Background and literature gaps

Despite the growing importance of open innovation (OI) as a key driver to stimulate the innovative performance of firms (Borgers, Foss, & Jacob, 2018; Burcharth, Knudsen, & Søndergaard, 2017; Chesbrough, 2006; Chesbrough & Borgers, 2014; Expósito, Fernández-Serrano, & Liñán, 2019; Hervas-Oliver, Sempere-Ripoll, & Boronat-Moll, 2021; Vrande, Jong, Vanhaverbeke, & Rochemont, 2009), organization scholars have so far devoted only limited attention to the role that HRM practices may play in fostering this approach (Engelsberger, Halvorsen, Cavanagh, & Bartram, 2021). Consistently, academics have recently underlined the need for further research to shed more light on the "human side" of OI (Borgers et al., 2018; Zhu et al., 2019). In addition, those that timidly have tried to investigate this kind of relation, they have mainly focused on single, specific and diverse HRM practices, whithout drawing on a specific theoretical framework, and thus fail to provide a comprehensive picture of the HRM-OI link (Naqshbandi et al., 2019; Popa, Soto-Acosta, & Martinez-Conesa, 2017; Singh et al., 2019).

At the same time, while extensive reseach has been done in analyzing how HRM practices influence firms' innovative performance (Colakoglu et al., 2019; Gooderhama, Parryb, & Ringdalc, 2008; Seeck & Diehl, 2017; Stavrou, Brewster, & Charalambous, 2010), the understanding of the linking mechanisms through which such a beneficial effect occur is still partial. Some studies, which investigates the mediating role of exploration activities (i.e. the search for novel external knowledge) (Barba-Aragón & Jiménez-Jiménez, 2020; Chen & Huang, 2009; Malik et al., 2019), suggest that open innovation may be a key factor explaining the HRM practices-innovation linkage. However, this hypothesis has been largely overlooked, hence further work in this direction is needed.

Objectives

The first aim of this study is to examine whether HRM practices may encourage open innovation activities (defined as inbound knowledge flows) in European companies. For doing this, we use a large-scale sample of more than 20,000 establishments at European level, which is representative in terms of establishments distribution across sectors, size and countries. We do this by drawing upon the ability, motivation and opportunity (Appelbaum, Bailey, Berg, & Kalleberg, 2000) (AMO) framework to address the issue of the HRM- OI relationship.

In addition, as second aim of this study, we attempt to shed light on the driving belt mechanisms which link HRM and innovation. Therefore, we extend our analysis by investigating whether open innovation can be considered a significant mediator in the linkage between the AMO-enhancing practices and firms' innovativeness.

Results

Implications for theory and practice

The results show that motivation and opportunity enhancing practices are key to promote organizations engagement in collaborative open innovation activites (i.e. design and development of new products and services in collaboration with external companies or through outsourcing). Hence, we suggest that those organizations that want undergo to an OI process should take advantage of motivation (i.e. job security, individual-and team rewards, performance appraisal) and opportunity-enhancing practices (i.e. teamwork, autonomy and information-sharing) because these kind of practices are more likely to reduce OI barriers and obstacles (i.e. not invented here syndrome). This results extend the current understanding about the role that HRM practices have in fostering OI, hence answering to the calls about the "human side" of open innovation (Borgers, Foss, & Jacob, 2018; Hong, Zhao, & Snell, 2019). Moreover, the findings suggest that managers can improve their innovative performance by investing in those practices aimed at motivating employees and giving them the opportunity to collaborate and express their talents, since are those that that reduce the obstacles that arise in the collaborative innovation process.

As second contribution is that the positive effect that HRM practices have on firms' innovative output innovation can be partially explained by the mediating effect that OI innovation has in depicting this relationship. Hence, this result enhances the literature understanding about the possible mediating mechanisms that can explain the between HRM practices and innovation activities.

Contribution 3

HRM and the moderating role of digital technologies and employee empowerment on different kinds of radical innovations. Evidence from Europe

Background and literature gaps

Innovation is a complex process that typically takes place within the boundaries of companies (Shipton, Sparrow, Budhwar, & Brown, 2017) and relies on different enabling factors such as human capital and technology (Al-Ajlouni, 2021). In this sense, Human Resource Management (HRM) practices are key in fostering the innovation process within the firm, and the literature has widely proven this direct relationship (Cai-Hui & Sanders, 2017; Ceylan, 2013; Jiménez-Jiménez & Sanz-Valle, 2005; Lin & Sanders, 2017; Nieves, Quintana, & Osorio, 2016; Shipton, West, Dawson, Birdi, & Patterson, 2006; Stavrou, Brewster, & Charalambous, 2010). Nevertheless, the effect that HRM have on radical innovation is still underexplored (Barba-Aragón & Jiménez-Jiménez, 2020), especially considering radical process innovation.

Radical innovation requires not only human resources and knowledge but also technology (Garcia & Calantone, 2002). Hence, a lively debate on the role of digital technologies in the workplace has been developed in recent years (Minbaeva, 2021) since digital technologies influence and interact with human resources (Connelly, Fieseler, Černe, Giessner, & Wong, 2021; Kim, Wang, & Boon, 2021). At the same time, those studies which investigate the interaction effect of digital technologies and HRM practices fail to find this kind of association (Arvanitis, 2005; Kintana, Alonso, & Olaverri, 2006). Therefore, it is possible to hypothesisize that this interaction depends on the level of a third variable. In this strand, some articles underline how employee empowerment may mitigate or enhance the effects that technologies have on human actions and practices (Dedrick, Gurbaxani, & Kraemer, 2003; Martin, Wllen, & Grimmer, 2016). However, further investigation in this direction is needed (Vrontis, et al., 2021), especially regarding the HRM-technology and innovation relationship Kim, et al., 2021)

Objectives

The first aim of the present work is to analyze the direct relationship between High Performance Work Systems (HPWS) (Appelbaum, Bailey, Berg, & Kalleberg, 2000) and both product and process radical innovations. For doing this we use a large-scale sample of more than 20,000 establishments at European level, which is representative in terms of establishments distribution across sectors, size and countries. HPWS is conceived as a coherent and reinforcing system of practices which to create a high performing workforce (Haar, O'Kane, & Daellenbach, 2021) which foster workers' creativity and enable companies to reach a higher level of product and process innovation (Do & Shipton, 2019; Shin, Jeong, & Bae, 2018).

The second objective of this study is to investigate the moderating role that digital technologies in the workplace have in the relationship between HPWS and radical innovation, in order to answers to the calls which suggest further investigation on the way by which digital technologies interact with HRM practices (Jonsson, Mathiassen, & Holmström, 2018; Kim et al., 2021).

Since there is not clear theoretical consensus whether digital technologies may amplify or inhibit the effect of practices (Kim et al., 2021; Meijerink, Boons, Keegan, & Marler, 2021), we hypothesize that this association depends on the level of employee empowerment in the workplace, thanks to the suggestions of some empirical (Martin, Wllen, & Grimmer, 2016) and theoretical contributions (Vrontis, et al., 2021). Hence, the third aim of this study is to test a three-way interaction between digital technologies adoption, employee empowerment and HPWS on radical innovations.

Results

Implications for theory and practice

The first contribution relates on the direct influence that HPWS have on radical product and process innovation, in order to give empirical answer to a current literature gap in the HRM-innovation relationship (Barba-Aragón & Jiménez-Jiménez, 2020). Our results show that HPWS have a positive and significant effect on product and process radical innovation, hence those companies that make larger use of practices aimed at motivating employees and providing them the opportunities and abilities to contribute to the development of radical innovations have higher probability to innovate. Moreover, find that HPWS have higher association with radical process innovation with respect to radical product one, suggesting that the effect of practices is different with respect to the innovation type.

The second cluster of findings show a positive and statistically significant association between the conditional effect of digital technologies and both kinds of radical innovation, hence we highlight how digital technology highly increase the likelihood of having a radical product and process innovation, complementing and confirming recent literature on technology and innovation (Bresciani et al., 2021; Usai, et al., 2021). However, we do not find any significant interaction effect between digital technologies' adoption and HPWS in line with prior studies (Arvanitis, 2005; Kintana, Alonso, & Olaverri, 2006).

The third and main contribution of this article regards the moderating role that employee empowerment played in further shaping the interaction between digital technologies' adoption and HPWS in the relationship with radical product and process innovation. Our results show that employee empowerment is the triggering variable which enables the moderating effect of digital technologies on HRM practices. The results are worth of attention because they deliver a powerful and compelling message. The analysis reveals that at low levels of employee empowerment, digital technologies' adoption has a positive significant moderating effect since they enhance the effect of HRM practices on the introduction of a product/process radical innovation. Such positive effect is reversed when we consider high levels of empowerment, because the interaction shows that at high levels of digital technologies' adoption, HRM practices are less likely to produce radical innovation with respect to cases where digital technologies' adoption is lower, especially for process innovation. This result has important implications for managers because if they decide to decentralize the decision-making power in order to promote innovation, they should be cautious because excessive use of decentralization in high technological context can have backfires effects on the HRM practices targeted to boost the generation of radical ideas. If they desire to reach a stronger innovative output, our results show that they have to make large use of HPWP combined with high levels of digital technologies, as long as low levels of decentralization.

The current findings have important implications for the literature as well because we add understanding about the interplay of employee empowerment, technology and HPWS which to the best of our knowledge has not been addressed in the literature, especially regarding radical innovation.

Chapter 1

A TOPSIS analysis of regional competitiveness at European level

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Abstract

Regional competitiveness is a complex, dynamic, and multidimensional concept that requires a comprehensive measurement. However, the literature does not provide a clear-cut answer to the question of how to measure regional competitiveness. Although the most common approach consists in the calculation of a composite indices, some scholars highlight how regional competitiveness can be intended as a Multiple Criteria Decision Making (MCDM) problem since the evaluation of competitiveness is the optimization of different criteria. As a result, we revisit the EU Regional Competitiveness Index 2019 (RCI) using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. By considering TOPSIS based on three different distance measures, i.e. the Manhattan, Euclidean and Mahalanobis distance measures, we assess regional competitiveness through a comparative approach, taking the RCI as a reference. First, as the RCI coincides with the TOPSIS ranking based on the Manhattan distance measure, we are able to provide a bridge between the two approaches and properly position our results, as well as providing a reliable alternative for measuring regional competitiveness. Second, the TOPSIS ranking based on the Mahalanobis distance measure is the most dissimilar to the RCI, highlighting the fact that regional competitiveness is driven by interrelated factors. Finally, by comparing the TOPSIS rankings obtained, we observe that some regions remain in the same cluster of competitiveness as defined by the RCI across rankings, especially overperforming and underperforming regions, while other regions do not, since they are sensitive to the distance measure used, particularly those with a middle-ranking level of competitiveness. This comparative approach offers a fresh perspective on regional competitiveness that could be useful for policy-makers addressing territorial disparities. Theory and policy implications are discussed.

Keywords: competitiveness, RCI, TOPSIS, regional economy, ranking, Europe

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1.1 Introduction

The European Union (EU) is going through a process of deep transformation (Iammarino & Rodríguez-Pose, 2017). Although several policy actions have been taken at European level (European Union, 2014), gaps in the economic growth of European countries still remain (Annoni & Dijkstra, 2019; Borsekova, Korony, & Nijkamp, 2021b; Iammarino & Rodríguez-Pose, 2017; Pontarollo & Serpieri, 2020). In the last decades, special attention was given to the economic development of European regions since regions are the primary entities that “offer an attractive and sustainable environment for firms and residents to live and work” (Annoni & Dijkstra, 2019, 3). Nevertheless, the development of these territories in the European Union is highly uneven (Borsekova, Koróny, & Nijkamp, 2021a; Iammarino & Rodríguez-Pose, 2017) because some capital regions are experiencing major growth while outermost ones are challenging to improve their level of development (Annoni & Dijkstra, 2019). In this framework, the measurement of regional competitiveness is becoming essential for policy-makers, since competitiveness is one of the major elements to sustain and enhance the economic progress of countries (Annoni & Dijkstra, 2019).

However, due to the multidimensional nature of this concept, the literature does not provide a clear-cut answer to the question of how to measure regional competitiveness, and several approaches have been taken by scholars. In particular, the construction of composite indices which amount to the combination of several single variables examining a specific facet of the regional economy is the predominant approach adopted by researchers (Annoni, Dijkstra & Gargano, 2016; Borsekova et al., 2021a; Bristow, 2010a; Huggins, 2003; Huggins, Izushi & Thompson, 2013).

Along this vein, the EU Regional Competitive Index (RCI) is one of the best-known periodic studies of regional competitiveness at EU level. This index measures the territorial competitiveness of the 268 EU regions at NUTS 2 (Nomenclature of Units for Territorial Statistics) level considering eleven pillars which are grouped in three macro dimensions. The RCI is computed as a weighted average and is useful for comparing regions with a similar level of economic development in order to coordinate policies across member states and address heterogeneities among territories, by identifying and implementing ‘best practices’ (Annoni & Dijkstra, 2019).

Nevertheless, questions have been raised about estimating regional competitiveness with an index, since rankings suffer from significant criticalities (Arcagni, Fattore, & Maggino, 2021; Bristow, 2010a; Fernandez, Navarro, Duarte, & Ibarra, 2013). One of the major critics is that rankings do not offer enough information for providing possible policy actions (Bristow, 2010a; Fattore & Maggino, 2014; Fattore, Maggino, & Colombo, 2012). For example, Arcagni, Fattore, & Maggino (2021) highlight how aggregated indicators as the RCI are hard to interpret since they dilute information though their method of aggregation, hence they do not convey useful evidence for policy making.

The same advice is given by Bristow (2010a) who highlights the weaknesses arising from relying on a single measure of competitiveness derived from an index: saying for instance that one region is 1.6 points more competitive than another may not tell us much about the real level of competitiveness of those regions. Therefore, "translating a composite index into concrete policy messages and actions has proven to be a complex task in practice for regional policy makers" (Arcagni, Fattore, & Maggino 2021, 2) since precision does not mean faithful representation of complex concepts (i.e. regional competitiveness) (Fattore & Maggino, 2014). Hence, the question, have been raising how provide results in the measurement of multidimensional concepts which are effective to understand what researchers are interested in (Fattore & Maggino, 2014).

Therefore, on the evidence presented above, we questioned ourselves *"How is it possible to improve such lack of information with a method which is easy and adaptable to measure regional competitiveness and at the same time is able to deliver a compelling policy message?"*

In this strand, different scholars underline how the measurement of competitiveness is intended as a multiple criterial decision-making problem (Bilbao-Terol, Arenas-Parra, and Onopko-Onopko 2019, Fernandez et al., 2013; Pérez-Moreno, Rodríguez, & Luque, 2016, Wang & Wang, 2014), since the evaluation of competitiveness is the optimization of different criteria. Thus, Multiple Criteria Decision-making Method (MCDM) can assist policy-makers in the evaluation of territorial competitiveness by building rankings which optimize the criteria selection (Bilbao-Terol et al., 2019; Pérez-Moreno et al., 2016; Wang & Wang, 2014) in order to draw possible policy actions.

As a result, we decided to measure regional competitiveness at European level, by revisiting the EU Regional Competitiveness Index 2019 (RCI) following a comparative approach by means of a popular MCDM called *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) (Hwang & Yoon, 1981). The TOPSIS method has been successfully used in many different fields given its suitability to solve real life decision-making problems by ranking alternatives (Behzadian, Otaghsara, Yazdani & Ignatius, 2012). In this study we apply three different distance measures, namely the Manhattan, Euclidean and Mahalanobis (Mahalanobis, 1936) distance measures. The motivation is the following: the Manhattan distance measure has already been used in the computation of indices (Sánchez de la Vega, Buendía Azorín, Segura & Yago, 2019), whereas the Euclidean distance measure is the default in the TOPSIS method (Ishizaka & Nemery, 2013). Neither the Manhattan nor the Euclidean distance measures consider correlations among indicators, while regional competitiveness is considered as a multidimensional and intertwined concept (Annoni & Dijkstra, 2019). Hence, the literature highlights the fact that its dimensions are normally not independent (Aiginger & Firgo, 2017; Cheng, Long, Chen, & Li, 2018; Dima, Begu, Vasilescu, & Maassen, 2018; Pontarollo & Serpieri, 2021; Schwab, 2012). Even the RCI does not take correlations into account and considerers dimensions independent from each other, it may cause factors to be overestimated or underestimated when ranking alternatives. The use of the Mahalanobis distance measure can overcome to this problem, by considering correlations among indicators. This prevents information overlaps and makes assessments more accurate. The outcome is three (different) rankings according to regional competitiveness (for the sake of brevity, we will refer to these rankings as the Manhattan, Euclidean and Mahalanobis rankings) that are compared with the RCI, which is taken as a reference.

The application of TOPSIS to the measurement of regional competitiveness is still limited (Bilbao-Terol et al., 2019; Wang & Wang, 2014). Moreover, the latter studies that apply the TOPSIS method focus mainly in providing an alternative approach for the evaluation of competitiveness, rather than providing a comprehensive assessment of regional competitiveness in order to draw possible policy interventions.

Our comparative approach entails significant advantages. Firstly, the use of the TOPSIS method resolves the problem of compensations among criteria derived from a weighted average since it ranks alternatives on the basis of a ratio based on the distance from a positive ideal solution and the distance from a negative ideal solution, while conserving the same weighting system of the RCI. Moreover, it does not require the attributes to be independent (Behzadian et al., 2012; Carayannis, Goletsis, and Grigoroudis, 2018). At the same time, the application of different distance measures makes possible a comparative assessment regional competitiveness with a reference, which is rarely done in the literature. In particular, our comparison considers not only the aspects of rankings (i.e. Pérez-Moreno et al., 2016) but also the clusters of competitiveness. This decision is made because rankings are very sensitive to the distance measure used, hence it is very easy that regions change positions across the analysis, while it is more difficult that they change cluster. In addition, only looking at rankings does not provide a clear overview of regional competitiveness which can be linked to policy-making actions. Therefore, focusing also on clusters permits on the one hand, to have a much more information about the competitiveness level of European regions since scholars tend to analyze clusters of regions when addressing territorial disparities (Annoni & Dijkstra, 2019; Bartkowska & Riedl, 2012; Iammarino & Rodríguez-Pose, 2017; Pontarollo & Serpieri, 2020). On the other hand, it permits to identify those regions that maintain membership of the same cluster of competitiveness (top, medium or low) across the overall analysis and those that do not, being more sensitive to the distance measure used. The kind of analysis offers a more comprehensive picture of regional competitiveness that may help to provide major insights that were not evident through the use of a single ranking, which inevitably provides only a single take on such a complex matter, in order to identify possible actions to address territorial disparities.

In the following sections, we firstly present a literature review on regional competitiveness in the EU and its measurement. In Section 1.3, we explain the methodology adopted, while comprehensively summarizing the results of the comparative evaluation in Section 1.4. We conclude with some overall remarks and policy suggestions as well as limitations of the study in the final section.

1.2 Literature review

1.2.1 Regional competitiveness in the EU

Defining territorial competitiveness is problematic, controversial, and far from being comprehensively understood (Kitson, Martin & Tyler, 2004). Nevertheless, the measurement of territorial competitiveness is becoming essential for the planning and assessment of policies. At the beginning of the millennium, Porter analyzed the concept of competitiveness at regional level and highlighted the influence of micro-level dynamics on the competitive capabilities of firms. Since then, the assessment of competitiveness at regional level has attracted more and more interest, as competitiveness is influenced by regional authorities, and regions are the spatial units that show the most dynamism in exploiting knowledge and attracting investment (Annoni & Dijkstra, 2017; Carayannis et al., 2018).

Meanwhile, when analyzing regional competitiveness, scholars argue that one of the main determinants of regional competitiveness are the socio-economic territorial characteristics (Huggins et al., 2013; Lengyel, 2004). In this strand, is well known how in Europe the socio-economic regional development is heterogeneous and uneven (Borsekova et al., 2021b; Ertur, Le Gallo, and Baumont 2006; European Union, 2017a; Iammarino & Rodríguez-Pose, 2017; Rizzi, Graziano, & Dallara, 2018). After the economic crisis of 2008, Europe adopted a wide range of policy actions in order to improve the economic development of the European territories (Annoni & Dijkstra, 2019). Programmes such as Horizon 2020 and Europe 2020 strategy were designed to be the main driver for growth enhancement in Europe, consisting in a series of goals to create growth and foster innovation, as well as support employment and face environmental challenges. (European Union, 2010; European Union, 2014). At the same time, regional policy measures were launched to address territorial disparities, such as the Cohesion Policy 2014-2020, a framework strategy targeting all regions and cities in the European Union, whose aim was to boost Europe's economic competitiveness by fostering social cohesion and reducing territorial dissimilarities among European regions (European Union, 2014).

Nevertheless, gaps still remain because not all regions have same resilience, hence, disparities in regional development (Camagni & Capello, 2013; Pontarollo & Serpieri, 2020) and regional competitiveness (Annoni & Dijkstra, 2019; Annoni et al., 2016; Pontarollo & Serpieri, 2020) persists. Möbius & Althammer (2020) for example, in their spatial econometric analysis of sustainable competitiveness of European regions, find that northern EU regions perform better in sustainable competitiveness than southern regions, hence they provide policy indications on how address these differences. Borsekova et al., (2021b) in their analysis of regional cohesion, affirm that is Europe regional disparities continue. In particular post-socialist regions are significantly behind in regional development with respect to capitalist regions, therefore despite the amount of money that have been used to improve their competitiveness, the results are far from being satisfactory. Similarly, a previous work from Lengyel & Rechnitzer (2013), found similar results, so, post-socialist regions constitute a detached group that is more competitive than other central European regions. In this extent, the RCI report itself highlights how not all regions have benefitted from economic growth in the equal way, since the benefits from economic development are distributed unequally, because there are strong capital regions which perform particularly well in all indicators due to their economic activities and linkages with the rest of Europe as well as their and human-capital flow. At the same time, on the one hand, there are many medium competitive regions that are not benefitting of the same advantages of highly competitive regions, hence are trying to catch up with regional disparities (Iammarino & Rodríguez-Pose, 2017). On the other hand, there are several outermost regions struggle to take advantage from spillover effects due to their geographical location as well as their structural weaknesses (Annoni & Dijkstra, 2019). This because regions are dynamic entities that move along learning trajectories (Boschma, 2004; Huggins, Izushi, Prokop & Thompson, 2014). At the same time, regional growth is endogenous because it is embedded in a local socio-economic system that evolves as a result of the capacity of local actors to generate and acquire knowledge over a process of development Capello & Nijkamp (2009). Factors like human and institutional capital, but also knowledge, infrastructure, as well as cultural and social aspects are the lay foundation and the elements that determine the ability of regions to be resilient and to adapt to an unstable environment (Boschma, 2004; Bristow, 2010b; Cappellin, 2003; Christopherson, Michie, & Tyler, 2010; European Union, 2017b; Kitson et al., 2004; Lengyel, 2004).

In this framework, the measurement of regional competitiveness is becoming essential since a sustained increase of competitiveness is an indispensable prerequisite for growth (Sánchez de la Vega et al., 2019). Moreover, it is important to assess regional competitiveness to provide policy actions for addressing regional disparities.

1.2.2 The measurement of regional competitiveness and the proposed method

The measurement of competitiveness at regional level is not clearly defined (Kresl & Singh, 1999). Although there are numerous studies measuring competitiveness at national level, country indices fail to analyze subnational trends and performance gaps across regions (Huggins et al., 2013). At the same time measuring regional competitiveness is challenging since reliable indicators are not always available at regional level (Čučković, Jurlin, & Vučković, 2013).

In the literature different approaches are adopted to the measurement of regional competitiveness (Lengyel & Rechnitzer, 2013; Möbius & Althammer, 2020; Porter & Stern, 1999; Ülengin, Ulengin, & Önsel, 2002). One of the most common approaches for the measurement of regional competitiveness in Europe relies on the construction of a composite index, which amounts to the combination of several single variables examining a specific facet of the regional economy which is useful for comparing the competitive performance of territorial entities (Annoni & Dijkstra, 2019; Annoni et al., 2016; Bronisz, Heijman, & Miszczuk, 2008; Čučković et al., 2013; Huggins, 2003; Huggins, Prokop, & Thompson, 2021; Huovari, Kangasharju, & Alanen, 2002; Önsel, et al., 2008).

In this strand, the EU Regional Competitiveness Index is the main periodic study of regional competitiveness in Europe. This RCI has been published by the European Commission every three years since 2010 and provides a comparable and multifaceted picture of the level of competitiveness of 268 territories at NUTS 2 regional level. The NUTS classification is a hierarchical system for dividing the territory of the EU into spatial units from NUT-1 (larger) to NUTS-3 (smaller) for statistical purposes (Bilbao-Terol et al. 2019). The framework of the RCI consists of 11 pillars which cover different competitiveness aspects and are grouped into three macro-dimensions: the Basic dimension, the Efficiency dimension and the Innovation dimension. These three dimensions are conceptually nested, meaning that the Basic dimension is an enabling factor of the Efficiency dimension, which is instrumental for the Innovation dimension. The RCI is computed as a weighted average, the weights of which are related to the different stages of the development of regions, according to their GDP per head, following the Global Competitiveness Index (GCI) methodology (Schwab, 2018). Each pillar is calculated by computing the simple average of the indicators that compose it (see Annoni & Kozovska, 2010 for the full methodology). Likewise, the Basic, the Efficiency and Innovation macro-dimensions are computed by averaging across the pillars constituting each dimension. The structure of the RCI is depicted in Figure 1.1.

However, the literature underlines how these kinds of indices suffer of significant criticalities. For instance, critiques arise on the fact that such indices for are not very informative and fails to reveal what really matters for a region. There is a number of scholar who underline how composite indeces do not provide a clear guide for policy-makers how to adress possble policy interventions since they rely only on a single output measure (i.e. final index score), which does not provide a clar picture about the competitiveness level of a region (Arcagni, Fattore, & Maggino, 2021; Bristow, 2010a; Fattore, Maggino, & Colombo, 2012). Moreover, composite indices are hard to interpret, hence compelling policy messages are difficult to be delivered (Arcagni, Fattore, & Maggino, 2021).

Therefore, there is the need of a method which can assess regional competitiveness in a comprehensive way, in oder to deliver majour information about regional competitiveness and whose results can be as a leverage in identifying possible policy interventions.

Along this vein, regional competitiveness is seen as a multiple criteria decision-making problem (Fernandez et al., 2013; Pérez-Moreno et al., 2016; Wang & Wang, 2014) in which each indicator is optimized by providing a reference point though which the objective function is optimized. Hence, MCDM methods can assist policy-makers in sorting and ranking alternatives in order to make faster and easier decisions (Fernandez et al., 2013). Among the several MCDM methods available in the literature, the TOPSIS method has been proven to be a simple and successful method to be applied in different fields such as business management, human resource management, engineering and logistics (Behzadian et al., 2012). The TOPSIS method involves finding the best alternative among a range of alternatives and ranking all alternatives in the presence of multiple criteria (Kuo, 2017). The procedure of TOPSIS consists of the following six steps: (1) normalize the decision matrix, (2) compute the weighted normalized decision matrix, (3) determine the positive ideal solution and the negative ideal solution, (4) calculate the distance of an alternative from the positive ideal solution and from the negative ideal solution, (5) calculate the relative proximity of an alternative to the positive ideal solution, (6) rank alternatives in descending order. The TOPSIS method enables to overcome the compensatory problem derived from an average since it uses a ratio based on the distance from a positive ideal solution and the distance from a negative ideal solution. Moreover, it does not require indicators to be independent from each other (Behzadian et al., 2012). Finally, it allows the use of multiple distance measures (i.e. Manhattan, Euclidean and Mahalanobis) which enable to draw a clearer picture of regional competitiveness in Europe, which permits to identify possible conditions of regional development in Europe which can be linked to possible policy interventions.

The literature offers a few reports on the application of the TOPSIS method for the measurement of regional competitiveness. Wang & Wang (2014) use the Mahalanobis distance measures for assessing the competitiveness level of Chinese high-tech provinces; however, they are focused in showing the methodological improvement of such distance rather than making a comparative assessment though which derive policy measures. Similarly, Zhang, Gu, Gu & Zhang (2011) apply TOPSIS in the evaluation of tourism competitiveness of cities, but their conclusions draw mainly in providing an effective method for ranking alternatives. To the best of our knowledge, there is only one application of the TOPSIS method to the RCI. Bilbao-Terol et al. (2019) extend the RCI 2013 with environmental indicators that provide information about the sustainable competitiveness of the regions. Using TOPSIS, they obtain an overall index of the attractiveness of NUTS 2 Spanish regions with respect to their sustainable competitiveness. Nevertheless, all articles cited above apply the

TOPSIS method only to a limited number of territories; furthermore, their conclusions are mainly addressed for providing alternative methods for ranking alternatives or computing new indices rather than making a comprehensive assessment of regional competitiveness useful to policy guidance. In this study we extend the analysis of the RCI by using the TOPSIS method and applying three different distance measures to the 268 European regions at NUTS 2 level with the RCI as reference point by considering both ranking and clusters of competitiveness which is almost absent in the literature.

This comparative approach offers significant advantages because it permits to go beyond the analysis of rankings (Pérez-Moreno, Rodríguez, & Luque, 2016), hence considering cluster of competitiveness in order to convey major information about the level of competitiveness of European regions. This kind on approach is to the best of our knowledge the first in his kind, and it permits not only to overcome to the problems of compensation of criteria derived by a composite index, but also it is helpful to highlight those regions that keep a membership to a specific cluster of competitiveness across rankings and those that do not, in order to link the analysis to possible actions to address competitive differences among European regions.

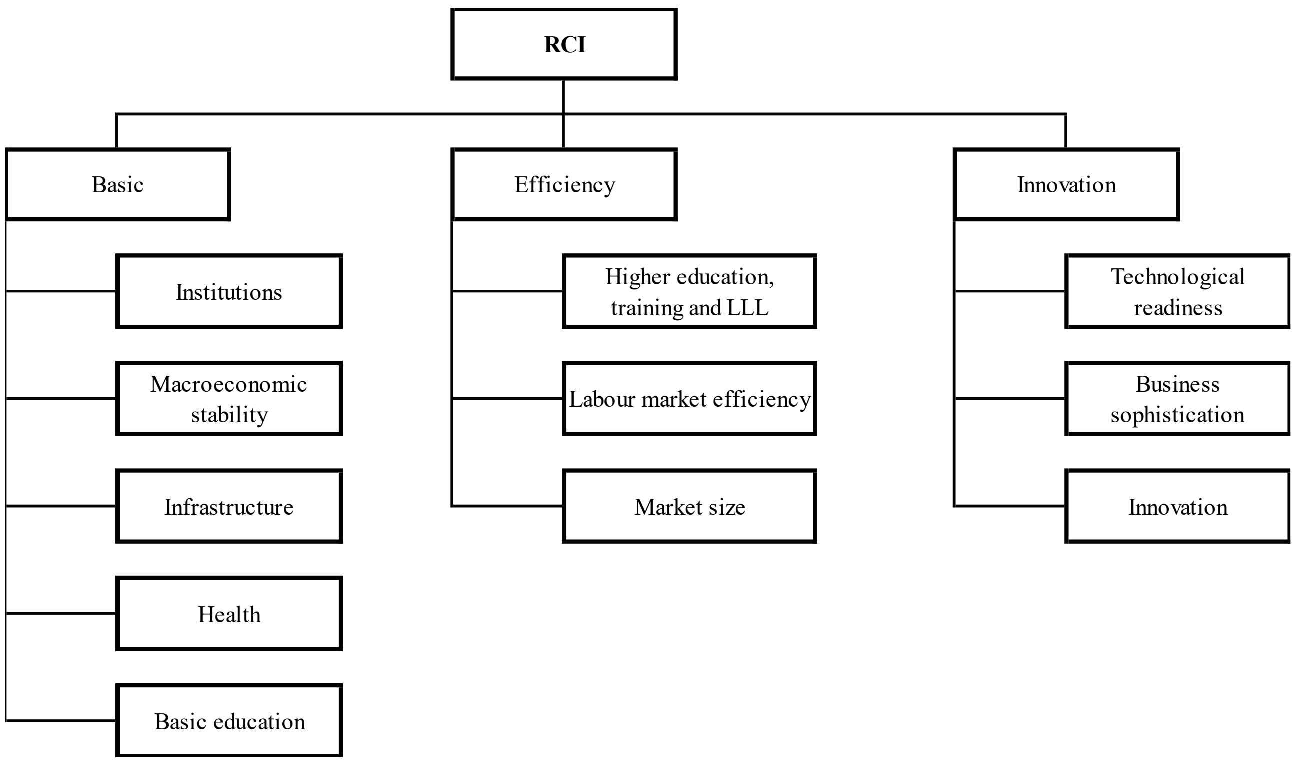


Figure 1.1: The RCI with the three dimensions and the eleven pillars

1.3 Material and methods

The first step was to download the data from the website of the European Union (European Union, 2019), already providing the standardized z-scores pillars of the RCI, which were then weighted according to the weighting scheme of the RCI (see Annoni & Dijkstra, 2019, 19), which depends on the regions' GDP level, forming a weighted normalized decision matrix $\boldsymbol{V} = (v_{ij})_{mxn.}$

The next step was to determine the positive ideal solution A^+ and negative ideal solution A^- as $A^+ = (v_1^+, v_2^+, \dots, v_n^+)$ where $v_j^+ = \max(v_{ij}), i = 1, 2, \dots, m$ and $A^- = (v_1^-, v_2^-, \dots, v_n^-)$ where $v_j^- = \min(v_{ij}), i = 1, 2, \dots, m$. The positive ideal solution $A^+$is a hypothetical region that has the best score for each criterion and the negative ideal solution A^- is a hypothetical region that has the worst score for each criterion.

The Manhattan, Euclidean and Mahalanobis distance measures were then used to calculate the distance s_i^+ from the positive ideal solution and the distance s_i^- from the negative ideal solution for each region a_i. The superscript symbols m, e and p were used for the Manhattan, Euclidean and Mahalanobis distance measures, respectively.

For the Manhattan distance measure, we have:

$$s_i^{m+} = \Sigma_{j=1}^{n} \left| v_i^+ - v_{ij} \right|, i = 1, 2, \dots, m, \tag{1}$$

$$s_i^{m-} = \Sigma_{j=1}^{n} \left| v_i^- - v_{ij} \right|, i = 1, 2, \dots, m. \tag{2}$$

The Manhattan distance considers indicators as independent and takes the sum of the absolute values of the differences. For the Euclidean distance measure, we have:

$$s_i^{e+} = \sqrt{\Sigma_{j=1}^{n} (v_i^+ - v_{ij})^2}, i = 1, 2, \dots, m, \tag{3}$$

$$s_i^{e-} = \sqrt{\Sigma_{j=1}^{n} (v_i^- - v_{ij})^2}, i = 1, 2, \dots, m. \tag{4}$$

The Euclidean distance considers indicators as independent and takes the square root of the sum of the squared differences. Finally, for the Mahalanobis distance measure, we have:

$$s_i^{p+} = \sqrt{(v_i^+ - v_{ij})^T \, \Sigma^{-1} (v_i^+ - v_{ij})}, i = 1, 2, \dots, m, \tag{5}$$

$$s_i^{p-} = \sqrt{(v_i^- - v_{ij})^T \, \Sigma^{-1} (v_i^- - v_{ij})}, i = 1, 2, \dots, m. \tag{6}$$

The Mahalanobis distance measure takes the square root of the sum of the squared differences and considers correlations among pillars. In fact, it weights the squared differences by the inverse of the covariance matrix (Σ^{-1}). If the pillars are not correlated, the Mahalanobis distance measure coincides with the Euclidean distance measure.

Table 1.1 shows that the RCI pillars are positively and significantly correlated among each other. This reflects what outlined by the literature that those indicators of competitiveness are normally not independent, and they tend to reinforce each other (Schwab, 2012). Hence, as argued by Huovari et al. (2002), the high correlation between indicators provides evidence that regional competitiveness is subject to cumulative causations, hence improvement in one dimension of competitiveness tends to improve other dimensions as well.

	Basic					Efficiency			Innovation		
	1	2	3	4	5	6	7	8	9	10	11
1. Institutions	1.000										
2. Macroeconomic Stability	.575**	1.000									
3. Infrastructure	.550**	.292**	1.000								
4. Health	.438**	-.039	.474**	1.000							
5. Basic Education	.716**	.716**	.442**	.308**	1.000						
6. Higher Education and LLL	.642**	.473**	.327**	.271**	.457**	1.000					
7. Labor Market Efficiency	.770**	.683**	.521**	.291**	.567**	.652**	1.000				
8. Market Size	.473**	.366**	.809**	.373**	.348**	.310**	.636**	1.000			
9. Techonological Readiness	.929**	.552**	.646**	.484**	.646**	.588**	.775**	.603**	1.000		
10. Business Sophistication	.606**	.235**	.727**	.460**	.392**	.458**	.552**	.729**	.660**	1.000	
11. Innovation Pillar	.676**	.401**	.686**	.501**	.459**	.731**	.734**	.690**	.724**	.757**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Table 1.1: The correlation matrix of the 11 pillars of the RCI

For each region a_i, we compute the relative closeness coefficient C_i^*:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}. \qquad (7)$$

This relative closeness coefficient belongs to the unit interval [0,1] and constitutes the final score of the region. Regions are ranked in descending order of these scores, with the most competitive regions ranked in the highest positions, and the least competitive in the lowest positions. This final ranking is computed for each distance measure; thus, we obtain three (different) rankings, according to the three distance measures used.

To compare the rankings obtained, we use two permutation metrics: the Kendall tau and the Spearman footrule. The Kendall tau distance measure computes the dissimilarity $K(\sigma^r, \sigma^p)$ between two rankings $\sigma^r = (\sigma_1^r, \dots, \sigma_n^r)$ and $\sigma^p = \left(\sigma_1^p, \dots, \sigma_n^p\right)$ of the same set of objects (in our case regions) by counting the number of pairwise disagreements between these two rankings (Fagin, Kumar, Mahdian, Sivakumar & Vee, 2006). To facilitate the interpretation, we use the normalized Kendall tau K^* (Beg & Ahmad, 2003):

$$K^*(\sigma^r, \sigma^p) = \frac{K(\sigma^r, \sigma^p)}{0.5n(n-1)}. \qquad (8)$$

This value belongs to the unit interval [0,1]; if σ^r and σ^p are in the same order, then the value is 0, whereas if σ^r and σ^p are in the opposite order, then the value is 1. An alternative method to compute a distance between two rankings is the Spearman footrule (Diaconis & Graham, 1977), that computes the sum $F\ (\sigma^r, \sigma^p)$ of the absolute differences between the positions of all regions in the rankings. Also in this case, we use the normalized variant (Beg & Ahmad, 2003):

$$F^*(\sigma^r, \sigma^p) = \frac{F\ (\sigma^r, \sigma^p)}{0.5n^2}. \qquad (9)$$

This value also belongs to the unit interval [0,1]; if σ^r and σ^p are in the same order, then the value is 0, whereas if σ^r and σ^p are in the opposite order, then the value is 1. In addition, we employ a candlestick chart for visualizing the position of the regions across rankings.

In the RCI, regions are grouped into eight clusters, according to their final score. Regions that score above 1 are considered the most competitive, while regions scoring below -1 are considered the least competitive. Between 1 and -1 there are six other clusters of regions, according to the scores obtained, (see Annoni & Dijkstra, 2019, 6). Since we are also interested in examining how the clusters of the RCI change their composition when the TOPSIS method is applied, we keep the cardinality of the clusters of the RCI for the clusters of the TOPSIS analysis in order to facilitate the comparison. For this last part, maps at NUTS-2 level are provided. They are elaborated using https://mapchart.net/ a website for map customization.

1.4 Results

1.4.1 The RCI and the rankings obtained by TOPSIS

In this section we show the results of the comparison of the Manhattan, Euclidean and Mahalanobis rankings with the RCI.

Normalized Kendall tau	1	2	3	4
1. RCI	0			
2. Manhattan	0	0		
3. Euclidean	0.046	0.046	0	
4. Mahalanobis	0.143	0.143	0.107	0

Table 1.2: Normalized Kendall tau matrix

Normalized Spearman footrule	1	2	3	4
1. RCI	0			
2. Manhattan	0	0		
3. Euclidean	0.066	0.066	0	
4. Mahalanobis	0.207	0.207	0.155	0

Table 1.3: Normalized Spearman's footrule matrix

Tables 1.2 and 1.3 present the matrices of the normalized Kendall tau K^* (Eq. (8)) and the normalized Spearman footrule F^* (Eq. (9)). Both tables show that the Manhattan ranking perfectly replicates the RCI since all regions are in the same order. This is an interesting finding, allowing us to take the RCI as the reference for our analysis. Sánchez de la Vega et al., (2019, 113) in constructing a regional competitiveness index of Spanish regions by means of the P-distance argue that "the Manhattan distance measure is used in the RCI, drawn up by the European Commission". Moreover, Euzenat & Shvaiko (2007, 124) note that "the weighted sum can be thought of as a generalisation of the Manhattan distance measure in which each dimension is weighted. It also corresponds to weighted average with normalised weights". Therefore, given the fact that the computation of the RCI relies on a weighted average, this result suggests that the use of standardized data of the RCI results in the same ranking obtained by TOPSIS when the Manhattan distance measure is used. Moreover, we are able to provide a bridge between the two approaches, providing a starting point for considering other distance measures. In addition, this kind of finding outlines on the one hand, that it is possible to overcome to the compensatory problems derived by a composite index based on a weighted average. On the other hand, that TOPSIS is a good and reliable method for measuring regional competitiveness, hence decision makers should take into accunt this approach when measuring the competitiveness of their territories. The Euclidean ranking is similar to the RCI since $K^* = 0.046$ and $F^* = 0.066$. In fact, both the RCI and the Euclidean consider pillars as independent from each other. As expected, the Mahalanobis distance measure is the one that presents the greatest dissimilarity from the RCI, having $K^* = 0.143$. and $F^* = 0.207$. This is not surprising since the Mahalanobis distance measure considers correlations among the pillars of the RCI, which are significant in our sample as shown in Table 1.1.

The candlestick chart in Figure 1.2 provides an overview of the position of regions across rankings. The x-axis represents the rank of each region in the RCI, while the y-axis refers to the rank of the same regions across the different rankings, specifically representing the RCI (orange dots), the Manhattan ranking (green dots), the Euclidean ranking (blue dots) and the Mahalanobis ranking (red dots). From the figure we can make two observations. First, the RCI coincides with the Manhattan ranking (the former not being visible in the figure), confirming the appropriateness of the TOPSIS method in measuring regional competitiveness. Second, in the Euclidean and Mahalanobis rankings, regions are ranked differently depending on the distance measure used. In some cases, the effect is the same since in both the Euclidean and Mahalanobis rankings, regions improve (or worsen) their position with respect to their position in the RCI, while in other cases the effect is opposite because sometimes in the Euclidean ranking regions improve their position, while they worsen their position in the Mahalanobis ranking and vice versa. The analysis shows that changes in the ranking are moderate in the Euclidean ranking since regions change nine positions on average, while they are remarkable in the Mahalanobis ranking since regions change 28 positions on average. As it pointed in the previous chapter is evident how rankings are very sensitive to the distance measure used since regions change position easily. However, from Figure 1.2 it is evident that generally, regions that are ranked very high and very low in the RCI are subject to less variation in their position in the TOPSIS rankings, compared to the middle-ranking regions. For instance, Inner London is ranked second in both the RCI and the Manhattan ranking; moreover, it maintains the same position in the Euclidean ranking, whereas it is ranked first in the Manhattan ranking. The same holds for Guyane, which is ranked number 266 in the RCI and in the Manhattan ranking, while it improves just one position in the Euclidean ranking and two positions in the Manhattan ranking. The situation is different for middle-ranking regions such as Pays de la Loire for example, which is ranked in position 114 in both the RCI and Manhattan rankings, while it goes to position 102 in the Euclidean ranking and to position 30 in the Mahalanobis ranking. Generally, we assist to a less variation in the ranking for highly competitive (position 1-48) and low competitive regions (192-268) with respect to medium competitive ones (49-191). The average standard deviation for the positions of regions across rankings for medium competitive regions is 18.46, while it is 13.99 and 9.93 for high and low competitive ones. This finding might be attributed to the fact that, in line with Annoni & Dijkstra (2019), the dimensions of the RCI are conceptually nested, hence a good performer in the Innovation dimension is expected to be a good performer in the Basic and Efficiency dimensions, while bad performers in the Basic dimension are not expected to perform well on the Efficiency and Innovation dimensions. Therefore, as outlined by Bartkowska & Riedl (2012), this suggests a certain degree of stability for top-performing and bottom-performing regions, which may depend on their endogenous structural characteristics and socio-economic situation. At the same time, although middle-ranking regions perform well in some pillars, they present weaknesses in others, resulting in a greater sensitivity to the different distance measures. The positions of all 268 regions across the different rankings are provided in the annex.

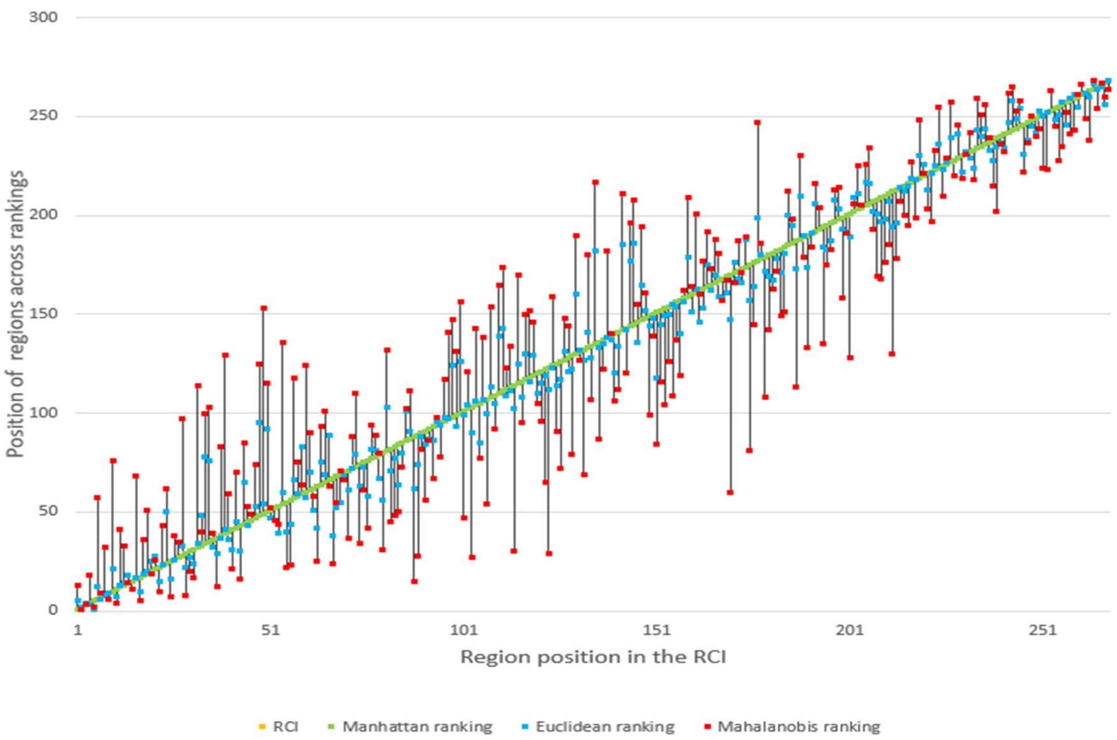


Figure 1.2: Positions of regions across rankings.

1.4.2 Analysis by clusters

As noted above, in the RCI, regions are clustered according to their stage of competitiveness depending on the final score of the index. Regions that score above 1 are considered the most competitive, while regions that score below -1 are considered the least competitive. In this part of the analysis, we examine how the composition of the clusters of the RCI changes when the TOPSIS method is applied. To do so, in the TOPSIS rankings clusters are subjectively predetermined by keeping the same cardinality as the clusters of the RCI to compare the results. Regions that switch cluster membership also change their competitiveness level with respect to the ranking considered. To facilitate the identification of the clusters, the RCI clusters are labelled according to their stage of competitiveness.

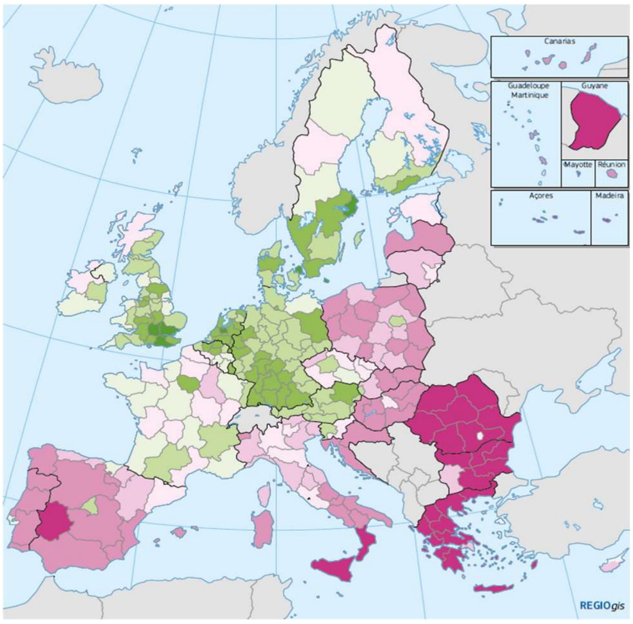
Table 1.4 shows the clusters of the RCI, which are ordered from cluster 1 (most competitive regions) to cluster 8 (least competitive regions). In addition, the number of regions in each cluster and the highest and lowest positions in each cluster are displayed according to the RCI. Examining the table, we observe that the composition of the RCI clusters is unaltered in the Manhattan ranking since it replicates the index, hence clusters are not subject to any variation. However, in both the Euclidean and Mahalanobis rankings, the composition of the clusters is altered. For instance, if we take cluster 1 (most competitive regions), it is evident that in the Euclidean ranking the composition of this cluster changes by 16.67% since one region is replaced by a new one. At the same time, the composition of the same cluster is altered by 50.00% in the Mahalanobis ranking, since three regions are replaced by three new ones. The modification of RCI clusters differs depending on both the distance measure and on the typology of the cluster. For example, in the Euclidean ranking, cluster 6 (not very competitive regions) is the cluster that changes the most, while in the Mahalanobis ranking this is the case for cluster 4 (slightly competitive regions). Above all, we observe that the composition of the clusters varies the most in the Mahalanobis ranking, once again showing that the indicators of regional competitiveness are not independent (Fagerberg & Srholec, 2017; Huovari et al., 2002). Moreover, it may be seen that in both the Euclidean and the Mahalanobis rankings, the clusters that are subject to most variation in their composition are the central ones (fairly competitive, slightly competitive, competitive, not very competitive regions), while extreme clusters (most competitive, highly competitive, hardly competitive, not competitive at all regions) are subject to less variation. This finding is in line with the findings in Section 1.4.1.

Cluster	1	2	3	4	5	6	7	8
RCI score	> 1	0.5 – 1	0.2 – 0.5	0 – 0.2	-0.2 – 0	-0.5 – -0.2	-1 – -0.5	< -1
Label	Most competitive	Highly competitive	Fairly Competitive	Slightly competitive	Competitive	Not very competitive	Hardly competitive	Not competitive at all
RCI								
Ranks	1-6	7-48	49-110	111-136	137-164	165-191	192-235	236-268
N. of regions	6	42	62	26	28	27	44	33
Regions that change cluster membership								
Manhattan								
N. of regions	0	0	0	0	0	0	0	0
%	%	%	%	%	%	%	%	%
Euclidean								
N. of regions	1	8	11	8	11	11	9	5
%	16.67%	19.05%	17.74%	30.77%	39.29%	40.74%	20.45%	15.15%
Mahalanobis								
N. of regions	3	20	33	23	20	15	19	8
%	50.00%	47.62%	53.23%	88.46%	71.43%	55.56%	43.18%	24.24%

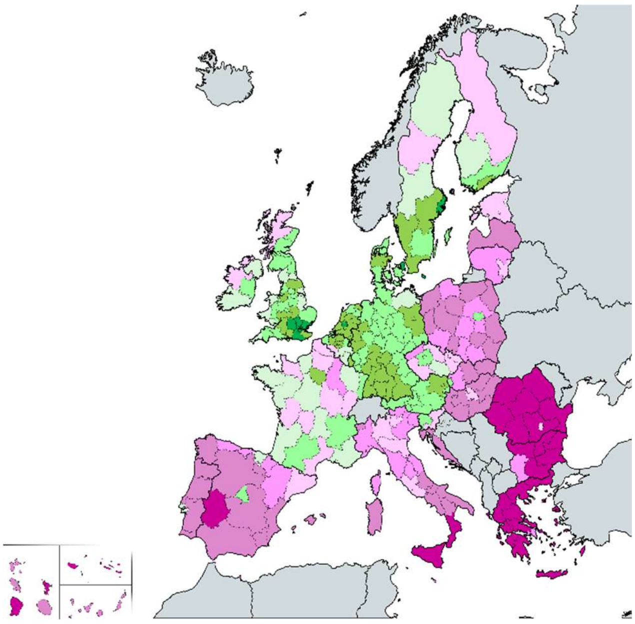
Table 1.4: Clusters of regions according to the RCI and number of regions that change cluster when using the TOPSIS method

Figure 1.3 displays the maps of Europe according to the three TOPSIS rankings that are compared with the map of the RCI. It may be seen that the map of the Manhattan ranking is the same as the map of the RCI. The map of the Euclidean ranking instead presents some differences. In fact, while some regions improve their competitive performance, such as some regions of northern Italy, and some in northern-eastern Greece or western Romania, as well as some regions of Bulgaria and Hungary, and some regions of central England, other regions worsen their competitive position, moving to a lower competitive cluster, such as some regions of southern Spain and southern Italy, as well as some European Nordic regions of Sweden and Finland.

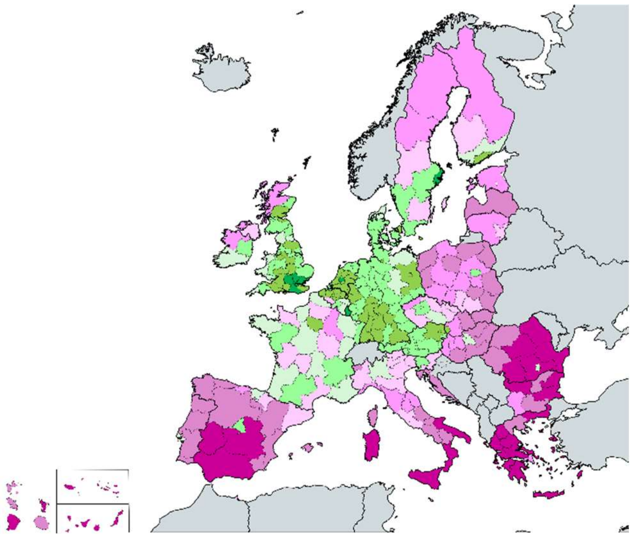
In the European map of the Mahalanobis ranking the effect of correlations on the clusters is more evident. In fact, the map presents the greatest dissimilarities compared to the map of the RCI. On the one hand, we observe a general improvement in the competitiveness level of some regions of southern countries, for instance, regions in central-northern Greece, some regions of central and eastern European countries of Poland, Hungary, Slovakia and some regions of central European countries such as France and Austria. On the other hand, some top-competitive regions in the RCI are placed in a lower competitive cluster, such as some regions of northern European countries of Finland, Sweden (including Stockholm, which is the most competitive region in the RCI), middle-ranking regions of Ireland and northern Scotland, as well as some regions of central European countries like eastern Germany and northern Denmark. This result highlights the effect of the correlations of the RCI pillars on the final ranking of regions.



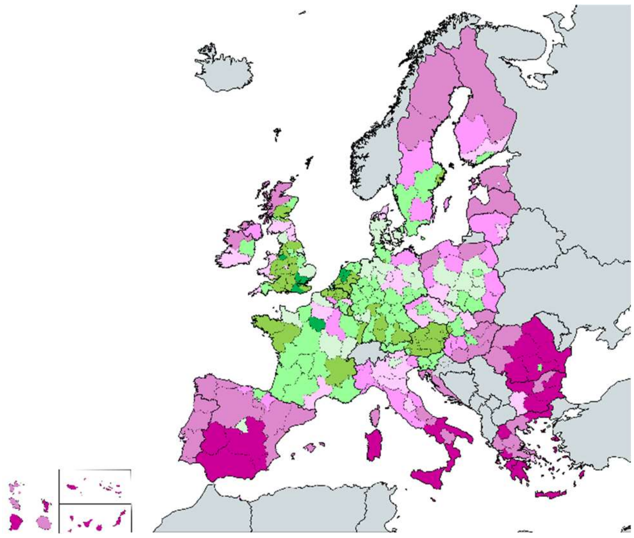
Map of the RCI (source Annoni & Dijkstra, 2019 p. 6)



Map of the Manhattan ranking



Map of the Euclidean Ranking



Map of the Mahalanobis ranking

Legend: Cluster of competitiveness

- Cluster 1 - Most competitive
- Cluster 2 - Highly competitive
- Cluster 3 - Fairly competitive
- Cluster 4 - Slightly competitive
- Cluster 5 - Competitive
- Cluster 6 - Not very competitive
- Cluster 7 - Hardly competitive
- Cluster 8 - Not competitive at all

Figure 1.3: European maps of the RCI and of the TOPSIS rankings

Form the comparative analysis of the results it is possible to depict Table 1.5, which highlights how in Europe some regions maintain their level of competitiveness across rankings since they keep the membership of the same cluster across the overall analysis, while other regions do not, since they are sensitive to the distance measure used. Specifically, it is possible to draw a certain picture of competitiveness in Europe since generally highly competitive regions (cluster 1 and 2) and low competitive regions (cluster 7 and 8) are subject to less variation in their competitiveness level because most of them consistently remain top or low performer across the overall analysis, while it not occurs for medium performing regions (cluster 3 to 6) because most of them shift to another level of competitiveness when a distance measure is applied. Therefore, they are subject to more variation.

Regions \ Cluster	1	2	3	4	5	6	7	8	Overall index
Same cluster membership across rankings (%)	50.00%	50,00%	45,16%	7,69%	25,00%	33,33%	56,82%	72,73%	44.40%
Different cluster membership across rankings (%)	50.00%	50,00%	54,84%	92,31%	75,00%	66,67%	43,18%	27,27%	55.60%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 1.5: % of regions in each cluster that maintain (and do not maintain) the same cluster membership across rankings

For instance, some top-competitive regions of the RCI, such as Inner London, Surrey or Utrecht, as well as some highly competitive regions of the Netherlands or Belgium, maintain their membership to the top-performing clusters throughout the analysis. Most of these regions belong to the so called "blue banana" which is the strong performing and industrialized corridor which is the backbone of European economy. These territories are the leading regions of European prosperity. Therefore, it is possible to suggest that these regions have reached a sort of development equilibrium and a high steady state path (Annoni & Dijkstra, 2019; Bartkowska & Riedl, 2012; Iammarino & Rodríguez-Pose, 2017). Several reports affirm that these regions are the leading regions of European prosperity since they share similar level of economic factors such as institution, infrastructure, education and technological innovation (Annoni & Dijkstra, 2019; Iammarino & Rodríguez-Pose, 2017). We confirm this, by showing that these top-competitive regions are more capable of maintaining a high competitiveness level compared to other regions. Therefore, it is plausible to affirm that regional policy making in these territories are working, hence on the one hand, they should continue in this trend of high development (Iammarino & Rodríguez-Pose, 2017), on the other hand, we argue that they should be taken as virtuous benchmark for other highly competitive regions which cannot clearly categorized as highly competitive, such as some regions of inner Germany or southern Sweden.

At the same time, we observe an opposite situation for some regions belonging to the underperforming clusters (cluster 7 and 8). For instance, some of the outermost regions of southern and eastern Europe like regions of southern Italy, as well as regions of southern Greece, eastern Romania and Bulgaria show a low competitive profile across the overall analysis. Therefore, we can affirm that these regions are experiencing a situation of under competitiveness which may bring them even more far away from more performing regions. This situation is confirmed by some reports which underlines how peripheral regions are suffering from a sort of stagnancy in their development (European Commission, 2017; Iammarino & Rodríguez-Pose, 2017) which is also exacerbated by their geographical location that excludes them from spillover effects of more advanced regions (Annoni & Dijkstra, 2019). Moreover, these kinds of regions have been experiencing a sort of vicious circles of skill and human capital loss, due to the weaknesses of their fundamentals (European Commission, 2017). Therefore, a possible policy message is that low competitive regions urge policy interventions in order to catch up with the gap they are experiencing with respect to other European regions and they have to commit themselves to go out from the trap of low competitiveness, which may even more exclude them from economic development. Therefore, policy makers are highly encouraged is taking opportune policy actions to tackle this sort of stagnancy which may exacerbate regional differences in the EU.

Regions belonging to central clusters (3 to 6) are hard to be unequivocally classified within a competitiveness category according to our results, since they change cluster of competitiveness depending on the distance measure used. This result suggests that the process of competitiveness convergence is far from being completely achieved (Corrado, Martin, & Weeks, 2005). At the same time, these kinds of regions seem in transition to a lower or higher cluster, hence they are moving along different development paths (Annoni & Dijkstra, 2019; Bartkowska & Riedl, 2012). Although they perform well in some pillars (and benefit from spillover effects derived by top regions) these are not sufficient for a general improvement in their level of competitiveness, hence they are somehow struggling to find their level of competitiveness. Therefore, policy makers should take into consideration this aspect in their policy planning, which highlights how regional competitiveness convergence needs further work. Hence, we argue that for medium competitive regions they should design customized actions aimed at accompanying these territories to find a clear level of competitiveness, maybe in combination with similar regions who have experiencing the same situation. The map merging these findings is available in the Annex.

Generally, we can affirm that the regional competitiveness in Europe exhibits great differences and disparities (Borsekova et al., 2021b; Ertur et al., 2006; European Union, 2011; European Union, 2017a; Rizzi et al., 2018). Our results on the one hand, are in line with evidence provided by other authors: Camagni & Capello (2013); Lengyel & Rechnitzer (2013); Möbius & Althammer (2020), Annoni et al. (2016). On the other hand, our comparative analysis provides an insightful picture of regional competitiveness at European level, which highlights how European regions are far from having a common level of regional competitiveness and how policy interventions need to make to tackle competitiveness disparities. In particular, the analysis of clusters is far more informative with respect to an analysis only ranking-based. We identified a group of core leading regions which maintain their over performing level of competitiveness, while most of European regions are medium performing where the great majority of them are in a sort of economic transition and should be accompanied with policy interventions. Finally, southern and eastern Europe presents a great number of low performing regions which suffer from a sort of stagnancy in their competitive level and urgently needs policy interventions in order to catch up with other territories.

1.5 Concluding remarks, limitations and future research

This paper proposed a comparative analysis to assess regional competitiveness of European regions at NUTS 2 level based on the Technique for Order Preference by Similarity to Ideal Solution. Using data from the EU Regional Competitiveness Index 2019, the paper explored the use of the TOPSIS method based on three different distance measures, i.e. the Manhattan, Euclidean and Mahalanobis distance measures, taking the RCI as the reference of the analysis. The results are three rankings of regions that are compared to the RCI by considering both rankings and clusters, leading to different considerations.

The first finding concerns the methodology used in the measurement of regional competitiveness. We find that the TOPSIS method can replicate the RCI ranking with the use of the Manhattan distance measure. Hence, we are able to overcome to the criticalities derived from a composite index and the use of a weighted average which leads to compensatory problems in the analysis. Moreover, from this result we suggest that decision makers should use the TOPSIS method in the measurement of regional competitiveness since it provides reliable evaluations of the performance of territories. Furthermore, this finding confirms the suitability of the RCI as the reference of the study and providing a bridge between the two approaches.

Another implication derived from the use of distance measures used is that we find that the TOPSIS ranking based on the Mahalanobis distance measure is the ranking that presents the greatest dissimilarity in the final ranking of regions compared to the RCI. Therefore, this result confirms the insights from previous studies, namely that regional competitiveness is driven by interrelated factors (Aiginger & Firgo, 2017; Pike, Rodríguez-Pose, & Tomaney, 2016; Wang & Wang, 2014). Hence, the TOPSIS method does not require indicators to be independent as composite indices instead need, so we encourage decision makers in the use of TOPSIS with the Mahalanobis distance measure when they want to provide a ranking of regions which consider the interaction among the indicators, in order to properly reflect the characteristics of the territory analysed (Wang & Wang, 2014).

Third, by the comparative analysis of the results of the three different rankings we are able to identify those regions that maintain membership of the same cluster of competitiveness across the overall analysis and those that do not. Specifically, while the comparison of rankings provides preliminary information regarding the on overall picture European regions, the analysis of the clusters goes much deeper, highlighting some interesting insights. Firstly, the results show that in Europe there are a few leading regions which according to our analysis can be unambiguously categorized as highly competitive. These regions are those that belong to the blue banana strip, hence, they are considered the economic backbone of European prosperity. These regions have achieved a sort of high development equilibrium and a stable steady high level of development as highlighted by several authors (Annoni & Dijkstra, 2019; Bartkowska & Riedl, 2012; Iammarino & Rodríguez-Pose, 2017). Therefore, highly competitive regions should continue in this path of high development and effective policy making. At the same time, they should be used as possible benchmark for those regions that are considered highly competitive but cannot clearly categorized as highly competitive, in order to target policy actions on the footsteps of the former.

Next to a few numbers of highly competitive regions we find that most European regions belong to the medium level of competitiveness. The majority of medium competitive regions cannot be clearly categorized within a specific level of competitiveness. This because although they perform well in some indicators, they also experience deficiencies in others, which make for them challenging to reach a development equilibrium. Hence, the finding highlights how medium performing regions seem in transition toward different clusters of competitiveness (Bartkowska & Riedl, 2012), hence the process of convergence in Europe needs further work (Bartkowska & Riedl, 2012; Borsekova et al., 2021b; Corrado et al., 2005; Iammarino & Rodríguez-Pose, 2017). Thus, a possible policy message for decision makers is that medium competitive regions should be accompanied in their transition path with tailored policy actions in order to lead them toward a more clear level of competitiveness, maybe in conjunction with other medium performing regions who are experiencing the same situation, especially those that are more dinamic and are experiencing higher growth.

Finally, our research reveal that there is a great number of low competitive regions which are maintain their low level of competitiveness. Hence, this highlights how there are territories which are trapped in a sort of low level of competitiveness, showing a sort of stagnancy in their development which may accentuate regional differences in Europe (Iammarino & Rodríguez-Pose, 2017). These regions are the most vulnerable since they are far from spilloever effects derived by mainland regions and are suffering from a persistent decline (Annoni & Dijkstra, 2019; European Commission, 2017; Iammarino & Rodríguez-Pose, 2017). For these perpheral regions we suggest that urgent policy actions should be taken in order to not keep them too behind in their development in order to become more attractive, and improving their fundamentals, since some of them are more dynamic and seem to react to this trap of low competitivess. Therefore, policy makers are highly encouraged to actively committing is taking opportune policy intervention to tackle this sort of stagnancy which may accentuate regional differences in the EU.

Overall, we can affirm that regional development in Europe is still highly etherogeneous and steps ahead must be taken in order to improve the competitiveness of European territories. This analysis is not aimed at leading to an overall solution since the assessment of regional competitiveness in Europe is difficult to be accurately evaluated. However, our work porvides some interenting insights about the current competitive level of European regions which complement the literature (Huggins, 2003; Lengyel & Rechnitzer, 2013) and can be juxapposed to policy interventions. At the same time, it demonstrates that TOPSIS method can be a suitable and easy method which can be easily adopted by policy makers in oder to provide reliable rankings of regions and conveying majour information with respect to a single ranking-based output.

The present analysis considers cross-section data, which provide only an image of the regional competitive situation in Europe. However, when investigating regional competitiveness or territorial disparities, scholars opt for time-series data (Bartkowska & Riedl, 2012; Bosker, 2009; Ertur et al., 2006). Therefore, as a further step of this analysis it might be interesting to replicate it on a different point in time, by examining the RCI from 2010 to 2019 in order to investigate how the rankings of regions and the composition of clusters change over time.

Author statement

Filippo Ferrarini: Conceptualization, Data processing, Formal analysis, Investigation, Writing of first draft, Visualization; **Silvia Muzzioli**: Conceptualization, Project Administration, Supervision, Writing review & Editing; **Bernard De Baets**: Methodology, Supervision, Validation, Writing review & Editing.

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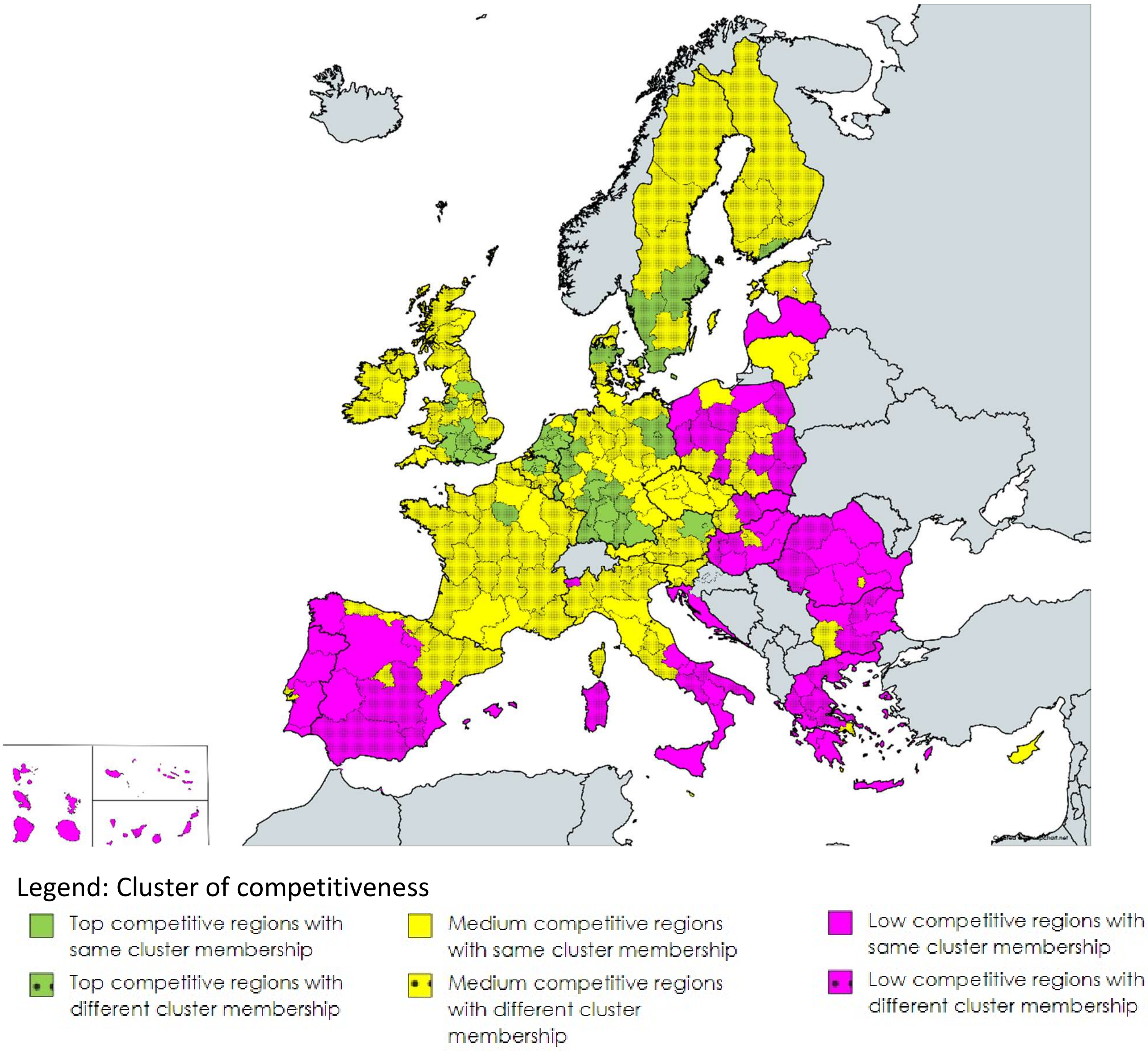
Annex 1

Annex 1.1: Comparative analysis of clusters of competitiveness derived by TOPSIS analysis.



Annex 1.2: Position of the European regions in the different ranking (RCI as reference)

Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking	Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking
Stockholm	1	5	13	Antwerpen	30	27	20
Inner London & other	2	2	1	Oost-Vlaanderen	31	24	17
Utrecht	3	4	3	Berlin & other	32	34	114
Berkshire & other	4	3	18	Overijssel	33	48	40
Surrey & other	5	1	2	Östra Mellansverige	34	78	100
Hovedstaden	6	12	57	Västsverige	35	76	103
Luxembourg	7	6	9	Herefordshire & other	36	32	39
Oberbayern	8	8	32	North Yorkshire	37	29	12
Flevoland & other	9	9	6	Freiburg	38	37	83
Helsinki	10	21	76	Rheinhessen-Pfalz	39	41	129
Île de France	11	7	4	Gießen	40	36	59
Hamburg	12	13	41	Leicestershire & other	41	31	21
Darmstadt	13	14	33	Düsseldorf	42	45	70
Zuid-Holland	14	18	14	Gr Manchst.	43	30	16
Hampshire & other	15	11	11	Groningen	44	65	85
Karlsruhe	16	17	68	Unterfranken	45	43	53
Cheshire	17	10	5	Schwaben	46	49	49
Stuttgart	18	19	36	Münster	47	53	74
Köln	19	20	51	Midtjylland	48	95	125
Noord-Brabant	20	25	19	Braunschweig	49	54	153
Gelderland	21	28	26	Sjælland	50	92	115
Gloucestershire & other	22	15	10	Leipzig	51	47	52
Tübingen	23	23	43	Eastern Scotland	52	46	46
Sydsverige	24	50	62	Derbs. & other	53	39	44
Bruxelles & other	25	16	7	Bremen	54	60	136
Kent	26	26	38	Dorset & other	55	40	22
Limburg	27	35	35	Limburg	56	44	23
Mittelfranken	28	33	97	Hannover	57	66	118
Wien & other	29	22	8	Dresden	58	59	75

Continued

Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking	Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking
Zeeland	59	83	64	Lüneburg	87	91	111
East Anglia	60	57	124	Rhône-Alpes	88	62	15
Arnsberg	61	70	90	Burgenland	89	74	28
West Central Scotland	62	51	58	Thüringen	90	88	82
West-Vlaanderen	63	42	25	Tirol	91	84	56
Koblenz	64	75	93	Kassel	92	87	86
Oberpfalz	65	69	101	Chemnitz	93	86	67
Drenthe	66	89	63	Niederbayern	94	96	98
Bratislavský kraj	67	38	24	Devon	95	94	78
West Yorkshire	68	52	55	Saarland	96	98	117
Praha & other	69	55	71	West Midlands	97	97	141
Oberfranken	70	68	66	Etelä-Suomi	98	124	147
East Wales	71	61	37	Comunidad de Madrid	99	93	131
Schleswig-Holstein	72	72	88	Nordjylland	100	126	156
North Eastern Scotland	73	79	110	Kärnten	101	99	47
Oberösterreich	74	63	34	Weser-Ems	102	104	121
Vorarlberg	75	73	61	Alsace	103	90	27
Shropshire & other	76	58	42	Northumberland and other	104	106	143
Eastern and Midland	77	82	94	Warszawski stołeczny	105	85	77
Detmold	78	81	89	Southern Scotland	106	107	138
Merseyside	79	67	80	Midi-Pyrénées	107	100	54
Lancashire	80	56	31	Sachsen-Anhalt	108	113	154
Syddanmark	81	103	132	Zahodna Slovenija	109	105	92
Steiermark	82	71	45	Småland med öarna	110	139	165
Salzburg	83	77	48	Länsi-Suomi	111	143	174
South Yorkshire	84	64	50	East Yorkshire & other	112	109	123
Trier	85	80	73	Cumbria	113	111	134
Friesland	86	101	102	Pays de la Loire	114	102	30

Continued

Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking	Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking
Mecklenburg-Vorpommern	115	125	170	Bourgogne	143	142	120
Lincolnshire	116	108	95	Åland	144	177	196
Southern	117	130	150	Pohjois- ja Itä-Suomi	145	186	208
Tees Valley & other	118	116	152	Lombardia	146	136	155
Cornwall & other	119	129	146	Highlands & other	147	165	194
Namur	120	110	105	Languedoc-Roussillon	148	152	161
Provence-Alpes-Côte d'Azur	121	115	96	Limousin	149	144	99
Aquitaine	122	119	65	Severovýchod	150	148	139
Bretagne	123	112	29	București - Ilfov	151	118	84
Liège	124	123	159	Basse-Normandie	152	145	116
País Vasco	125	114	91	Poitou-Charentes	153	149	104
Centre - Val de Loire	126	117	72	Moravskoslezsko	154	150	126
West Wales & other	127	131	148	Vzhodna Slovenija	155	155	109
Área Metr. de Lisboa	128	121	144	Střední Morava	156	154	137
Haute-Normandie	129	122	79	Provincia Aut. Trento	157	140	119
Norra Mellansverige	130	160	190	Jihozápad	158	156	162
Jihovýchod	131	132	127	Eesti	159	179	209
Lorraine	132	127	69	Sostinės regionas	160	151	164
Northern Ireland	133	141	180	Cataluña	161	163	201
Luxembourg	134	128	107	Emilia-Romagna	162	146	160
Övre Norrland	135	182	217	Lazio	163	153	177
Auvergne	136	133	87	Northern and Western	164	175	192
Nord-Pas de Calais	137	135	122	Comunidad Foral de Navarra	165	162	173
Hainaut	138	138	182	Champagne-Ardenne	166	170	188
Picardie	139	137	140	Piemonte	167	159	181
Közép-Magy.	140	120	106	Veneto	168	158	157
Franche-Comté	141	134	112	Friuli-V. Giulia	169	161	167
Mellersta Norrland	142	185	211	Śląskie	170	147	60

Continued

Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking	Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking
Kýpros	171	176	166	Opolskie	201	189	128
Liguria	172	168	187	Latvija	202	209	206
Toscana	173	166	171	Norte	203	211	225
Cantabria	174	188	189	Martinique	204	205	205
Małopolskie	175	157	81	Castilla y León	205	217	226
Prov. Aut. Bolz.	176	164	145	Illes Balears	206	216	234
Malta	177	199	247	Zachodniopomorskie	207	202	193
Severozápad	178	180	186	Podkarpackie	208	201	169
Západné Slovensko	179	172	108	Lubelskie	209	197	168
Attiki	180	169	142	Kujawsko-pomorskie	210	198	176
Yugozapaden	181	167	163	Podlaskie	211	207	185
Pomorskie	182	178	172	Świętokrzyskie	212	194	130
Dolnośląskie	183	171	149	Lubuskie	213	196	178
Umbria	184	181	151	Abruzzo	214	214	207
Corse	185	200	212	Molise	215	212	200
Principado de Asturias	186	195	198	Kontinentalna Hrvatska	216	215	195
Mazowiecki regionalny	187	173	113	La Réunion	217	219	227
Aragón	188	210	230	Východné Slovensko	218	218	199
Marche	189	190	179	Región de Murcia	219	230	248
Łódzkie	190	174	133	Algarve	220	226	221
Vidurio vakarų Lietuv.	191	191	184	Dél-Alföld	221	213	203
Comunidad Valenciana	192	206	216	Jadranska Hrvatska	222	221	197
La Rioja	193	204	204	Alentejo	223	225	233
Wielkopolskie	194	184	135	Castilla-La Mancha	224	236	255
Közép-Dunántúl	195	183	175	Warmińsko-mazurskie	225	223	210
Nyugat-Dunántúl	196	187	183	Guadeloupe	226	227	229
Galicia	197	208	213	Andalucía	227	239	257
Centro	198	203	214	Észak-Magyarország	228	220	220
Stredné Slovensko	199	193	158	Canarias	229	241	246
Valle d'Aosta	200	192	191	Dél-Dunántúl	230	222	219

Continued

Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking	Regions	RCI and Manhattan ranking	Euclidean ranking	Mahalanobis ranking
Basilicata	231	232	231	Ciudad Aut. Melilla	261	266	266
Campania	232	229	242	Dytiki Ellada	262	262	249
Észak-Alföld	233	224	218	Dytiki Makedonia	263	260	238
Sardegna	234	243	259	Mayotte	264	267	268
Puglia	235	240	251	Anatoliki Makedonia, Thraki	265	264	254
Região Aut. da Madeira	236	244	256	Guyane	266	265	267
Yuzhen tsentralen	237	233	239	Sud-Est	267	256	260
Vest	238	228	215	Voreio Aigaio	268	268	264
Kentriki Makedonia	239	235	202				
Severoiztochen	240	237	236				
Severen tsentralen	241	234	232				
Sicilia	242	247	262				
Extremadura	243	258	265				
Calabria	244	249	253				
Ciudad Aut. de Ceuta	245	254	258				
Nord-Vest	246	231	222				
Sud - Muntenia	247	238	237				
Yugoiztochen	248	245	250				
Centru	249	242	240				
Kriti	250	253	244				
Ipeiros	251	250	224				
Thessalia	252	252	223				
Região Aut. dos Açores	253	263	263				
Sud-Vest Oltenia	254	248	245				
Sterea Ellada	255	251	228				
Ionia Nisia	256	257	235				
Nord-Est	257	246	252				
Peloponnisos	258	259	241				
Notio Aigaio	259	261	243				
Severozapaden	260	255	261				

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Chapter 2

AMO-enhancing practices, open innovation and organizations' innovation in the European context: testing a mediation model

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Abstract

The literature has recognized the key role of the HRM practices for enhancing firms' innovative performance. At the same time, scholars have consistently demonstrated open innovation to be an effective approach for boosting companies' innovative outcome. Nevertheless, academics have largely overlooked to investigate the complex relationship between HRM practices, open innovation and organizations' innovativeness.

Using the AMO framework as analytical lens and data drawn from the European Company Survey 2019, a large-scale representative dataset at European level, this study investigates the direct and indirect relationship between the ability, motivation and opportunities-enhancing practices and firms' innovation capacity, hypothesizing a potential mediating role of open innovation.

The results show that companies that motivate workers and give them the opportunity to contribute with their skills, knowledge and abilities not only have higher probability to innovate, but also are more inclined to collaborate with external partners. Moreover, open innovation not only enhance the innovation capacity of the firm, but also partially mediates the relationship between HRM and organizations' innovativeness. These results shed further lights on both "the human side" of open innovation, as well as in the mechanisms linking HRM practices with innovation.

Keywords: AMO-enhancing practices, open innovation, HRM, Mediation, Europe

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2.1 Introduction

In contemporary business environment, innovation is an increasingly important source of competitive advantage for companies (OECD, 2018). In recent years, open innovation (Chesbrough, 2003) (OI) has been proposed as a novel approach for fostering the organizations' innovation process (Borgers, Foss, & Jacob, 2018; Burcharth, Knudsen, & Søndergaard, 2017; Chesbrough, 2006; Chesbrough & Borgers, 2014; Expósito, Fernández-Serrano, & Liñán, 2019; Hervas-Oliver, Sempere-Ripoll, & Boronat-Moll, 2021; Vrande, Jong, Vanhaverbeke, & Rochemont, 2009). Open innovation is defined as the "use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough, 2006, 1). Inbound knowledge flows consist in the acquisition of external knowledge and its integration within the inner boundaries of the firm, whereas the outbound knowledge flows occur when a company empowers other organizations in the use or development of its own knowledge (Chesbrough, 2006; Nedon, 2015; OECD, 2018; Parida, Westerberg, & Frishammar, 2012). Specifically, inbound knowledge flows, also defined exploration activities (Nedon, 2015; Vrande et al., 2009) are those OI practices that have been mostly investigated in the literature (West & Bogers, 2017). These kind of activities often deal with the collaboration with external firms to produce innovations (Greco, Grimaldi, & Cricelli, 2016; Hervas-Oliver et al., 2021; Xie & Wang, 2021; Vrande et al., 2009) or the contracting out of R&D processes (Gassmann, Enkel, & Chesbrough, 2010; Lee, Park, Yoon, & Park, 2010; Vrande et al., 2009).

The successful management of these inbound knowledge flows depends on the effective implementation of specific human resource management (HRM) practices (Barba-Aragón & Jiménez-Jiménez, 2020; Chen & Huang, 2009) and existing research suggests that HR practices might be a key factor for a company to integrate and exploit knowledge across organizational boundaries (Hansen, Güttel, & Swart, 2019; Lenz, Pinhanez, Urtubey De Césaris, & Jacobs, 2016; Malik, Froese, & Sharma, 2020; Malik, Sinha, Pereira, & Rowley, 2019; Zhou, Fey, & Yildiz, 2020) in order to develop new innovations (Colakoglu, Erhardt, Pougnet-Rozan, & Martin-Rios, 2019). Despite this, extant literature has so far mainly examined how specific HRM configurations influence the innovative performance of firms (Chowhan, 2016; Colakoglu et al., 2019; Haar, O'Kane, & Daellenbach, 2021; Seeck & Diehl, 2017; Shipton, Sparrow, Budhwar, & Brown, 2017; Shipton, West, Dawson, Birdi, & Patterson, 2006), thereby overlooking the relationship between HRM practices and OI (Engelsberger, Halvorsen, Cavanagh, & Bartram, 2021).

Open innovation is essentially associated with knowledge management and such knowledge management is nourished by workers' contributions fostered by appropriate HRM practices (Hong et al., 2019). In other words, HRM practices may be an important organizational antecedent and facilitator of open innovation because they are a key leverage influencing employees' ability to engage in a process of knowledge exploration (Barba-Aragón & Jiménez-Jiménez, 2020). It has been recently theorized that HRM practices may foster these abilities, since practices such as teamwork, communication, training, job design underpin the attitude of employees involved in collaborative activities and in the sharing of knowledge (Hong et al., 2019). Only a handful of studies have however addressed this issue (Lenz et al., 2016; Petroni et al., 2012).

Consistently, researchers have recently stressed the need to pay more attention on the "human side" of OI in order to better understand this kinf od process (Borgers et al., 2018; Zhu et al., 2019). Bigliardi et al. (2021), for instance, in their recent literature review on potential avenues for future research on open innovation, highlight how the organizational antecedents of OI (i.e. HR practices) is a potential thematic cluster which may furnish a deeper understanding of why firms may decide to open up their barriers toward external actors. Despite the many calls to attend to this "human side" in order to have a better picture on the drivers of open innovation, the topic still remains largely underexplored. Therefore, the present paper seeks to provide a better understading of the organizational antecedents of the OI process by examining whether HRM practices can be a facilitator of open innovation. In this paper we refer to OI activities as inbound knowledge flows following two of the categories defined by Vrande et al (2009). Moreover, following the suggestion made by Seeck and Diehl (2017), in order to overcome a limitation of the existing literature which focuses on single HRM practices, without drawing upon a theoretical framework, we will use the ability, motivation and opportunity (Appelbaum et al., 2000) (AMO) framework to address the issue of the HRM- OI relationship. This is important because the AMO framework has been already recognized as key in promoting employee performance (Appelbaum et al., 2000) and innovation (Haar et al., 2021); specifically authors in this stream of research have argued that this kind of processes are fostered not by single practices that function in isolation, but rather by a system of consistent and interrelated HRM practices which work in concert. Hence the first research question that this article aims to address is: *do ability-enhancing, motivation-enhancing, opportunity-enhancing HRM practices increase the likelihood for firms to engage in an OI process?*

The second objective of this work is related to the role of open innovation in the relationship between HRM practices and organizations' ability to innovate. Even though innovation can be considered as an outcome of HRM practices (Seeck & Diehl, 2017), the mechanisms that link such practices and organizations' innovation are still far to be fully understood. Scholars have widely explored those intermediate factors or 'black-box' that contribute to explaining the linkage between HRM and firm's innovative outcome by considering different mediators (Haar et al., 2021; Seeck & Diehl, 2017). Along this vein, the literature has provided evidence on the influence of HRM on innovation by means of exploration activities (Barba-Aragón & Jiménez-Jiménez, 2020; Chen & Huang, 2009; Malik et al., 2019). This finding, and the idea that OI in fact comprises the search for external knowledge to accelerate the innovation process (Chesbrough, 2003; Cohen & Levinthal, 1990; OECD, 2018; Vrande et al., 2009), suggest that OI may be a key factor in explaining how HRM practices affect organizations' innovation. Surprisingly however, this hypothesis has been largely overlooked in the scientific debate, thus, the second aim of this work is to shed further light on the transmission mechanisms linking HRM and innovation, and more specifically on the new products or processes introduced, by investigating whether OI can be considered a significant mediator in the linkage between the AMO-enhancing practices and firms' innovativeness. Hence, the second research question is: *do ability-enhancing, motivation-enhancing, opportunity-enhancing HRM practices influence innovation by means of OI?*

To address the above research questions, we use data drawn from the European Company Survey (ECS) 2019 (European Foundation for the improvement of Living and Working Conditions, 2020), a recent large-scale survey, which comprises more than 20.000 establishments at European level. In addressing the two research questions, this paper seeks to contribute to the research in three distinct ways. With respect to the first research question, we enrich the literature on open innovation by establishing a link with the literature on HRM practices, and specifically the AMO framework. By examining whether and to what extent AMO-enhancing practices affect in bound knowledge flows, this study casts new light on the organizational antecedents of open innovation.

We argue this to be a key contribution to open innovation scholarship which has recently recognized the key role of human contributions to open innovation but has so far devoted only limited empirical attention to the issue of how it can be nurtured (Borgers et al., 2018; Zhu et al., 2019). Moreover, by using the AMO framework as analytical lens to empirically investigate the HRM-OI link, this study contributes to the strategic human resource management scholarship - which argue for a focus on bundles of interrelated HRM practices when examining the impact on organizational performance-, by showing that some specific and popular bundles of practices (the AMO ones) are not only relevant for enhancing the innovative capacity of firms as depicted by prior scholars (Haar et al., 2021), but also form a powerful system for seeking and capturing external knowledge.

Finally, in addressing the second research question, this study tests the potential mediating role of open innovation in the relationship between HRM and innovative organizational performance. In so doing, it seeks to contribute to the HRM stream of research focusing on the driving belt mechanisms which explain how HRM practices may foster innovation, by drawing attention to a variable (i.e. open innovation) that has been left so far largely unattended by HRM scholarship, despite its increasing importance as a booster of today's organizations' ability to innovate. The paper is structured as follows: the following section presents the literature review and hypothesis about HRM and open innovation. Then, we describe the sample and the methodology, while empirical results are presented in the section 2.4. The section 2.5 discusses the results and presents theoretical and managerial implications as well as limitations of the study.

2.2 Theoretical background and hypothesis

2.2.1 HRM practices and Open Innovation

In the last years, the literature has extensively recognized open innovation as one of the main contributors of firm's innovative capacity (Ebersberger, Bloch, Herstad, & De Velde, 2012; Greco et al., 2016; Parida et al., 2012; Xie & Wang, 2021 ; Vrande et al., 2009). OI is defined as the use of inflows and outflows of knowledge to boost internal innovation and expand markets opportunities (Chesbrough, 2006). Firms may enhance their innovative capability with inbound knowledge flow, also defined as exploration activities, by which they seek and capture knowledge from sources outside the firm's boundaries. These kinds of activties may entail, for example, R&D outsourcing or collaborating with external partners (Vrande et al., 2009). When engaging with the OI process, organizations need to manage challenges and obstacles derived from the management and exchange of knowledge with external actors (Hong, Zhao, & Snell, 2019; Naqshbandi, Tabche, & Choudhary, 2019; Nedon, 2015). At the organizational level, these barriers are related to capability factors (i.e absortive capacity), while at individual level are related to the cognitive aspects such as the 'Not invented here' (NIH) syndrome, which refers to the unwillingness of adopting ideas coming from external partners (Hong et al., 2019; Nedon, 2015).

Extant literature already provides some insignts into the key role of HRM practices in removing such barriers and enabling companies to create the context in which different sources of knowledge are integrated (Colakoglu et al., 2019; Malik et al., 2019; Malik et al., 2020; Park, Bae, & Hong, 2019; Patel et al., 2013; Singh, Gupta, Busso, & Kambo, 2019). HRM practices strengthen workers competences, flexibility, while enhancing their capacity to acquire and use external knowledge (Barba-Aragón & Jiménez-Jiménez, 2020; Hong et al., 2019; Nedon, 2015). Nevertheless, the current understanding of the relationship between HRM and OI is still limited and fragmented (Borgers et al., 2018; Colakoglu et al., 2019; Hong et al., 2019; Zhu et al. 2019). In fact, the few studies that address the issue mainly focus on single and very diverse HRM practices, without drawing upon a comprehensive framework, thus failing to provide a coherent picture of the HRM-OI link. In order to overcome this limitation, the present study uses the AMO framework as analytical lens.

The AMO framework focuses on three bundles of practices (i.e. ability-, motivation-, and opportunity-enhancing practices) as key to explain the influence of HRM on organizational performance. The primary aim of these three bundles is to optimize employees' work-related knowledge, skills and abilities; motivate and offer them the opportunity to put forth discretionary behavior, share ideas, develop their job skills, and utilize their knowledge for the good of their organization, thereby influencing individuals' behavior and attitudes and ensuring the alignment between individual-level outcomes and the organizations' strategic goals. The AMO framework, thus, provides the explanatory mechanisms for how HRM influences organizational-level outcomes or, as we argue, an organization's ability to engage with OI. In particular, the literature affirms that the implementation of OI depends on the inclination, attitude and capability of employees to engage collaborative processes, which is influlenced by appropriate HRM practices (Engelsberger et al., 2021; Hong et al., 2019). More specifically, the capability of a firm to perform explorative activities is generated by employees who are engaged in the working activities (Colakoglu et al., 2019) and specific HRM systems can support workers decision to how and when conduct these kind of explorative activities (Ferraris, Erhardt, & Bresciani, 2019), since organizational level HRM practices influence individual behaviors (Malik et al., 2020; Shin, Jeong, & Bae, 2018). In this strand, the AMO model is an appropriate framework for understanding how firm-level HRM practices can support open innovation at organizational level.

Ability-enhancing practices for instance, which refer to those practices- such as training and learning- that are aimed at improving employees' skills, abilities and knowledge, help in building a positive attitude toward external partners. In explorative activities for example, formal and informal training are an important aspect because they are the drivers for encouraging employees' self-exploration (Malik, Pereira, & Tarba, 2019). If workers do not have the right competences to recognize and assimilate external knowledge, they would be more unwilling to seek and collaborate with external partners, with the risk of developing the NIH syndrome (Hong et al., 2019). Therefore, training activities help in reducing insecurity and aversion toward external knowledge because workers are more skilled and open-minded in order to fruitfully interact with external partners and enhancing the knowledge exchange (Hong et al., 2019). These fruitful relational aspects are also underlined by Ferraris et al., (2019), where in their qualitative study on smart city projects affirm that training and learning help in building stronger ties with external partners, because project managers are better able to understand the needs of external actors, which then turns in a more effective management of the knowledge flows among the parts involved in the collaborative partnership. Moreover, training activities on the one hand, reduce the distance from external knowledge (Borgers et al., 2018), on the other hand, enhance individual workers creativity (Jiang, Wang, & Zhao, 2012) that, integrated with external knowledge (Malik et al., 2020), favors the execution and implementation of new ideas (Ferraris et al., 2019), which lead to organization innovation (Colakoglu et al., 2019; Malik et al., 2019; Park et al., 2019). In addition, training and learning leverage internal capacity to adapt, integrate and combine external knowledge with internal knowledge by enhancing employees' level of knowledge base, which icreases the overall firm's absortive capacity (Borgers et al., 2018; Shiptoven et al., 2010). Therefore ability-enhancing practices are an important aspect for a sucessuful OI implementation (Podmetina, Volchek, Dąbrowska, & Fiegenbaum, 2013).

Motivation-enhancing practices are related to those practices which enhance the willingness of employees to perform according to organization' goals (Colakoglu et al., 2019; Jiang K. , Lepak, Hu, & Baer, 2012). In the open innovation context, motivation-enhancing practices should motivate employees both in the exploration of new sources of external valuable knowledge, as well as foster internal and external collaborative behavior in order to enhance the innovative capacity of the organization (Podmetina et al., 2013). Individual and group rewards for example, encourage cooperative work behavior (Park et al., 2019; Prieto-Pastor & Martin-Perez, 2015) because they help in creating interdependence among workers, which may turn in a facilitation of the knowledge transfer and by then, to an icrease of the absortive capacity of the overall organization (Hong et al., 2019). Moreover, intrinsic motivational practices aimed at providing recognition, sense of belonging and stimulating jobs, bring very high contribution in fostering open innovation (Antikainen et al., 2010). Performance appraisal linked to employee cooperative and idea-sharing behavior are also an important aspect in the OI process. In fact on the one hand, they empasize the organizational efforts toward group outcomes, which enhance the collaborative behavior of individuals and by then of the organization as a whole (Prieto-Pastor & Martin-Perez, 2015), on the other hand, they motivate workers to use the external new knowledge to improve the work process which may turn up as innovative solutions. In addition, both rewads and behavioral appraisal enable workers to understand which kind of knowledge is valuable to be shared and capable to generate innovativeness within the organization (Andreeva, Vanhala, Sergeeva, Ritala, & Kianto, 2017). Therefore, these kinds of practices assist employees in their explorative process since they are better capable to scan the external environment for the right partner to collaborate with. Along this vein, Ferraris and colleagues (2019) show that, when appraisal and compensation practices are tailored for building relationships with external partners, the organization benefits of stronger ties with project allies. Hence, motivation-enhancing practices are useful drivers for aligning employees to organizational OI objectives and activities (Colakoglu et al., 2019).

Opportunity-enhancing practices target the structure of work and the participation of employees in decision-making (Boon, Hartog, & Lepak, 2019; Jiang, Lepak, Han, Hong, Kim, & Winkler, 2012; Lepak, Liao, Chung, & Harden, 2006), with a view to provide employees with effective opportunities to contribute with and express their talents. With specific reference to OI inbound knowledge flows, some scholars underline the key role of opportunity-enhancing practices in integrating new knowledge (Garaus, et al., 2016; Malik et al., 2020; Malik et al., 2019) since they enhance cooperative behavior and reinforce collaborative ties with external partners (Ferraris et al., 2019). Practices related to job design, such as flexible work and job rotation enhance the opportunity to cooperate and to increase the knowledge flow among individuals (Prieto-Pastor & Martin-Perez, 2015), by generating opportunities of role switching between internal and external actors, which facilitates the knowledge flows by reducing insecurity and aversion (Hong et al., 2019). In dealing with the OI process, benefits are mainly captured if firms provide employees with time and freedom since on the one hand, independent workers tend to be creative, cooperative, entrepreneurial, and capable to manage problems, on the other hand, with a speedy decision-making process companies take advantage of the new knowledge coming from external partners (Burcharth et al., 2017). Practices such as teamwork act as facilitators of collaborative practices with actors outside the company (Hong et al., 2019). Teamwork skills reduce insecurity to external partners, diminishing the potential risk of the NIH syndrome since employees with those skills are more open to interaction, communication and knowledge sharing (Hong et al., 2019). In other words, workers that are not used to collaborate with internal actors may be even more reluctant to collaborate with external players, whereas employees who are given the opportunity to collaborate within the company may be more prone to involve also external partners, since collaborative practices reduce the barriers to external actors (Hong et al., 2019; Zhou, Hong, & Liu, 2013). At the same time, teamwork promotes the cross-pollination of ideas and supports the knowledge flows among individuals (Malik et al., 2019).

Acquiring external knowledge and integrating it into the organization's existing knowledge base call for good knowledge sharing practices that spread information within the company's boundaries. Ferraris et al. (2019) for instance, show that information sharing practices are essential in the exploration process for alliances in smart-city projects, because they stimulate the knowledge exchange and promote the collaborative knowledge creation among the organization and its partners. Employee involvement practices, such as participation in management decision or information-sharing practices among employees and between employees and managers, help to spread the knowledge inside the organization and enhance the opportunity for employees to contribute to the integration of new external knowledge inside the organization (Prieto-Pastor & Martin-Perez, 2015; Park et al., 2019). Moreover, expanding knowledge across organizational levels helps to reduce barriers to OI- (Nedon, 2015), since they support the information exchange and the reciprocal problem solving, for instance by informing workers on how to use the newest procedures, techniques and arrangement for improving certain working processes (Patel et al., 2013; Singh et al., 2019).

Therefore, based on the above arguments we formulate the following hypothesis:

Hypothesis 1: Ability, motivation, and opportunity-enhancing practices relate positively to open innovation endeavours.

2.2.2 The mediating role of Open Innovation

The driving belt mechanisms that link HRM and organizations' innovation still remains an under researched area in HRM (Seeck & Diehl, 2017). In the attempt to explore the 'black-box' of these processes more deeply, scholars have investigated the role of potential different mediators (Seeck & Diehl, 2017). However, the research done in this direction of analysis has surprisingly almost completely ignored the potential mediating role of open innovation in the relation between HRM and innovation (Engelsberger et al.,2021; Singh et al., 2019). Accordingly, in light of the previous Hypothesis 1 – which states a positive relationship between the HRM dimensions of the AMO model and open innovation – and the extensive body of research which highlights the key role of open innovation in boosting firm's innovative capacity (Ebersberger et al., 2012; Parida et al., 2012; Vrande et al., 2009) in the present paper we argue for an indirect relation between AMO-enhancing practices and innovation via open innovation.

Although they are not specifically focused on open innovation, the studies showing the mediating role of explorative activities in the relationship between HRM and innovative outcomes (Barba-Aragón & Jiménez-Jiménez, 2020; Chen & Huang, 2009; Malik et al., 2019) suggest the plausibility of the above hypothesis. Explorative activities comprise the search for and use of external new knowledge, and thus are very much related to in-bound OI activities (Hong et al., 2019; Raisch, Birkinshaw, Probst, & Tushman, 2009). More in detail, Barba-Aragón & Jiménez-Jiménez (2020), show that empowerment, selection, training, performance appraisal and compensation influence competence exploration, which in turn mediates the relationship between HRM practices and radical innovation. Similarly, Chen & Huang (2009) provide evidence of the positive relation between HRM practices such as training, participation, performance appraisal, compensation and the acquisition and use of knowledge coming from external partnerns, which consequently have a positive effect on innovation performance. Along this vein, some studies confirm that practices related to skill development, along with motivational practices such as performance appraisal and reward, as well as opportunity-enhancing practices like job design and information-sharing practices, facilitate inbound OI, making workers more effective in their interactions and more inclined in taking risks and experimentation, thereby improving the performance and the innovation capacity of the firm (Malik et al., 2019; Malik et al., 2019). Although these results suggest that open innovation may play a significant mediating role in the explanation of the relation between HRM practices and the innovative firms' output, empirical evidence on this issue still remain scarce. Moreover, the above-mentioned studies do not explicitly use the lens of AMO framework to test the mediating role of open innovation. Finally, these studies are applied to small or non-representative datasets or to single countries dataset such as Spain, Taiwan or India.

Therefore, in an attempt to contribute to address these issues, we formulate our second research hypothesis as follows:

Hypothesis 2: Open innovation mediates the relationships between ability, motivation and opportunity-enhancing practices and firm's innovation capacity

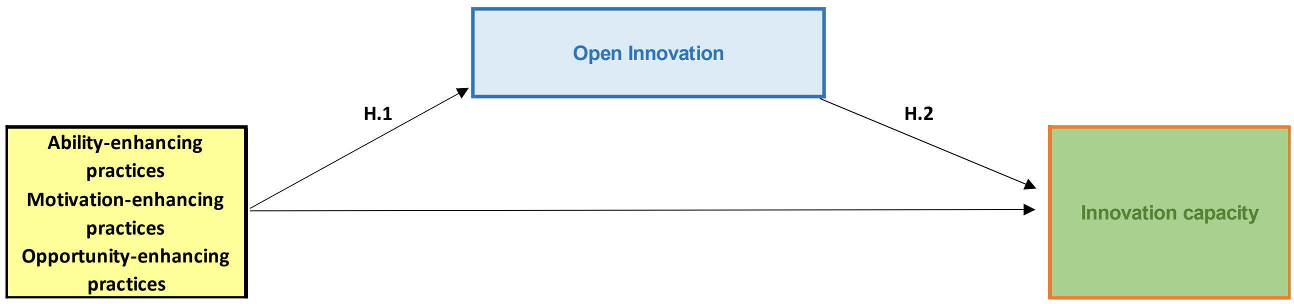

Figure 2.1: Conceptual model

2.3 Material and methods

2.3.1 Data

The European Company Survey carried out in 2019 by Eurofound and Cedefop is a large-scale, cross-national survey which collects data on workplace practices regarding work organization, human resource management, skills use and strategies, digitalization, employee participation and social dialogue implemented in 21,869 establishments across all 27 European Union (EU) member states and United Kingdom. The number of interviews completed ranges from 122 in Cyprus to 1,498 in Italy. The unit of enquiry for the survey is the establishment: the local unit or site. The survey collects data from both managers and employee representatives at each establishment. We used the dataset of manager respondents (Eurofound & Cedefop, 2020a) collected by Eurofound and Cedefop according to the following procedure: establishments were contacted via telephone to identify a management respondent, who were then asked to fill out the survey questionnaire online. This approach reduced the burden on respondents and improved the quality of responses (Eurofound & Cedefop, 2020b). Being the sample highly heterogeneous, a weighting is applied to ensure the results of the analysis are representative in terms of establishments distribution across sectors, size and countries (Eurofound and Cedefop, 2020c). There is a trade-off in terms of types of data in using european-level representative surveys across countries. On the one hand, they normally do not provide extensive questionnaire batteries for the measurement of specific concepts (Gallie, 2013). Moreover, cross-national surveys might suffer from comparability and interpretation because of inconsistencies in how questions are administred and coded (Donnelly & Pop-Eleches, 2018). On the other hand, however, they have the benefit of higher generalizability.

2.3.2 Measurement and variables

AMO dimensions

In the present study, the AMO-enhancing practices were operationalized through the variables of the ECS questionnaire, which in this respect offers multiple items measured with different scales. More specifically, in doing so, we followed on the one hand, the theoretical work by Lepak et al., (2006) and Jiang K., et al. (2012) who comprehensively identify those practices which are important to be included in the AMO framework, and on the other, the literature regarding HRM and innovation, as well as HRM and explorative activities. The practice of combining practices following the literature has been extensively used by scholars (Barba-Aragón & Jiménez-Jiménez, 2020; Chowhan, 2016; Macky & Boxall, 2007). Since we relied on already existing data, which was not developed for this specific purpose, we had some issues in the construction of the abillity dimension. Despite these difficulties, we were able to use 24 items so as to include the majority of the HRM practices included in the AMO model; limitations both on the constructs of the AMO model and their internal consistency are not new in the literature, especially when using already exisiting data (Vermeeren, Kuipers, & Steijn, 2014). The Cronbach's alpha of the bundles ranged between 0.6 and 0.7, a little below the threshold of 0.7. Nevertheless, these internal consistency are acceptable since in the literature there is a lack of coherence in defining complex constructs; moreover we are far above the levels of previous studies which measured the AMO framework using multi-dimensional surveys (Ramsay, Scholarios, & Harley, 2000).

For the *ability-enhancing practices*, we included formal and informal training, which measured the proportion of employees that participated in training sessions inside or outside the establishment; frequency of the training and development opportunities provided to employees; skill-enhancing job diffusion, and the proportion of employees covered by jobs that required continuous training. Moreover, we included two items that measured the use of training to allow job rotation and to improve the capacity to articulate ideas (Cronbach's alpha 0.685).

For the *motivation-enhancing practices*, we included variable pay schemes, which measured the proportion of employees that received a variable pay liked to the individual, team or establishment performance; job security, which measured the proportion of employees with an open-ended contract; performance appraisal based on workplace behaviors such as "helping colleagues without being asked" or " making suggestions for improving the way things are done in the company", and the use of monetary rewards as a motivational lever (Cronbach's alpha 0.626).

In the *opportunity-enhancing practices*, we included items measuring job design and knowledge-sharing. For job design we included two items that measured the proportion of employees performing jobs that required problem solving and the independent organization of their working time; two items measuring the use of autonomous teams and one dummy measuring the adoption of a managerial style which allows employees to make discretionary decisions about their methods of work. For knowledge-sharing we used four items measuring the extent to which employees were involved in making decisions concerning the ways of organizing work (on regular basis, on irregular basis or not involved). Moreover, we included a dummy variable assessing the presence of suggestion programs in the establishment (Cronbach's alpha 0.619).

The practices included in each bundle were measured through different variables and scales; therefore, following other scholars (e.g., Chowhan, 2016; Macky & Boxall, 2007), they were standardized into z-score to have equal weights in the creation of bundles. Finally, in line with prior studies (Boon et al., 2019; Chowhan, 2016), the AMO dimensions were created by additively combining the scores of the standardized variables into single aggregated indices.

Open Innovation

Open innovation derived from a multinomial variable which assessed the approach of the establishment to the design and development of new products or services: internal (mainly carried out internally or in collaboration with other establishment within the company), external (mainly carried out in collaboration with other companies, or through outsourcing), not performed. Following (Vrande *et al*. 2009) we selected only the two dimensions that measured the external R&D (exploration) activities; hence the final variable assumed the value of 1 if the establishment was engaged in the design and development of new products or services in collaboration with other companies or through outsourcing and 0 if it had not performed any R&D activity, in line with prior scholars (Cassiman and Valentini, 2016). We excluded from the analysis those establishments that mainly performed internal R&D activity (7,273 cases). The number of establishments engaged in OI activities was 2,328 units, representing the 16.18 % of the final subsample.

Innovation capacity

Following (De Marchi, 2012; Hervas-Oliver *et al*., 2021), the variable 'innovation capacity' was measured with a dichotomous variable that took the value of 1 if the firm indicated that had introduced at least: (1) a new or significantly changed product service since 2016, (2) a new or significantly changed process since 2016. Although our measure of OI uniquely refers to new product/service development, we included also process innovation in the measure of innovation capacity because the literature points out that new product development also leads to process innovation (Theyel, 2013), the two types of innovation being thus intertwined (OECD, 2018) (Cronbach's alpha 0.690).

Control variables

In line with the literature, we used several control variables. More specifically, following Chang, Gong, Way, & Jia (2013), we included establishment years (log years) for reducing outliers' effect; in line with Meuer (2017) we also controlled for establishment size (0=large – above 249 employees versus 1=SME up to 249 employees), industry sectors (0=manufacturing versus 1=service and construction sectors) and for the level of market competitiveness (1=very competitive, 0=otherwise). The strategic orientation of a firm directly influence its innovation activities (OECD, 2018), hence establishment strategy was measured by two dummy variables indicating whether the establishment aims at regularly developing products or services that are new to the market (1=the establishment follows an innovation strategy; 0=otherwise), or whether the establishment aims at offering product or services at lower price than competitors (1=the establishment follows a cost strategy, 0=otherwise). Following Jeong & Shin (2019), we controlled for market uncertainty (1=the demand of products is unpredictable, 0=otherwise). Finally, we introduced controls for capturing regional diversity, since in Europe there are great differences in the innovation performance across EU member states (European Union, 2019). Hence, we introduced three dummies which clustered European countries into four groups, following the European Innovation Scoreboard 2019 (0=innovation leaders versus 1=strong, moderate, and modest innovators).

Variables considered in the model are specified in more details in the Annex. To treat variables and to carry out the analysis we used SPSS 23.0 and R 3.6.2 version.

2.3.3 Analysis

Hypothesis 1 stated that ability, motivation and opportunity-enhancing practices relate positively to open innovation. More specifically, we were interested in exploring the potential influence of the former on the latter. However, the survey was cross-sectional, rising a potential issue of reverse causality; indeed, also the literature demonstrates that the opposite relation is also plausible (Burcharth et al., 2017; Lenz et al., 2016; Petroni et al., 2012). To explore this possibility, we used some retrospective questions provided by the survey and regarding the extent to which employees had influenced management decisions in some organization's areas since 2016. A new variable named 'Employees' empowerment in last years' was then added in the model. It was composed by five items ranging from 1 (not at all) to 4 (to great extent) which measured the influence of employees in five areas such as the organization and efficiency of work processes, training and skill development, payment schemes, working time arrangements and dismissals since 2016. The items were then transformed into five dummies, which assumed the value of 1 if the influence was great or moderate. The final variable was computed with a scale ranging from 0 (no influence) to 5 (influence in all areas) measuring the amount of influence of employees within the organization over the last years (Cronbach's alpha 0.707).

Since open innovation was measured through a dichotomous variable, the binary logistic regression was used to test the first hypothesis. In line with other studies (De Marchi, 2012; García-Cabrera, Lucia-Casademunt, & Cuéllar-Molina, 2018), we focused in particular on the direction and significance of the coefficients of the logistic regression, rather than assessing the marginal effects, since we were mainly interested in the relation patterns among variables. Since innovation capacity too was a dichotomous variable, the same regression analysis approach was used to test the second hypothesis about the potential mediating role of open innovation in the relationship between AMO-enhancing practices and innovation. Therefore, for the mediation effect with a dummy variable, we followed Iacobucci (2012). Moreover, for testing the mediation model, we followed the three steps approach of Baron & Kenny (1986). In addition, to assess the significance of the indirect effect, we employed a bootstrap procedure resampling 1,000 times using the 95% confidence interval. To perform the bootstrapping, we used the library '*boot*' in R.

2.4 Results

Table 2.1 presents the correlations of the main variables of the model. All variables are positively and significantly correlated and the descriptive statistics exclude the multi-collinearity issue among the regressors included in the model. The correlations among the variables are in line with prior studies (Prieto Pastor et al., 2010) and consistent with the relationships depicted in Figure 2.1.

	N.	Weighted N.	Mean	S.D.	1	2	3	4	5
Ability_enhancing	21,864	2,350,013	.000	3.722	1				
Motivation_enhancing	21,868	2,350,234	.000	4.145	,330**	1			
Opportunity_enhancing	21,866	2,350,209	.000	4,429	,478**	,279**	1		
Open_Inn	14,384	1,628,434	.136	0.343	,042**	,091**	,114**	1	
InnovationCapacity	21,803	2,344,370	.407	0.491	,114**	,143**	,147**	,261**	1

Ability, motivation and opportunity-enhancing practices are all composite scales (z-score standardized values)

All other variables are dummies. We did not include controls due to limited space. **p<.01; *p<.05.

Table 2.1. Descriptive statistics and correlations of the main variables of the model.

Table 2.2 presents the first two models of the logistic regression analysis. The fits of the models are similar to those estimated in other studies on HRM at European level (García-Cabrera et al., 2018) and open innovation (De Marchi, 2012); they can be considered acceptable also in light of the large scale, cross-sectional nature of the dataset and the use of data on size, industry, and sectors which result in a heterogeneous survey and in a highly variable structure of the dataset which may reduce the strength of the correlations among variables.

Model 1 in Table 2.2 shows the estimated relationship between the AMO - enhancing practices and OI. Ability-enhancing practices are not significant (β=-.015, p≥.10), however, both of the bundles aimed at enhancing employees' motivation (β=.031, p≤.01) and opportunity (β=.095, p≤.01) reveal to be positive and significant predictors of open innovation activities; opportunity in particular has the strongest effect OI. This is not surprising because this bundle is formed by job design practics such as teamwork and autonomy, as well as information sharing practices, which are key in the OI approach (Hong, Zhao, & Snell, 2019). Table 2.2 also presents an additional model where the variable 'Employees' empowerment in the last years' is added to the previous model testing the influence of AMO-enhancing practices on open innovation, in order to address the possibility of reverse causality. The results show that both the current levels of motivation and opportunity enhancing practices (respectively, β=.026, p≤.05; β=.086, p≤.01) as well as the level of influence on organizational decision-making processes experienced by the employees since 2016 (β=.089, p≤.01) are significantly associated with open innovation. This last result is also in line with prior studies. For instance, Naqshbandi et al.,(2019) affirms that companies which trust employees and involve them in decision-making are better able to engage with OI processes.

	Model 1 Open innovation		Model 2 Open innovation	
Variables	β	S.E.	β	S.E.
Empl._Empowerement_last_years			0.089**	0.029
Ability_enhancing	-0.015	0.014	-0.021	0.014
Motivation_enhancing	0.031**	0.011	0.026*	0.011
Opportunity_enhancing	0.095***	0.013	0.086***	0.013
SmallComp	-0.710***	0.157	-0.726***	0.159
MediumComp	-0.434*	0.172	-0.453**	0.173
Construct_sec	-1.075***	0.147	-1.055***	0.148
Service_sec	-1.012***	0.102	-0.983***	0.102
Logyears	-0.141	0.129	-0.123	0.129
CostStrategy	-0.131	0.090	-0.122	0.090
InnStrategy	0.483***	0.092	0.477***	0.092
MarketComp	0.354*	0.139	0.396**	0.140
Predict_demand	-0.215*	0.094	-0.228*	0.094
Modest_inn	-0.253.	0.149	-0.305*	0.151
Moderate_inn	0.151	0.104	0.110	0.106
Strong_inn	-0.325**	0.117	-0.325**	0.118
Pseudo R^2	0.067		0.068	
Observations	13,664		13,393	
Chi-square (df)	281.86(15)***		272.66(16)***	
Robust standard errors.				
Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.10				
Odds ratio are not reported due to limited space.				

Table 2.2. Results of logistic regression analysis

When doing collaborative R&D projects, workers need a certain degree of freedom and decision authority to foster the OI process (Nedon, 2015). Based on the above results, we then conclude that Hypothesis 1 is partially supported.

Table 2.3 presents the further models estimated to test the hypothesis 2 concerning the mediating role of open innovation in the relationship between AMO-enhancing practices and firms' innovative capacity. More specifically, Model 3 estimates the relationships between ability, motivation and opportunity-enhancing practices and firm's innovation capacity, when also the control variables are included. The results show that almost all control variables are significant ($p \leq .05$) and the sign of their coefficients is in line with the findings of previous studies (Anzola-Román, Bayona-Sáez, & García-Marco, 2018; Meuer, 2017; Zheng, Morrison, & O'Neill, 2006). Specifically, small companies have lower probability to innovate ($\beta=-.429$, $p \leq .01$); in the manufacturing sector occur more innovation with respect to service and construction ($\beta=-.683$, $p \leq .01$; $\beta=-1.387$, $p \leq .01$). The age of the company seems uninfluential ($\beta=.009$, $p \geq .10$), while establishments that follow an innovation strategy ($\beta=.388$, $p \leq .01$) are more innovative compared to those that follow a cost strategy ($\beta= -.171$, $p \leq 01$). Low predictable demand for company products has no effect on innovation ($\beta=-.096$, $p \geq .10$). In line with the literature that points to highly competitive markets as a key contextual factor determining firms' innovation (OECD, 2018), we also found that market competitiveness is a strong predictor of firms' innovative capacity ($\beta=.473$, $p \leq .01$). Moreover, differences in the innovation capacity of European countries are present. For what concerns the influence of the practices considered in the AMO framework, the findings show the significant and positive association between ability ($\beta=.021$, $p \leq .05$), motivation ($\beta=.039$, $p \leq .01$), and opportunity ($\beta=.069$, $p \leq .01$), on the one hand, and innovation on the other, thus confirming the direct relationship between the AMO-enhancing practices and the innovative performance of firms in line with recent studies (Haar et al., 2021). Even in this case, opportunity bundle has the greatest effect.

Model 4 estimates the relationship between the mediator (i.e. open innovation) and innovation capacity. In line with previous studies (Burcharth et al., 2017; Ebersberger et al., 2012; Expósito et al., 2019), the findings confirm the role of open innovation as a booster of the innovative outcome of companies ($\beta=1.401$, $p \leq .01$). Finally, Model 5 explores the mediating role of open innovation in the relationship between the AMO dimensions and innovation capacity. We observe that when open innovation is introduced in the full model, motivation ($\beta=.035$, $p \leq .01$) and opportunity ($\beta=.045$, $p \leq .01$) remain significant, but their coefficients' power reduces in particular the opportunity one, which passes from 0.069 (Model 3) to 0.045; hence the mediation is partial. Ability bundle instead increases its coefficient ($\beta=.032$, $p \leq .01$), hence mediation for this bundle does not occur.

	Model 3 Innovation capacity		Model 4 Innovation capacity		Model 5 Innovation capacity	
Variables	β	S.E.	β	S.E.	β	S.E.
Open_Inn			1.401***	0.091	1.309***	0.093
Ability_enhancing	0.021*	0.009			0.032**	0.012
Motivation_enhancing	0.039***	0.007			0.035***	0.009
Opportunity_enhancing	0.069***	0.007			0.045***	0.009
SmallComp	-0.429***	0.106	-0.138	0.149	-0.077	0.156
MediumComp	-0.186	0.114	-0.032	0.160	0.021	0.167
Construct_sec	-1.387***	0.099	-0.913***	0.130	-0.959***	0.131
Service_sec	-0.683***	0.065	-0.189*	0.094	-0.308**	0.097
Logyears	0.009	0.081	0.118	0.104	0.202.	0.106
CostStrategy	-0.172**	0.058	-0.071	0.073	0.021	0.074
InnStrategy	0.388***	0.056	0.311***	0.073	0.251***	0.075
MarketComp	0.473***	0.082	0.564***	0.107	0.522***	0.108
Predict_demand	-0.096.	0.057	0.148*	0.075	0.084	0.076
Modest_inn	0.182*	0.090	0.216*	0.103	0.256*	0.113
Moderate_inn	0.317***	0.063	0.143.	0.074	0.235**	0.081
Strong_inn	-0.262***	0.068	-0.214*	0.084	-0.239**	0.088
Pseudo R^2	0.075		0.074		0.091	
Observations	20,824		13,652		13,650	
Chi-square (df)	622.04(15)***		426.04(13)***		510.45(16)***	
Robust standard errors.						
Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.10						
Odds ratio are not reported due to limited space.						

Table 2.3. Results of the logistic regression analysis

The results of 1,000 bootstrapped samples (Table 2.4) confirms the significance of the indirect effect of motivation (estimate=.0402, 95% CI=[.0149, .0688]) and opportunity-enhancing practices(estimate=.1243, 95% CI=[.0841, .1640]), but it disconfirms the significance of the indirect effect of ability-enhancing practices (estimate=-.0202, 95% CI=[-.0538, .0158]). Therefore, hypothesis 2 is partially supported.

Indirect effects	Bootstrapping		95% C.I.	
Paths	Estimate	SE	Lower	Upper
Ability → Open_Inn → Innov. Capacity	-0.0202	0.0177	-.0538	0.0158
Motivation → Open_Inn → Innov. Capacity	0.0402	0.0149	0.0104	0.0688
Opportunity → Open_Inn → Innov. Capacity	0.1243	0.0204	0.0841	0.1640

Table 2.4. Mediation testing: bootstrap results (n=1,000)

2.5 Discussion

Despite the growing importance of open innovation as a key driver to stimulate the innovative performance of firms (Ebersberger et al., 2012; Hervas-Oliver et al., 2021; Parida et al. 2012), the scholarly literature on HRM has so far devoted only limited attention to the role that HRM practices may play in fostering this approach. Consistently, some scholars have recently underlined the need for further research to shed more light on the "human side" of OI (Borgers et al., 2018; Zhu et al., 2019) and on the organizational antecedents of OI (Bigliardi et al., 2021) in oder to provide a deeper understanding of the OI prcess. Moreover, our reading of the available literature suggests another limitation of the existing studies, that is they mainly focus on single, specific and diverse HRM practices, whithout drawing on a specific theoretical framework, and thus fail to provide a comprehensive picture of the HRM-OI link (Naqshbandi et al., 2019; Popa, Soto-Acosta, & Martinez-Conesa, 2017; Singh et al., 2019).

In an attempt to contribute to address both the above issues, this study drew upon the AMO framework to quantitatively explore the relationships between HRM practices and open innovation in a large-scale representative sample of more than 20,000 establishments at European level which is representative in term of establishments distribution across sectors, size and countries. Our results showed that motivation- and opportunity enhancing practices are key to promote organizations engagement in open innovation activites such as design and development of new products and services in collaboration with external companies or outsourcing them. In particular, the greatest effect derives from the opportunity bundle, since it represent the dimensions that cover collaborative practices, including variables targeting teamwork, autonomy and information-sharing. Therefore, opportunity practices are those that mostly favour the process of collaboration. This is in line with the literature, because tensions and obstacles both at organizational and at individual level may arise (Hong et al., 2019; Nedon, 2015) since the the successful implementation of a OI depends also on the attitude and inclinations of those who are envolved in the collaborative process. Hence, our empirical results suggest that those organizations that want undergo to an OI process (specifically external R&D collaborations and outsourcing) should use not only motivation practices, but also and most importantly opportunity-enhancing practices, because those are more likely to reduce these obstacles by enhancing the probability to engage OI activities with external partners. Our findings extend the current understanding about the role that HRM practices and OI, since we demostrates the positive and significant direct effect of motivation and opportunity-enhancing practices to external collaborative activities. Specifically, since inbound knowledge flows involve the exploration of external knowledge and its integration into the existing knolwedge base (Chesbrough, 2006; Vrande et al., 2009), which is a critical driver of firms' innovative performance (Borgers et al., 2018), motivational practices may be a key factor, since one of the main OI barriers relates to the motivational aspects of being engaged in OI activities and knowledge exchange (Nedon, 2015). Practices such as group and individual rewards are key in fostering the willigness to be engaged in OI activities (Malik et al., 2020; Nedon, 2015) because they motivate collective behavior toward cooperation and knowledge exchange (Hong et al., 2019), while increasing the inclination in the building of strong ties with external partners (Ferraris et al., 2019), as well as fostering exploration activties, where employees are incetivized to seek and select the right knowledge for the organization (Ferraris et al., 2019; Podmetina et al., 2013). Our study provides empirical evidence for this hypothesis, showing that European establishments that make extensive use of motivation-enhancing practices such as job security, monetary rewards- including individual-, team- and company performance-related schemes-, and appraisals that value employees' collaborative attitudes towards their colleagues and ideas-sharing behavior are more likely to engage inbound open innovation practices.

Moreover, our findings show that the beneficial effect is even stronger when companies focus on opportunity-enhancing practices such as job autonomy, autonomous teams, knowledge-sharing. Opportunity-enhancing practices are determinant for the success of OI activities, since they focus on those practices related to the cooperative and knowledge-sharing behavior which are the essence of OI. For instance, teamwork is essential because it enhances the collaborative attitude of employees toward external partners (Ferraris et al., 2019) by reducing the NIH syndrome and fostering the knowledge exchange (Hansen et al., 2019; Hong et al., 2019; Malik et al., 2019), while specific job design structures which involve antonomy and distrectionality speed-up the decision process and enable workers to better integrate and utilize external knowledge (Burcharth et al., 2017). Lastly, good communication channels and information sharing practices are key for supporting a smooth knowledge flow within the organization and between the company and external partners. Knowledge-sharing practices enhance the knowledge exchange (Singh et al., 2019), which lead to a higher absortive capacity of single employees and of the organization as a whole. Even here, our analysis support the positive and significant relationship between opportunity-enhancing practices and OI, empirically confirming what has been mainly developed theoretically so far.

In contrast with our expectations, we found no support for a significant and positive effect of ability-enhancing practices on open innovation. This counterintuitive finding is not new to the literature on innovation and knowledge management (see for instance, (Chen & Huang, 2009; Prieto Pastor et al., 2010) and a possible explanation may be that ability-enhancing practices are a necessary but not a sufficient condition to foster the effective engagement of employees in OI processes. Although workers can have the appropriate competences and abilities to recognize, assimilate and exploit valuable external knowledge, they must be also motivated or have the opportunity to share and create knowledge. Prieto et al. (2010) affirm that the use of knowledge within the organization is discretionary, hence managers should stimulate the use of such knowledge by creating the appropriate conditions in the organization. Similarly, Chen & Huang (2009) show that training practices are highly effective in the knowledge application, whereas they are not significant in the knowledge sharing. Based on these and other studies (Kim, Pathak, & Werner, 2015, Shipton et al., 2006), we therefore argue that in order to enleash its full potential of boosting open innovation, ability-enhancing practices need to be deployed in combination with motivation and opporunity-enhancing ones.

A second innovative and important contribution of the present study is the analysis of open innovation as a mediator of the complex relationship between HRM practices and organizations' innovativeness. An extensive body of research underlines the key role of HRM practices in boosting firms' innovative performance (Colakoglu et al., 2019; Gooderhama, Parryb, & Ringdalc, 2008; Seeck & Diehl, 2017; Stavrou, Brewster, & Charalambous, 2010), but our understanding of the linking mechanisms through which such a beneficial effect occur is still partial. Some studies, which investigates the mediating role of exploration activities (i.e. the search for novel external knowledge, Barba-Aragón & Jiménez-Jiménez, 2020; Chen & Huang, 2009; Malik et al., 2019), suggest that open innovation may be a key factor explaining the HRM practices-innovation linkage. However, the empirical evidence is still scarce, limited to single specific countries or mixed (see for instance the study by Singh et al., 2019 which found no support for this hypothesis). The present study contributes to this debate showing that the positive relationship between HRM practices and innovative outcomes of firms at European level can be partially explained by the positive impact of motivation and opportunity-enhancing practices on open innovation organizational practices: European companies that extenstively adopt such practices are more likely to design and develop new products or services in collaboration with external partners or to contract out their R&D activities, thus boosting their ability to innovate their products or processes by accessing to and capitalizing on new knowledge, skills and competences from external sources (Nedon, 2015). In particular, while for the motivation bundle the mediation effect is present but is less pronunced, for the opportunity enhancing practices such mediation effect is much more evident. Therefore, this additionally remarks the importance of the opportunity bundle in influencing innovation by means of OI .

These results extend the current understanding about the conditions under which the AMO model can influence innovation, by giving empirical evidence of suggestions made by previous scholars (Seeck & Diehl 2017, 930) "given the popularity of the AMO, we conclude by reflecting the 'black box' stage bwteen HRM and innovation using the AMO framework as lens". In particular, we show that on the one hand, all three dimensions of the AMO model are effective in fostering innovation within the firm, on the other hand, we disantangle its influence on open innovation practices, by showing that for these three dimensions, motivation and opportunities practices are those that can effectively foster a collaborative approach. The current research opens new frontiers of explorations which involve the further investigation of the "human side" of open innovation, especially at empirical level. Since the roles that HRM practices have on OI is just at the beginning and further research is needed (Borgers, Foss, & Jacob, 2018; Hong, Zhao, & Snell, 2019), we show that not all practices seem to have an effect on OI, but those aiming at motivating and enabling discretionary efforts and behaviour are those that moslty fit with the OI process. Finally, although not hypotized, our findings strengthen consolidated relationship. On the one hand, the analysis showed a strong direct effect of all dimensions of the AMO model (particularly the opportunity bundle) on innovation in line with recent studies (Haar et al., 2021), on the other hand, OI demonstrates to be an excellent driver in stimulating the innovative performance of firms at European level, reinforcing the current literature.

2.5.1 Theoretical contributions

The present study offers three main contributions to the research. First, we illuminate ability-enhancing, motivation-enhancing and opportunity-enhancing HRM practices as key determinants of European companies engagement in open innovation. In so doing, the present study replies to a recent call for greater empirical attention to the organizational antecedents of OI as key to advance our understanding of this complex process (Bigliardi et al., 2021; Borgers et al., 2018; Zhu et al., 2019). Specifically, we contribute to the debate in the innovation literature on the drivers of open innovation, by establishing a link with the HRM literature on bundles of practices. Our findings are consistent with papers theorizing the relevance of HRM practices as enabling factors for firms to open their barriers toward external actors (Hong et al., 2019), and deepen this understanding by drawing attention on the key role played by a system of practices that work in concert rather than by practices functioning in isolation.

The second contribution concerns the use of the AMO framework as analytical lens to empirically investigate the HRM-OI link. Strategic human resource management research has long argued for a focus on bundles of practices when examining the impact of HRM on organizational performance. In this perspective, several papers have already provided insights into the role of the AMO HRM practices in enhancing organizations' innovative performance (Haar et al., 2021; Seeck and Diehl 2017), but research has mainly focused on closed innovation. Our findings, thus, contribute to this debate, by showing that AMO – enhancing practices are key to innovation, also and precisely because they enhance an organization's ability to leverage in this process novel external ideas and knowledge.

The third contribution lies in elaborating open innovation as a mechanism which at least in part explains how HRM practices positively affect innovation. Our findings that open innovation partially mediates the relationship between AMO HRM practices and innovation are consistent with the insights already provided by a handful of studies that have examined the issue empirically (Engelsberger et al., 2021). Our findings extend this nascent body of research by paying attention not to individual but a system of HRM practices, thereby also contributing to redress an unbalance in HRM scholarship that has so far left largely unexplored the role of open innovation as a driving belt mechanism explaining the HRM-innovation link, despite its increasing importance as a booster of today's organizations' ability to innovate.

2.5.2 Managerial implications

The present work may have some interesting implications for managers. Firstly, our findings suggest that companies can improve their innovative performance by investing in those specific HRM practices that promote open innovation. More specifically, companies that seem to be more likely to succeed in managing the tensions or obstacles between the different knowledge management processes involved in collaborative innovation, such as the NIH-syndrome or the unwillingness to share crucial knowledge (Hong et al., 2019; Nedon, 2015) are those that fist invest in practices aimed at motivating employees and giving them the opportunity to collaborate, express their talents, develop innovative ideas and share their knowledge within the inner boundaries, and then start to collaborate, since such practices help to lay the ground for collaboration with external partners. Secondly, at European level, the AMO-enhancing practices confirm to be a good system for fostering firm's internal innovation capacity, hence managers who wants to pursue an innovation strategy should rely on and implement such practices even though they do not decide to collaborate with external actors. Finally, although not explicitly hypothesized, our study suggests that in order to reap the benefit of open innovation, companies should maintain a continuing high level of employees' influence on decisions making power, therefore employees can be an additional and important driver in further supporting a smooth OI approach.

2.5.3 Limitations and future research suggestions

The contributions of this study should be viewed in light of some limitations that open avenue for future research. Firstly, it uses a European-level representative survey, which offers the benefit of greater generalizability, but does not provide extensive questions for measuring specific concepts. Therefore, we had limitations in the constructions of the variables related to the AMO model and OI. More specifically, when measuring OI scholars use comprehensive constructs, often referred to both dimensions of OI (inbound and outbound) at organizational level, see for instance (Naqshbandi et al., 2019; Popa et al., 2017; Singh et al., 2019). In our study, instead, we had a dummy variable which did not capture much information and only refer to the engagement in collaborative or outsourced R&D, with the drawback of not having outstanding fit models. Therefore, we encourage future research by deeply investigating the relationship between the HRM and open innovation with the adoption of more comprehensive measures of the latter concept.

Moreover, when analysing the connection between HRM and OI, scholars consider intermediate factors such as organizational climate (Popa et al., 2017) or employee behavior (Engelsberger et al., 2021; Nedon, 2015). In particular, regarding employee behavior is worth mentioning the article of Prieto-Pastor & Martin-Perez (2015) where they analyse the influence of organizational level HRM practices on the organizational capability of the firm to conduct exploration and exploitation activities, by means of explorative and exploitative individual behavior. Due to the limitation in the dataset, we were not able to investigate these dimensions; however, developing empirical articles on this triple relationship: organization-level HRM practices→individual behavior→organizational outcome in the OI context would be important for further understating the "human side" of open innovation. Hence, we recommend investigating this kind of relationship levels. Finally, although we used a stratified and weighted dataset, which enhances the generalizability of the findings, significant differences in the relation patterns of the models may occur when considering single countries. In Europe there are great differences in the innovation performance across EU member states, hence the mediation effect of OI might differ according to the countries which are considered since institutional framework and context shape organizations' behavior and business model (García-Cabrera et al., 2018). Therefore, the country-effect may have a plausible moderating role (Wagner, 2015). In addition, the literature highlights that environmental factors, market competitiveness and organizational context moderate OI activities (Jansen, Van Den Bosch, & Volberda, 2006; Lazzarotti, Manzini, & Pellegrini, 2015; Popa et al., 2017). Hence, a moderated mediation relationship between HRM and innovation would be even more plausible. This issue definitely deserves further investigation.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data that support the findings of this study are available at UK Data Service: http://doi.org/10.5255/UKDA-SN-8691-1

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Annex 2

Annex 2.1 Model's variable and measures

Independent variables		
Description	*Item scale*	*Variable*
Ability		
How many employees have participated in training sessions at other locations? (% of employees)	1-7	Formal and informal Training
How many employees have received on-the-job training? (% of employees)	1-7	
How often are the following practices used to motivate employees: Providing opportunities for training and development	1-4	Frequency of training and development opportunities
How important are the following reasons for providing training to employees?		Training purpose
Allowing employees to acquire skills they need to do job rotation	1-4	
Increasing the capacity of employees to articulate ideas	1-4	
How many employees are in jobs that require continuous training? (% of employees)	1-7	Skill-enhancing job diffusion
Motivation		
How many employees at this establishment received the following types of variable pay? (% of employees)		Variable pay schemes intensity
Payment by results	1-7	
Individual performance	1-7	
Team performance	1-7	
Establishment performance	1-7	
How many employees in this establishment have an open-ended contract? (% of employees)	1-7	Job security
How often are the following practices used to motivate employees: offering monetary rewards	1-4	Monetary lever
To be evaluated positively, how important is it that employees show the following behavior?		Performance appraisal
Helping colleagues without being asked	1-4	
Making suggestions for improving the way things are done in the company	1-4	
Opportunity		
Does this establishment make use of suggestion schemes?	Yes/No	Suggestion program
Which of the following practices are used to involve employees in how work is organized?		Knowledge-sharing
Meetings between employees and manager	1-3	
Meetings open to all employees	1-3	
Dissemination of information	1-3	
Discussions with employees on-line	1-3	

(Continued)

For how many employees in this establishment does their job include finding solutions to unfamiliar problems? (% of employees)	1-7	Work time discretion and problem solving
For how many employees does their job include independently organizing their own time? (% of employees)	1-7	
Which of these two statements best describes the general approach to management? Managers control employees or employees can autonomously carry out their tasks	0-1	Work method discretion
Do employees work in a single team or in more than one team?	1-2	Autonomous teamwork
Who usually decides how the tasks are distributed within the team? Team members among themselves or tasks are distributed by a superior?	1-2	
	Mediator	
The establishment is engaged in the design or development of new product or services mainly in collaboration with other companies or product/service design and development are mainly contracted out	0-1	Open Innovation
	Lagged variable	
In your opinion, since the beginning of 2016 to what extent have employees directly influenced management decisions in the following areas?		
The organization and efficiency of work processes	1-4	Employees' empowerment in the last years
Dismissals	1-4	
Training and skill development	1-4	
Working time arrangements	1-4	
Payment schemes	1-4	
	Dependent variable	
Since the beginning of 2016, has his establishment introduced any new products or services? *Since the beginning of 2016, has this establishment introduced any new processes?*	0-1	Innovation capacity

Chapter 3

HRM and the moderating role of digital technologies and employee empowerment on different kinds of radical innovations. Evidence from Europe.

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Abstract

The literature has widely recognized the positive effect of human resource management (HRM) practices on firm's innovation. However, the relationship between HRM and radical innovation is still underexplored. Radical innovations require not only human resources, but also technology, hence scholars have recently begun to investigate the role of workplace digital technologies in sprinboarding innovation and have called for further investigation of their role as contextual, moderating factor influencing the effect of HRM practices in organizations. Therefore, using data from the European Company Survey 2019, a large-scale representative dataset at European level, this study investigates the direct relationship of high-performance work system (HPWS) on radical product and process innovation and the moderating role of digital technologies. We also consider the moderating role of employee empowerment in further enhancing this association by hypothesizing a three-way interaction with HPWS and digital technologies. Results show that HPWS have a positive a significant effect on both radical innovations and such effect is greater for process innovation. Moreover, we uncover that the interaction of HPWS with digital technologies depends on the level of employee empowerment. In a condition of low employee empowerment, digital technologies positively interact with HPWS so that high level of technologies enhances the positive effect of HPWS on innovation. In a condition of high employee empowerment, this relationship turns to be opposite, so that at high level of digital technology adoption the effect of HPWS in bringing innovation is reduced. These findings hold for both kinds of innovation, although for process innovation is more pronounced. Literature and managerial implications of our findings are discussed.

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3.1 Introduction

Innovation is nowadays an increasingly important source of competitive advantage for companies operating in highly turbulent business environments (OECD, 2018). Innovation is a complex process that typically takes place within the boundaries of companies (Shipton, Sparrow, Budhwar, & Brown, 2017) and relies on different enabling factors such as human capital and technology (Al-Ajlouni, 2021). In this sense, Human Resource Management (HRM) practices are key in fostering the innovation process within the firm, since they are aimed to maximize employee performance, commitment, and innovative potential (Guest, 1997). In this research strand, innovation can be considered as an outcome of HRM practices (Seeck & Diehl, 2017) and the literature has widely investigated the positive and direct effect that HRM practices have on firm innovativeness (Cai-Hui & Sanders, 2017; Ceylan, 2013; Jiménez-Jiménez & Sanz-Valle, 2005; Lin & Sanders, 2017; Nieves, Quintana, & Osorio, 2016; Shipton, West, Dawson, Birdi, & Patterson, 2006; Stavrou, Brewster, & Charalambous, 2010). Nevertheless, in analysing the HRM – innovation relationship gaps still remain. Firstly, some authors affirm that this relationship has been investigated without drawing upon a theoretical framework (Seeck & Diehl, 2017); secondly, the effect that HRM have on radical innovation is still underexplored (Barba-Aragón & Jiménez-Jiménez, 2020). With radical is intended an innovation that create a sort of discontinuous change to what was done previously (OECD, 2018), hence such innovation entails higher uncertainty and risks (Dewar & Dutton, 1986), as well as higher effort in terms of human resources skills and knowledge (Barba-Aragón & Jiménez-Jiménez, 2020). Moreover, while some contributions on the relationship between HRM radical product innovation are already present (Barba-Aragón & Jiménez-Jiménez, 2020), such contributions regarding radical process innovation are missing. Therefore, in order to answer to this gap, the first aim of the present work is to analyze the direct relationship between High Performance Work Systems (HPWS) (Appelbaum, Bailey, Berg, & Kalleberg, 2000) and both product and process radical innovations. HPWS is conceived as a coherent and reinforcing system of practices which are designed to maximize employee performance by focusing on the enhancement of ability, motivation and opportunity of workers in order to achieve the origination’s goals (Ngo, Jiang, & Loi, 2014). Therefore, HPWS help to create a high performing workforce (Haar, O'Kane, & Daellenbach, 2021) which foster workers’ creativity and enable companies to reach a higher level of product and process innovation (Do & Shipton, 2019; Shin, Jeong, & Bae, 2018).

Radical innovation requires not only human resources and knowledge but also technology (Garcia & Calantone, 2002). In this sense, a lively debate on the role of digital technologies in the workplace has been developed in recent years, and different journals on HRM have claimed further investigation of this issue, see for instance the 2021 International Journal of Human Resource Management special issue on "Digitization and the Transformation of Human Resource Management" or the Human Resource Management special issue on "The Ecosystem of Work and Organization: Theoretical Frameworks and Future Directions" (Minbaeva, 2021). In answering to these calls, scholars have been posing attention not only on how digital technologies are springboard for product and process innovation (Bresciani, Huarng, Malhotra, & Ferraris, 2021), but also on how digital technologies influence human resources (Connelly, Fieseler, Černe, Giessner, & Wong, 2021; Kim, Wang, & Boon, 2021) as well as the workplace (Minbaeva, 2021; Petriglieri, Ashford, & Wrzesniewski, 2019; Weatherbee, 2010).

Despite the important insights provided by this stream of literature, scholars call for further investigation (Jonsson, Mathiassen, & Holmström, 2018), especially on the way in which new digital technologies interact with other elements of the organizational system, including strategic HRM systems (Kim et al., 2021). Therefore, a second objective of this study is to investigate the moderating role those digital technologies in the workplace have in the relationship between HPWS and radical innovation. Along this vein there is not clear theoretical consensus whether digital technologies may amplify or inhibit the effect of practices (Kim et al., 2021; Meijerink, Boons, Keegan, & Marler, 2021). Some studies underline that digital technologies can be seen as complementary aspect of the workplace which leverages the impact of HRM activities (Bondarouk & Brewster, 2016; Ciarli, Kenney, Massini, & Piscitello, 2021; Kim et al., 2021; Minbaeva, 2021), while other entail a dark side of technology, which constraints human actions (Bondarouk & Brewster, 2016; Holland & Bardoel, 2016; Minbaeva, 2021; Park, 2018). Moreover, the few studies that empirically investigate the moderating role of digital technologies on HRM practices (Arvanitis, 2005; Kintana, Alonso, & Olaverri, 2006) fails to find this kind of interaction. Therefore, we hypothesize that this association depends on the level of employee empowerment in the workplace. This is suggested by some articles which affirm that employee empowerment mitigates the negative effects that technologies based on control have on employee behavior (Martin, Wllen, & Grimmer, 2016). At the same time, some theoretical studies underline how employee involvement in the decision-making process leverages the benefits derived by technology adoption (Dedrick, Gurbaxani, & Kraemer, 2003). Therefore, managers can take advantage by the complementary effect of technology by involving workers in organizational' decisions (Vrontis, et al., 2021). Hence, the third aim of this study is to contribute to this mixed and fragmented evidence, by testing a three-way interaction effect of digital technologies adoption, employee empowerment and HPWS on radical innovation.

In this study, we use data drawn from the European Company Survey (ECS) 2019 (European Foundation for the improvement of Living and Working Conditions, 2020), a recent large-scale survey, which comprises more than 20.000 establishments at European level.

The paper is structured as follows: the following section presents the literature review and hypothesis development. Then, we describe the sample and the methodology, while empirical results are presented in section 3.4. Section 3.5 discusses the results and presents managerial and theoretical implications as well as limitations of the study.

3.2 Theoretical background and hypothesis

3.2.1 Radical vs incremental innovation

According to the Oslo Manual (2018, 20) an innovation "is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)". The underling meaning is the marketable potential of an invention, since to become an innovation, the invention must go from the lab to the production and commercialization (Garcia & Calantone, 2002). In the literature two major distinctions of an innovation occur: radical vs incremental innovation. With radical is intended an innovation that create a sort of discontinuous change to what was done previously (Norman & Verganti, 2014; OECD, 2018) in terms of input (technology/knowledge/skills), output (performance/cost reduction), levels (macro level: world/industry/market, micro level: production unit/customer) (Garcia & Calantone, 2002). There are many distinctions of radical innovation in the literature (see Garcia & Calantone (2002) for a comprehensive review), however, the most widely used are whether an innovation is new to the firm, new to the market in which it operates, or new to the world (OECD, 2018).

On the other hand, incremental innovation is intended as improvement, changes or refinement from existing products in terms of features or technology (Garcia & Calantone, 2002), which may improve their performance or efficiency. Therefore, incremental innovation is conceptualized as doing something which is already done, but in a better way (Norman & Verganti, 2014). Normally, incremental innovations are easier to be developed and could give traction to mature market (Norman & Verganti, 2014), while radical innovation creates and catalyze new demands (Garcia & Calantone, 2002). Moreover, incremental innovations can rely on existing technologies borrowed from other industries, while radical ones rely more on new technologies (Garcia & Calantone, 2002). According to Norman & Verganti (2014) radical and incremental innovations are intertwined, because on the one hand, incremental innovation cannot exist without radical innovation, on the other hand, without incremental innovation, radical innovation would not achieve its maximum potential. What is true is that radical innovation require a higher concentration of efforts in terms of skills, knowledge and technology, with respect to incremental innovation, since organizations need more skilled workers and a higher concentration of new and diversified knowledge (Dewar & Dutton, 1986; Ettile, Bridges, & o'Keefe, 1984) due to the entailed risks, uncertainty and complexity (Cabrales at al., 2008). Moreover, radical innovation seems more driven by technological purposes, while incremental innovation is more driven by market and customer needs (Norman & Verganti, 2014).

Concerning the type of innovations the most studied in the literature are product/ services (Norman & Verganti, 2014), process (Dewar & Dutton, 1986; Ettile et al., 1984; Forés & Camisón, 2016), marketing and organizational (Forés & Camisón, 2016). In this paper we analyze radical innovation specifically concerning product and process for two reasons: in general terms, the relationship between HRM practices and radical innovation needs further attention (Seeck & Diehl, 2017); moreover while a few studies address the impact of HRM practices on radical product innovation (Barba-Aragón & Jiménez-Jiménez, 2020), radical process innovation has been largely overlooked so far. Therefore, one of the aims of this paper is providing a deeper understanding of the different impact of HRM practices on different kind of radical innovations.

3.2.2 HPWS and radical innovation

Innovation can be considered as an HRM output (Seeck & Diehl, 2017) and the positive relationship between HRM and innovation is widely consolidated in the literature (Jiménez-Jiménez & Sanz-Valle, 2008; Lin & Sanders, 2017; Meuer, 2017). For instance, Al-Ajlouni (2021) show that training, rewards, information sharing and performance appraisal influence employee behavior and creativity, that lead to a major innovation at organizational level, while Do & Shipton (2019) demonstrates that abilities, motivation and opportunity enhancing practices foster product and process innovation. However, although manager actions and human resources are key for developing radical innovations (Dewar & Dutton, 1986; O’Connor & McDermott, 2004), the direct relationship between HRM practices and radical innovation is currently understudied in the literature (Barba-Aragón & Jiménez-Jiménez, 2020; Seeck & Diehl, 2017). In this paper we consider the relationship between HPWS on radical product and process innovation for two main reasons.

Firstly, the idea of external fit argues that companies should focus on those HRM systems which maximize employee contribution to organization’s goals by leveraging their skills, motivation and opportunities (Colakoglu, Erhardt, Pougnet-Rozan, & Martin-Rios, 2019; Wei, Liu, & Herndon, 2011). In this sense, HPWS focuses on three different dimensions of practices ability, motivation, and opportunity as key to optimize employees’ knowledge, skills and abilities; motivate and offer them the opportunity to put forth discretionary behavior, share ideas, develop their job skills, and utilize their knowledge for the good of their organization, thereby influencing individuals' behavior and attitudes and ensuring the alignment between individual-level outcomes and the organizations' strategic goals; hence its adoption is conducive to the achievement of such external fit (Ngo et al., 2014). This is particularly important when developing radical innovation, because due to high uncertainty and risks, firms need workers with high skills and knowledge (Dewar & Dutton, 1986) and HPWS help to create a high performing workforce (Haar et al., 2021), while enhancing the knowledge flow among employees by making workers more effective in their interactions and more inclined in taking risks and experimentation (Malik, Sinha, Pereira, & Rowley, 2019). At the same time, there is some evidence showing that when developing radical innovations firms rely on a broad set of practices which can be related to the HPWS (Oltra, Donada, & Alegre, 2022).

Secondly, there is some evidence of the effect of HPWS related practices on radical innovations. Haar et al., (2021) for instance, demonstrate the positive relationship of HPWS and innovation measured with different degrees of radicalness, while Sanz-Valle & Jiménez-Jiménez (2018) show that the adoption HPWS leads to radical product innovation, and that such effect is mediated by IWB. Forés & Camisón (2016) show that radical innovation is influenced by internal knowledge creation, which is fostered and driven by ability, motivation and also opportunity-enhancing practices focused on idea/knowledge generation (i.e. teamwork, suggestion schemes/problem solving activities) knowledge processing and support (i.e. training activities) and knowledge dissemination (i.e. information-sharing practices). Since developing radical innovation is very risky, as well as time and effort consuming for employees involved in the process, workers need to be strongly motivated by managers with specific reward and compensation practices (O'Connor & McDermott, 2004). Along this vein, Andreeva et al. (2017), in analyzing the influence of motivation-enhancing practices in Finnish companies, show that reward in isolation has a positive effect on radical innovation, while appraisal do not. Moreover, the interaction effect of the two is significant and negative, therefore the use of appraisal reduces the effect of reward in fostering radical innovation. Cabrales et al. (2008) although they hypothesized a positive relationship of both long and short-term compensation practices on radical innovation, they find a counterintuitive negative result. Rampa & Agogué (2021) reveal that skill-related practices such as training for innovation and creativity, enhance skills and capabilities to cause radical innovation at individual, collective and organizational level, since innovation is an outcome of individual and organizational learning, which is deeply affected by training activities. At the same time, Oltra et al. (2022) affirm that such HRM practices as job design, training, autonomy, performance appraisal, recruitment and flexibility facilitates radical innovation. Therefore, based on above arguments, we posit the following hypothesis:

Hypothesis 1a: HPWS are positively related to radical product innovation.

Hypothesis 1b: HPWS are positively related to radical process innovation.

3.2.3 The moderating role of digital technologies

In the previous chapter we have seen that radical innovation entails a greater risks and uncertainty. At the same time, there are studies which underline the importance of digital technologies presence while developing radical innovation. This because radical innovation is often driven by the adoption of new technologies (Norman & Verganti, 2014) and those companies that pursue a radical innovation strategy often opt for an aggressive technology policy (Ettile et al., 1984). In this sense the introduction of new technologies in the workplace drives an organizational reconfiguration of the organization (Minbaeva, 2021; Orlikowski and Scott 2008; Petriglieri et al., 2019; Weatherbee, 2010), hence technology has gaining traction in the literature of HRM (Holland & Bardoel, 2016; Minbaeva, 2021). In this strand the literature considers technology as a contextual moderating factor which influences and interacts with certain aspects of the organization toward a specific outcome at organizational level (Kim et al., 2021; Kintana et al., 2006; Orlikowski & Scott 2008; Parker & Holman, 2017). In particular some studies underline how digital technologies shape the conditions that render work practices effective (Bondarouk & Brewster, 2016; Colbert, Yee, & George, 2016; Holland & Bardoel, 2016; Kim et al., 2021; Kintana et al., 2006; Meijerink et al., 2021). Moreover, recent contributions address the need to further investigate how technology interacts with other elements of the organization, in order to investigate further threats and opportunities of technology (Kim et al., 2021). Therefore, the aim in this paper is to analyze how digital technologies conceived as a workplace contextual factor may influence how HRM practices bring radical innovation, proxied by product and process radical innovations. Along this vein, there is no clear consensus among researchers in defining, explaining and investigating this phenomenon within the organizational context (Charlier, Guay, & Zimmerman, 2016; Cirillo, Evangelista, Guarascio, & Sostero, 2021; Orlikowski & Scott, 2008), and in clearly conceptualizing digital technologies (Cirillo et al., 2021). In the literature digital technologies are often defined as the acquisition and adoption of workplace technologies, such as computers, data analytics and robots (Cirillo et al., 2021; Santoro & Usai, 2018).

The findings of this stream of research are just at the beginning and are sometimes inconsistent. On the one hand, workplace digital technologies have been seen as an opportunity (Kim et al.,2021) since they have several advantages such as the increase of efficiency, lower costs and smooth processes and higher productivity (Nazareno & Schiff, 2021) as well as product and process innovation (Arvanitis, 2005). The adoption of technologies in the workplace is often associated with the need of skills in the workplace (Ciarli et al., 2021; Kim et al., 2021; Vrontis, et al., 2021). Since many digital technologies are “data giver” (Meijerink et al., 2021), to better understand and utilize such new information a high skilled and educated workforce is needed. Therefore, organization need to make greater investments in training and recruitment practices in order to create a high skilled workforce (Ramirez & Fornerino, 2007). This coupled process of skills and technology stimulates the overall absorptive capacity of the organization fostering radical innovation capability (Ciarli et al., 2021; Forés & Camisón, 2016). For instance, Kintana et al. (2006) affirm that as long as the technological intensity increases in the workplace, the higher the need for the firm to implement HRM practices, because the workplace require higher need of knowledge, especially when pursuing radical innovation. Therefore, following the idea that digital technologies are complementary organizational factor which enhances the human actions (Ciarli et al., 2021) by leveraging the opportunities to competences, exercise discretion, use skills and capabilities (Kim et al., 2021; Vrontis, et al., 2021), they can reinforce the positive effect that HPWS have on radical innovation

On the other hand, digital technologies also entail a dark side (Holland & Bardoel, 2016), since the provide alternatives to human actions (Vrontis, et al. 2021), like the increasing substitution of humans by machines even in the performance of non-routine cognitive tasks (Ciarli et al., 2021) and the focus of the organization more on technologies rather than in human resources in pursuing goals (Pereira, Hadjielias, Christofi, & Vrontis, 2021), as well as, potentially detrimental effects on workers, especially on their learning capabilities and creativity (Usai, et al., 2021). Along his vein, Park (2018) show that the introduction of technologies may lead to increasing automation of work processes, thereby curtailing the benefit of job autonomy, because of the reduced ability of workers involved in automated work processes to actually exercise discretion even if greater job autonomy is provided to them. Therefore, technology may reduce the positive effect that HPWS have on radical innovation.

Regarding the empirical evidence of the moderating role of digital technologies in the relationship between HRM practices and firm performance, empirical studies are scarce, and results differ among each other (Holland & Bardoel, 2016). For instance, in their study on 965 Spanish firm, Kintana et al (2006) analyze this issue and unexpectedly they do not find any moderating role of technologies, therefore they affirm that technologies are enough sufficient to improve firm performance without the need to invest in HRM practices to exploit their potential. They find a slightly moderating effect only on those firm belonging to high-tech sectors. Similar results were provided by Arvanitis (2005), who in analyzing the interaction between the use of digital technologies and HRM practices such as teamwork, job rotation, problem solving on labour productivity, found no interaction effect. The results were consistent after several robustness checks. More recent articles like Santoro & Usai (2018) instead, show that information and communication technologies (ICT), namely knowledge storage and collaborative technologies have a positive moderating role in the relationship between HRM practices (such as training, performance appraisal, rewards and selection) and the development of innovative ideas. However, they recommend further exploration based on quantitative analysis on this topic. In this paper we consider the adoption of robots, data analytics and computers (Cirillo et al., 2021); there is no direct empirical evidence of their moderating effect. However, studies drown from the literature suggest that this hypothesis migh be plausible, as detailed in the following sections.

3.2.3.1 Data analytics

Data analytics is seen as a disruptive technology (Minbaeva, 2021) and their use have been growing in HR filed, in particular those regarding the monitoring of employee performance (Cheng & Hackett, 2021; Sharma & Sharma, 2017). In this sense data analytics help to track the contribution of workers to the organization in a more precise way with real time feedback, which boosts the effectiveness of performance management practices and related compensation practices in achieving organizational goals (Sharma & Sharma, 2017; Zehir, Karaboğa, & Başar, 2020). Fair and accurate performance evaluations increase the workers satisfaction and acceptance of performance system which increase the willingness and motivation of employee to improve their performance, their commitment to the organization (Sharma & Sharma, 2017) and the generation of new ideas, especially when performance appraisal are tailored for innovative behavior (Nöhammer & Stichlberger, 2019). Through performance-based data analytics, companies can monitor employee performance and implement corrective actions with specific practices in order to foster employees' contribution. For example, it is plausible that when firms detect low performance of a particular category of employees, they would implement corrective actions like training practices in order to enhance skills and productivity or job rotation practices to find more suitable roles for low performing workers. At the same time, high performing employees might be further motivated by additional rewards/compensation practices in order to further enhance their performance. This is in line with evidence on the use of data analytics and workplace learning, since the data derived by performance analytics may support the allocation of skill-enhancing training activities and job design choices according to employee performance (Giacumo & Breman, 2016). At the same time, real time data on performance can be used as new knowledge (Meijerink et al., 2021), which go along with the use of information-sharing practices in order spread such new knowledge across organizational boundaries in order to improve the process of new innovations development. Therefore, in this sense data analytics may positively moderate the relationship between HRM practices and innovation activities.

Data analytics also entail a dark side (Chatterjee, Chaudhuri, Vrontis, & Siachou, 2021; Kellogg, Valentine, & Christin, 2020). For instance, there are studies (Abraham, et al., 2019) that affirm that when technology is used to monitor employee performance, employees may perceived to be subject to higher pressure and and to have lower autonomy. Therefore extensive adoption of data analytics may reduce the effectiveness of motivational practices aimed at enhancing a cetain behaviour (i.e.

generation of ideas or helping colleagues). Data analytics may constrain workers autonomy (Holland & Bardoel, 2016), thereby eroding the relationship between employee and managers, increasing workers stress and reducing their motivation (Holland, Cooper, & Hecker, 2015). Although these negative effects may be counterbalanced by HRM practices (Castanheira & Chambel, 2010), in such contingent conditions HRM practices may reduce their potential.

3.2.3.2 Robots

Robots are considered as authomated machines which are also capable to actively interact with workers (Arslan, Cary, Khan, Golgeci, & Ali, 2021; Montobbio, Staccioli, Virgillito, & Vivarelli, 2022) and the literature affirm that robots are capable to perform cognitive tasks that have been prerogative of humans so far (Tunç, 2020). Not only they replace humans in some working activities, but also offer the opportunity for employees (especially for those involved in more rountinary tasks) to be involved in more creative jobs (Smids, Nyholm, & Berkers, 2020). In such conditions, the organization may expand its invesment in learning and training activities in order to give the employees the necessary skills required for the new jobs (Vrontis, et al., 2021). Moreover, in a situation in which the adoption of robots increases the demand for highers skills, the organization might also make greater use of such staffing practices as the recruitment of high skilled labour force (Dixon, Hong, & Wud, 2021). The combination of a higher use of both training and recruitment practices laverages the knowledge base of the organization, which increases the likelihood of new idea generation and the overall innovation activity. Further, (Dixon et al., 2021) suggest that robot adoption is mainly motivated by the desire to improving product and service quality, therefore reinforcing the use of pay for performance based incentives in organizations.

On the other hand, however, there are scholars who have warned against negative side effects and potential risks associated with human-robot collaboration. Robots can be seen as a threat, since low-skilled employees have negative attitude toward them, because robots diminish job security (Chao & Kozlowski, 1986). Firstly, the adoption of robot is often associated with job replacement and there are a growing number of studies that make predictions on job displacement, especially for unskilled workers (Vrontis, et al., 2021). Therefore, human-robot collaboration can have negative effects on workers feelings and motivation (Arslan et al., 2021), especially for low-skilled ones, which reduce their commitment and productivity. Moreover, robots reduce workers self recognition, work motivation, authonomy, and job satisfaction, and increase insicurity and stress (Nazareno & Schiff, 2021), thereby challening the effect that HRM practices such as ability or motivation-enhancing practices may have on innovation. In addition, automated robots may threaten workers autonomy (Smids et al., 2020). For instance, Park (2018) explores the moderating role of automated technologies in the relationthip between authonomy and organizational citizenship behavior and argues that the more the processes are automated, the lower is the relationship between job authonomy and both organizational citizenship behaviour and organizational performance, because less authomated firms rely more on human resources to bring organizational performance, rather than those in which the use of technology and automation is high. Therefore, the author suggests that the effectiveness of certain HRM practices (in this case job authonomy) is attenuated in authomated processes since employees can not fully exploit their freedom and discretion.

3.2.3.3 Computers

Digital technologies also include computers. Extant research underlines mixed results concerning the potential implications of computers adoption (Menon, Salvatori, & Zwysen, 2020). For instance, there is a number of studies (Tortora, Chierici, Farina Briamonte, & Tiscini, 2021) which show how ICT platforms, such as social media, enhance the circulation of knowledge within the firm by expanding the knowledge through the entire organization. To the extent that communicating platform are empowered by the use of laptops or computer devices, such studies suggest that the effectiveness of information sharing practices such as the use of suggestion schemes for idea generation, and thus the overall capacity to create new knowledge and the overall innovation rate, might be greater in organizations with higher computers' adoption. In a similar vein, Menon et al. (2020) support the idea that in organizations where computers adoption is greater, employees have higher flexibility, because computers help to better allocate their time and tasks (Cascio & Montealegre, 2016) and allow employees to work from different locations. On the contrary, Strohmeier (2009), for instance, affirm that the use of computers enhances the amount of training performed (i.e. e-training) due to minor costs and higher accessibility. However, an increased amount of training is not always associated with an increase in the quality standards, since e-training has a different impact with respect to face to face training. Therefore, the effective impact of training activities on employees regarding their skill upgrades, might be reduced.

Therefore, based on above arguments, we hypothesize the following:

Hypothesis 2a: digital technologies moderate the direct effect that HPWS have on product radical innovations.

Hypothesis 2b: digital technologies moderate the direct effect that HPWS have on process radical innovations.

3.2.4 The moderating role of employee empowerment

We have seen that some studies outline that digital technologies can substitute or constraint human actions, while others underline that technology is a complementary activity which can provide opportunities for leveraging the work process and employee performance. Considering the mixed evidence on the moderating role of new digital technologies in the relationships between HPWS and radical innovation, in this work we argue that this may depend on the moderating stimulus of employee empowerment. In doing this, we hypothesize a three-way interaction between employee empowerment, digital technologies and HPWS on radical innovation. There are not prior contributions in the literature directly addressing this issue, hence it is not easy to disentangle. However, there are some insights that may render plausible this hypothesis.

Employee empowerment is defined as the delegation of decision power and responsibility at lower level of work employees (Baird & Wang, 2010). In our study, employee empowerment is intended as the capacity of employees to influence decisions on broader organizational issues beyond the level of jobs such as the at the levels of the work process and work organization. Employee empowerment has been largely adopted in those firms operating in high technological sectors (Arvanitis, 2005). At the same time, it has been recognized not only as one of the main practices for fostering innovation in the HRM context (Colakoglu et al., 2019; Della Torre, Gritti, & Salimi, 2021) also radical (Oltra et al., 2022), but also as powerful moderator of HPWS in fostering the firm's innovation process (Wei et al., 2011). However, evidence on its moderating effect on technology are lacking. The only empirical study which investigate this hypothesis is drawn by Martin et al. (2016). In their analysis of monitoring technologies and employee behavior they show that when technology is used as a tool of control of working activities, it leads to counterproductive work behavior since workers feel not trustworthy and with less freedom. This is confirmed by other scholars which affirm that controlling technology inhibits HRM practices and human actions (Maroufkhani, Tseng, Iranmaneshe, Wan Ismail, & Khalid, 2020; Park, 2018). However, the researchers demonstrate that empowering employees to have major control over work operations and work environment reduces the negative effect of such technologies, because worker have the feeling of having more control over the work environment, hence, are more likely to accept such kind of technology. Therefore, employee empowerment is conceived as a powerful boundary condition to lessen the possible negative effects of digital technologies.

On the basis of these findings, it is therefore plausible to hypothesized that when technology is seen as complementary organizational factor which render human activities more valuable (Nazareno & Schiff, 2021), the active involvement of employees in the decision making allow to grasp the major benefits brought by technology, hence boosting the effects of HR activities and practices. This is suggested by some theoretical studies which outline that technology adoption is associated with higher firm performance due to the enhancing effect of human contributions to organizational goals. However, those firms who combine digital technologies with the involvement of workers in the decision-making process outperform in performance (Dedrick et al., 2003). Therefore, technology can leverage the positive effect of human action when it does not substitute human resources, and managers can boost this effect by involving workers in organizational decisions (Vrontis, et al., 2021). For example, data analytics provide hard data on the work process which can be treated as new information (Meijerink et al.,2021). This new knowledge, combined with information sharing practices can increase the likelyhood of new innovation. This coupled interaction may be significantly enhanced if used in combination with delegation of power at level of employees since empowered workers are more entrepreneourial and inclined to taking risks and experimentation, hence they can better use such new knowledge. Similarly, for generating ideas workers require freedom and flexibility, hence the adoption of computers allows to increase such flexibility since they can from different locations (Cascio & Montealegre, 2016). This beneficial effect will be even higher if such workers are empowered in deciding their own working time and schedule, because employees will feel with higher degree of control over their operations, hence they will be more inclined in creativity and idea generation. Along this vein, digital technologies increase the investment of training due to major need of skills in the workplace (Ciarli et al., 2021). If workers are involved in deciding the kind of training that require (especially when developing radical innovation), this would have a boosting positive effect that such training investment have on innovation.

Therefore, based on above arguments, we posit the following hypotheses:

Hypothesis 3a: There is a three-way interaction between HPWS, digital technologies and employee empowerment on radical product innovation. Specifically, employee empowerment positively moderates the interaction of digital technologies and HPWS in the association with radical product innovation. That is, if technology amplifies the effect of HPWS on radical product innovation, such effect will be enhanced, while if technology reduces the effect of HPWS on radical product innovation, such effect will be softened.

Hypothesis 3b: There is a three-way interaction between HPWS, digital technologies and employee empowerment on radical process innovation. Specifically, employee empowerment positively moderates the interaction of digital technologies and HPWS in the association with radical process innovation. That is, if technology amplifies the effect of HPWS on radical process innovation, such effect will be enhanced, while if technology reduces the effect of HPWS on radical process innovation, such effect will be softened.

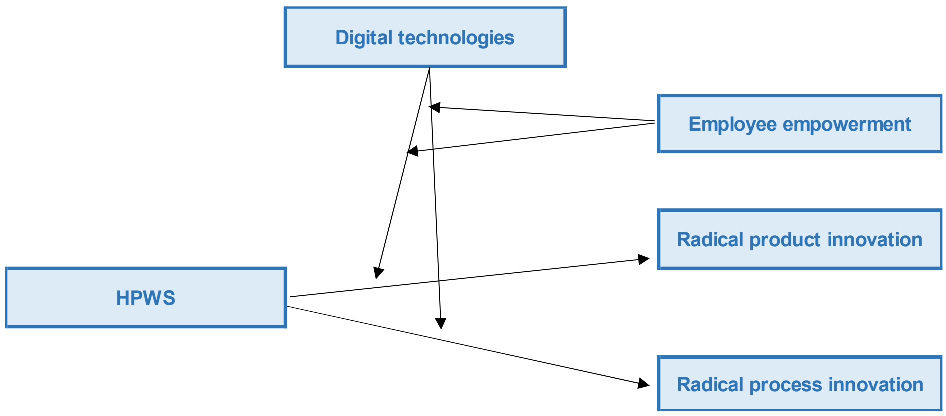

Figure 3.1: Conceptual model

3.3 Material and methods

3.3.1 Data

The conceptual model of the paper is presented in Figure 3.1. For the work we used the European Company Survey 2019 by Eurofound and Cedefop, which is a large-scale, cross-national survey which collects data on workplace practices regarding human resources, digital technologies, innovation, employee participation and social dialogue implemented in more than 20,000 establishments at European level. The unit of enquiry for the survey is the establishment: the local unit or site. The survey collects data from both managers and employee representatives at each establishment. In this work we used the dataset of manager respondents (Eurofound & Cedefop, 2020a) collected by Eurofound and Cedefop according to the following procedure: establishments were contacted via telephone to identify a management respondent, who were then asked to fill out the survey questionnaire online. This approach reduced the burden on respondents and improved the quality of responses (Eurofound & Cedefop, 2020b). Since the sample is highly heterogeneous, we applied a weighting to ensure the results of the analysis are representative in terms of establishments distribution across sectors, size and countries (Eurofound and Cedefop, 2020c). The advantage of using these king of data is the benefit of higher generalizability, however, the drawback is that the survey do not provide extensive questionnaire batteries for the measurement of specific concepts (Gallie, 2013).

3.3.2 Measurement and variables

HPWS

In the present study, HPWS are measured through the variables of the ECS questionnaire, which in this respect offers multiple items measured with different scales. More specifically, we adapted our practices following (Haar et al., 2021) by covering seven dimensions of practices, in particular training, recruitment, performance appraisal, rewards, intrinsic motivational practices, job design and information sharing by selecting 25 items. The practices included were measured through different variables and scales which measured the presence of certain practices (i.e. yes/no questions) or their intensity (i.e. % of use among employees), therefore, following other scholars (Chowhan, 2016), they were standardized into z-score to have equal weights in the creation of the system. Finally, the final construct of the was created by additively combining the scores of the standardized variables into single aggregated index in line with prior studies (Shin et al., 2018); Cronbach's alpha 0.793, far above the threshold level of 0.70.

Technology

Digital technologies were measured through an index (TECH) which captured the level of digital technologies adoption in line with other scholars (Cirillo et al., 2021). Specifically, it was computed by adding together yes/no questions regarding the use in the establishment of robots, data analytics to monitor employee performance, data analytics to improve the process of production or service delivery and the use of personal computer. The use of computers was measured with a 7-points scale item, which measured the proportion of employees that used computers to carry out their daily tasks. The variable was transformed into a dummy which assumed the value of 1 if its use was above 40% of total employees and then added to the index. The final index ranged from 0 (no technologies in the workplace) to 4 (all technologies were present).

Employee empowerment

Employee empowerment (EMPL_EMP) measured how much employees influenced managerial decision on five areas of the organization, following some of the dimensions of (Kuo, Ho, Lin, & Lai, 2010; Martin et al., 2016), which analyzed the influence of employee empowerment in high-technological environment. The variable was composed by five items ranging from 1 (not at all) to 4 (to great extent) which measured the influence of employees in the organization and efficiency of work processes, training and skill development, payment schemes, working time arrangements and dismissals. The items were summed together, and the final variable was computed with a scale ranging from 1 (no influence in any areas) to 20 (great influence in all areas) (Cronbach's alpha 0.759).

Radical innovation

Following the literature on radical innovation (Garcia & Calantone, 2002; O'Connor & McDermott, 2004) we distinguished between radical product and radical process innovation by using two dichotomous variables which assumed the value of 1 if the establishment had introduced a new or significantly changed product (or process) in the previous three years which were new for the establishment or new for both the establishment and the market in which the company operates; 0 otherwise.

Control variables

We used several control variables. We included establishment characteristics like establishment years (log years); establishment size (0=large – above 249 employees versus 1=SME up to 249 employees); industry sectors (0=manufacturing versus 1=service and construction sectors), strategic orientation of a firm (1=the establishment follows an innovation strategy; 0=otherwise) and market competitiveness (1=very competitive, 0=otherwise). We also controlled for regional diversity, since in Europe there are great differences in the innovation performance across EU member states (0=innovation leaders versus 1=strong, moderate, and modest innovators) (European Union, 2019).

3.3.3 Analysis

Since radical innovation is measured through a dichotomous variable, the binary logistic regression was used to test the three hypothesis formulated in this paper. We performed firstly the regressions to test the influence of HPWS on both product and process radical innovation. Then, we performed the regression with the interaction term TECH (mean-centered) on HPWS for measuring the moderation effect of digital technologies on HR practices. Subsequently, the second interaction term EMPL_EMP (standardized) was added, in order to test the three-way interaction. The simple slope analysis was performed to examine the moderating effect. Variables considered in the model and additional analysis (ANOVA and average marginal effects of the models) are specified in more details in the Annex. To treat variables and to carry out the analysis we used SPSS 23.0 and R 3.6.2 version

3.4 Results

Table 3.1 presents the descriptive statistics of the main variables of the model. All variables are positively and significantly correlated and the descriptive statistics exclude the multi-collinearity issue among the regressors included in the model

	N.	Weighted N.	Mean	S.D.	1	2	3	4	5
HPWS	21,869	2,350,279	0.0000	10.084	1				
TECH	21,868	2,350,268	0.0000	1.081	,327**	1			
EMPL_EMP	21,275	2,278,750	0.0765	0.987	,382**	,193**	1		
RAD_PROD	21,744	2,338,781	0.3469	0.476	,151**	,251**	,127**	1	
RAD_PROC	21,646	2,329,493	0.3349	0.472	,190**	,267**	,161**	,527**	1

HPWS and EMPL_EMP are a composite scale (z-score standardized values), while TECH is a mean centered index.

RAD_PROD/PROC are dummies. We did not include controls due to limited space. **p≤.01; *p≤.05.

Table 3.1 Descriptive statistics and correlations of the main variables of the model.

Table 3.2 show the direct relationship between HPWS and radical product innovation (Model 1) and radical process innovation (Model 2). The effect is positive and significant for both innovations (β=.036, p≤.01; β=.048, p≤.01) supporting hypothesis 1a and 1b, although it is greater for radical process innovation. The control variables mostly respond according to the literature, although there are some differences with respect to the kinds of innovation.

	Model 1		Model 2	
	Rad_Prod		Rad_Proc	
Variables	β	S.E.	β	S.E.
HPWS	0.036***	0.003	0.048***	0.003
SmallComp	-0.308**	0.107	-0.550***	0.106
MediumComp	-0.178	0.114	-0.184	0.114
Constr_sect	-1.451***	0.115	-1.135***	0.113
Service_sect	-0.581***	0.068	-0.678***	0.069
Logyears	-0.037	0.091	-0.166.	0.086
Inn_strat	0.618***	0.065	0.364***	0.066
MarketComp	0.385***	0.094	0.469***	0.093
Modest	0.305**	0.091	0.040	0.093
Moderate	0.242***	0.063	0.293***	0.063
Strong	-0.204**	0.072	-0.305***	0.074
Pseudo R^2	0.067		0.077	
Observations	18,554		18,490	
Wald Chi-square (df)	509.14(11)***		622.70(11)***	
Robust standard errors.				
Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.10				
Odds ratio are not reported due to limited space.				

Table 3.2 Results of the logit model for the direct effect of HPWS on radical product and process innovations

Small companies are less likely to innovate with respect to large ones (β=-.308, p≤.01; β=-.550 p≤.01), while both construction (β=-1.451, p≤.01; β=-1.135 p≤.01), and service sector (β=-.581, p≤.01; β=-.678 p≤.01), are less likely to bring radical innovation with respect to the production sector. The age of the company seems uninfluential (β=-.037, p≥.05; β=-.166, p≥.05), while both market competitiveness (β=.385, p≤.01; β=.496 p≤.01), and innovation strategy (β=.618, p≤.01; β=.364 p≤.01), are strong predictor of both radical innovations, while regional differences in the innovation capacity of European countries are also present.

Table 3.3 presents the interaction between HPWS and digital technologies' adoption (TECH) on product (model 3) and process (model 4) innovation. The interaction is not significant (β=.004, p>.10; β=.002, p>.10), hence hypothesis 2a and 2b are not supported. However, we observe a positive and statistically significant conditional effect of TECH on both innovations (β=.434; p≤.01; β=.471; p≤.01), hence we can affirm that at average level of HPWS in the workplace, digital technologies' adoption strongly increases the probability of radical innovations and that such probability is stronger for process innovation (see annex for details).

	Model 3 Rad_Prod		Model 4 Rad_Proc	
Variables	β	S.E.	β	S.E.
HPWSxTECH	0.004	0.003	0.002	0.003
TECH	0.434***	0.030	0.471***	0.030
HPWS	0.022***	0.003	0.035***	0.003
SmallComp	-0.077	0.116	-0.317**	0.117
MediumComp	-0.041	0.122	-0.046	0.124
Constr_sect	-1.247***	0.116	-0.905***	0.116
Service_sect	-0.632***	0.071	-0.738***	0.071
Logyears	-0.061	0.092	-0.197*	0.087
Inn_Strat	0.597***	0.066	0.330***	0.068
MarketComp	0.355***	0.094	0.440***	0.093
Modest	0.332***	0.093	0.060	0.097
Moderate	0.198**	0.065	0.248***	0.065
Strong	-0.158*	0.074	-0.256*	0.076
Pseudo R^2	0,094		0,108	
Observations	18,553		18,489	
Wald Chi-square (df)	728.88(13)***		883.20(13)***	

Robust standard errors.
Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.10
Odds ratio are not reported due to limited space.

Table 3.3 Results of the logit model for the moderating effect of technology on product and process innovations

Table 3.4 shows the findings regarding the three-way interaction between employee empowerment, digital technologies' adoption and HPWS on both innovations. We do find a significant and negative effect of the moderated moderation on product innovation (β=-.006; p≤.05) and process innovation (β=-.009; p≤.01), which is counterintuitive with respect to our hypothesis 3a and 3b. Therefore, they are disconfirmed. However, the results are anyway relevant and worth of attention. The simple slope analysis reported in Figure 3.2 and Figure 3.3 highlights that, when employee empowerment is low, digital technologies' adoption enhances the effect of HPWS on both radical innovations, so that as digital technologies' adoption increases, the effect of HRM practices increases as well. In contrast, when the level of employee empowerment is high, the higher the digital technologies' adoption, the lower the effect that HPWS have on both innovations. Such situation is greater for process innovation.

	Model 5		Model 6	
	Rad_Prod		Rad_Proc	
Variables	β	S.E.	β	S.E.
HPWSxTECHxEMPL_EMP	-0.006*	0.003	-0.009***	0.003
EMPL_EMPxTECH	-0.006	0.032	0.017	0.031
HPWSxEMPL_EMP	-0.002	0.003	-0.005.	0.003
HPWSxTECH	0.006*	0.003	0.005	0.003
EMPL_EMP	0.144***	0.033	0.221***	0.034
TECH	0.443***	0.031	0.479***	0.032
HPWS	0.018***	0.004	0.029***	0.004
SmallComp	-0.085	0.117	-0.304**	0.117
MediumComp	-0.061	0.122	-0.046	0.124
Constr_sect	-1.238***	0.117	-0.914***	0.117
Service_sect	-0.619***	0.072	-0.735***	0.072
Logyears	-0.039	0.093	-0.166.	0.088
Inn_strat	0.581***	0.067	0.323***	0.068
MarketComp	0.346***	0.095	0.429***	0.094
Modest	0.294**	0.095	-0.004	0.099
Moderate	0.168**	0.065	0.203**	0.066
Strong	-0.150*	0.075	-0.246**	0.076
Pseudo R^2	0.095		0.111	
Observations	18.230		18.173	
Wald Chi-square (df)	725.89(17)***		881.16(17)***	
Robust standard errors.				
Signif. codes: *** 0.001; ** 0.01; * 0.05; . 0.10				
Odds ratio are not reported due to limited space.				

Table 3.4 Results of the three-way interaction between HPWS, technology and employee empowerment on product and process innovation

The picture described is more evident in Table 3.5, which analyzes the effect of HPWS taking into account different levels of the moderators. Specifically, for *product* innovation when the employee empowerment is low and TECH is low, the effect of practices on innovation is not significant (β=-.0074; p.≥.05), but it far increases when digital technologies' adoption is high (β=.0323; p.≤.01). At the same time when employee empowerment is high, the effect of practices on product innovation is greater when TECH is low (β=.0165; p.≤.05), rather than high (β=.0163; p.≤.05). This situation is more pronounced when we consider *process* innovation; specifically, at low levels of EMPL_EMP the effect of HPWS is higher when TECH is high (β=.0480; p.≤.01) rather than low (β=.0202; p.≤.01), while at high levels of employee empowerment we have stronger effect of HPWP at low levels of TECH (β=.0288; p.≤.01) rather that at high levels of TECH (β=.0178; p.≤.01). In both kinds of innovations, the maximum enhancing effect occurs at low levels of employee empowerment and high levels digital technologies' adoption. These results have important implications both for theory and practice.

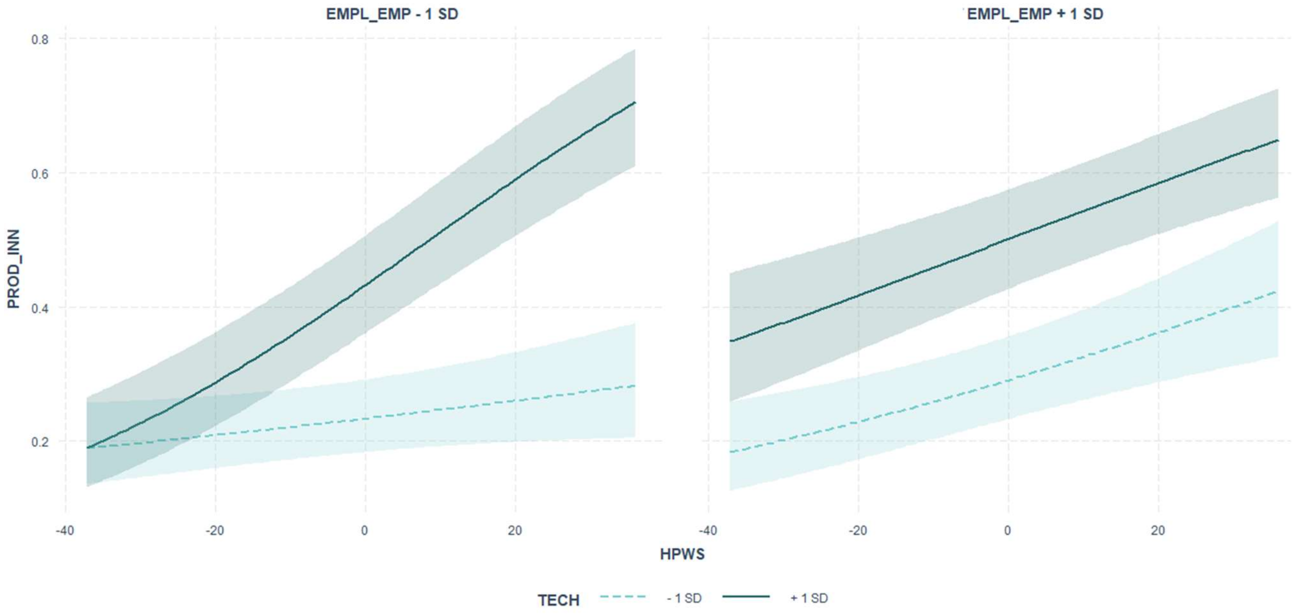

Figure 3.2 Three-way interaction among HPWS, digital technologies and employee empowerment on radical product innovation (± 1SD)

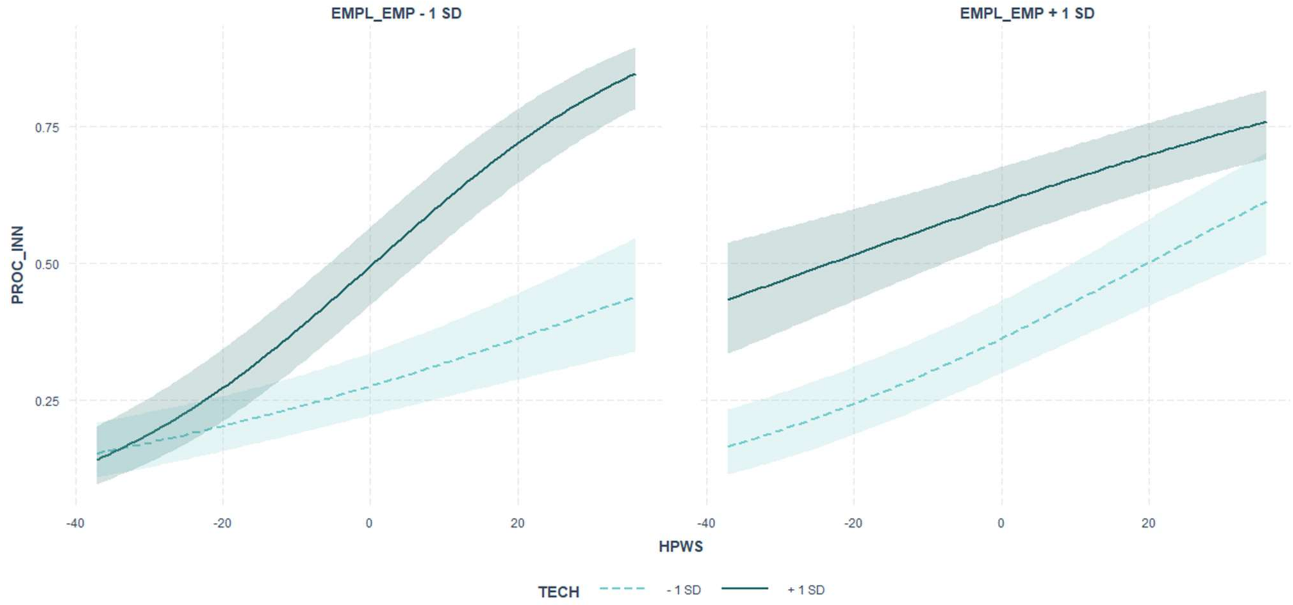

Figure 3.3 Three-way interaction among HPWS, digital technologies and employee empowerment on radical process innovation (± 1SD)

		Radical product innovation		
Empl_emp	Tech	HPWS	s.e. (robust)	p. value
Low	Low	0.0074	0.0061	0.2280
Low	High	0.0323	0.0061	0.0000
High	Low	0.0165	0.0065	0.0109
High	High	0.0163	0.0064	0.0116
		Radical process innovation		
Low	Low	0.0202	0.00614	0.0010
Low	High	0.0480	0.00615	0.0000
High	Low	0.0288	0.00654	0.0001
High	High	0.0178	0.00654	0.0063

Table 3.5 Effects of HPWS on radical product/process innovation at different levels of TECH and EMPL_EMP

3.5 Discussion and conclusions

Drawing from the European Company Survey 2019, a large-scale, cross-national survey which collects data on workplace practices regarding HRM practices, innovation, digital technologies and employee empowerment at European level, our analysis presents three main cluster of findings, which contribute to enhance the understanding of the effect of HRM practices on different kinds of radical innovations as well as the moderating effect that two variables have in influencing this relationship. The first contribution relates on the direct influence that HPWS have on radical product and process innovation, in order to give empirical answer to a current literature gap in the HRM-innovation relationship (Barba-Aragón & Jiménez-Jiménez, 2020). Our results show that HPWS have a positive and significant effect on product and process radical innovation, hence those companies that make larger use of practices aimed at motivating employees and providing them the opportunities and abilities to contribute to the development of radical innovations have higher probability to innovate. This underlines that the use of HPWS is a significant booster not only for innovation in general (Do & Shipton, 2019), but also for radical ones. We also find that HPWS have higher association with radical process innovation with respect to radical product one, suggesting that the effect of practices is different with respect to the innovation type. This result is in line with a handful of studies that have previously investigated the influence of HRM practices (intended as a system or bundles) on different types of innovations (Haneda & Ito, 2018; Jiménez-Jiménez & Sanz-Valle, 2008), showing that the effect is greater for process innovation.

To further open up this relationship this work explored the moderating role that digital technologies' adoption plays in shaping this relationship; although in the literature timid attempts are present (Kintana et al., 2006; Santoro & Usai, 2018), scholars have been currently devoting increasing attention to this association (Connelly et al., 2021; Kim et al., 2021). The second cluster of findings show a positive and statistically significant association between the conditional effect of digital technologies and both kinds of radical innovation, hence we highlight how digital technology highly increases the likelihood of having a radical product and process innovation, complementing and confirming recent literature on technology and innovation (Bresciani et al., 2021; Usai, et al., 2021). However, we do not find any significant interaction effect between digital technologies' adoption and

HPWS. This result is not new in the literature since there are studies that have similar findings (Arvanitis, 2005; Kintana et al., 2006), although they do not specifically address the association between HRM practices and innovation. Following the reasoning of Kintana et al., (2006) our result may indicate that technologies per se do not offer workers greater opportunities to contribute to developing radical innovation, or if they do, workers cannot grasp such additional potential, or that the HPWS and technologies' adoption contribute to radical innovation in ways which are not interrelated.

The third and main contribution of this article regards the moderating role that employee empowerment played in further shaping the interaction between digital technologies' adoption and HPWS in the relationship with radical product and process innovation. This kind of association was suggested by some empirical and theoretical articles with hypothesized this coupled relationship. In particular, there is evidence that when digital technologies are conceived as a tool of control, they reduce the effectiveness of practices on worker perforce (Maroufkhani et al., 2020; Martin et al., 2016; Park, 2018). However, this association can be softened by empowering employees since they have more control over organizational operations, thus they are more likely to accept control-related technologies (Martin et al., 2016). On the other hand, when technology is conceived as complementary tool for human activities, it enhances the effect of such practices by increasing employee performance (Dedrick et al., 2003; Nazareno & Schiff, 2021; Vrontis, et al., 2021). Therefore, we hypothesized a three-way interaction of employee empowerment with digital technologies and HPWS, arguing that employee empowerment positively moderates the interaction of digital technologies and HPWS on both kinds of innovations, so that if technology is conceived as tool of control such negative effect will be reduced, while if technology is intended as complementary tool, such effect will be boosted.

Our results show that employee empowerment is the triggering variable which enables the moderating effect of digital technologies on HRM practices, therefore we can affirm that digital technologies when conceived per se (hypothesis 2a and 2b) are not able to stimulate workers actions, but they do when they employee are involved in the decision-making process. This finding is remarkable because it enhances the results of prior studies which did not find any significant effect on the association between technology and practices (Arvanitis, 2005; Kintana et al., 2006). Moreover, although our results are counter intuitive with respect to our hypothesis and to the main suggestions of the literature since the logistic regression shows that such relationship significant and negative, the results are worth of attention because they deliver a powerful and compelling message. The simple slope analysis in Table 3.5 reveals that the effect is not negative as such, but it depends on the level of employee's decision-making power. In fact, when we consider low levels of employee empowerment, digital technologies' adoption has a positive and statistically significant moderating effect, because high levels of digital technologies enhance the positive effect of HRM practices on the introduction of a product/process radical innovation. Such positive effect is reversed when we consider high levels of empowerment, because the interaction of TECH and HPWS show that at high levels of digital technologies' adoption, HRM practices are less likely to produce radical innovation with respect to cases where digital technologies' adoption is lower, especially for process innovation. A possible explanation of these results is that workers are less forward-looking than managers. In cases of high level of employee empowerment, workers are willing to adopt technology in a perspective of efficiency and control rather than complementarity, hence they may use such technology to obtain major benefits derived by higher production (i.e. possible higher reward) rather than effectively improving their abilities, motivation and opportunities in order to increase the rate of innovation within the firm since.

Radical innovation entails great risks and uncertainty (Garcia & Calantone, 2002), therefore being involved in an uncertain process might generate uncertain results, therefore it seems that workers are more inclined to obtaining a short-term benefit derived by major productivity. This result recall to what outlined by previous schoars which hypothesized the degree of centralization to moderate technology's adoption. Dewar & Dutton (1986) for instance, affirm that when favouring radical technological innovations the major role its attributed to managers since they have the skills mtethods and procedures to encourage the change of attitude toward innovation. While with incremental innovation the decentralization of authority generates positive effects since employees may propose and adopt improving changes, this does not occur for radical innovation, since thise kind of innovation require a centralization of authority because they are complex and entail a high degree of uncertaincy. Moreover, when managers are innovation oriented, in decentralized organization that orientation toward innovation might be diluited due to group of interest within the organization.

This is what seem to happen in our results because when the level of employee empowerment is low, workers are better able to grasp technology's benefit in complementary with HRM practices, hence, enhancing latter's effect. Hence, our results highlight how centralization of activities rather than decentralization leads to major advantages toward radical innovation.

Therefore, in this framework the managers seem more far-sighted. They are those that are capable to trigger the complementary opportunities derived by technology in a medium-long term perspective since. Radical innovation is a long and complicated process, hence, when developing radical innovation managers are those that have the vision to adopt the technology which can enhance the effectiveness of human actions and practices in this direction. This is underlined by some papers which highlight how leaders are those that are better able to have the vision to integrate technology which may better support the learning process of the organization in a complementary way, leading to major innovation (Dixon et al., 2021; Ghobakhloo, Sabouri, & Hong, 2011; Giotopoulos, Kontolaimou, Korrac, & Aggelos, 2017). Therefore, are managers those that have a deeper undertraining of the innovation process and can act as enabler and technology adopter in order to enhance the effectiveness of practices, as well as, the skills, flexibility of employees to foster the idea generation, hence underpinning the radical innovation process within the firm.

3.5.1 Theoretical contributions

The current findings have important implications for the literature. Firstly, our results advance in the understanding about the direct effect of HRM practices on different kind of radical innovation, in particular highlighting how HPWS is a system which fits the development of radical product and process innovation. There are not many contributions in this regard (Barba-Aragón & Jiménez-Jiménez, 2020; Seeck & Diehl, 2017), hence our work highlights how HRM may have a different effect depending on the kind of innovation. Moreover, we give answers to some researchers who called for further investigation about the HRM – inovation relationship by using a clear theoretical framework in oder to better understand this kind of connetion (Seeck & Diehl, 2017). At the same time, we provide evidence of this relationship by considering the European framework, while most of the studies concentrate their attention on single countries (Barba-Aragón & Jiménez-Jiménez, 2020; Do & Shipton, 2019).

Secondly, we contribute to the advancement to the very recent literature regarding the impact that digital technologies have on different kinds of radical innovation (Bresciani et al., 2021; Ciarli et al., 2021; Usai, et al., 2021). This is a very recent stream of research which deserve further investigation in order to better understand the effect the workplace digitalization. We confirm the positive effect that digital technologies have on innovation, highlighting a strong contribution of the letter to new radical product and radical process.

Moreover, we also underline how the digitalization of the workplace can have negative effects when combined with other organizational factors. In particular, we demostrate that digital technologies interact with HPWS when combined with employee empowerment practices, hence we give answers to those researchers that failed to find effect on this regard (Arvanitis, 2005; Kintana, Alonso, & Olaverri, 2006), by extending the current knowledge about how digital technologies interact with HRM practices. This is the most important implication for the literature of this article since we shed new lights on the way by which digital technologies interact with HRM practices, drawing attention to the conditional effect played by the decentralization of the decision-making power. In particular, we show how employee empowerment is the triggering variable for this kind of interaction, hence we add understanding about the interplay of these dimensions, which to the best of our knowledge has not been addressed in the literature, especially considering radical innovation. The findings show that the effect of HRM practices on radical innovation can be reduced when used in combination with both high level of digital technologies and decentralization. At the same time the HRM practices exert major effect when used in combination with digital technologies and centralized decision making. Hence, we cast new light on the contribution of employee empowerment practices in the workplace. Since employee empowerment is widely recognized as one of the most beneficious organizational practices in the workplace (Martin et al. 2016; Oltra, Donada, & Alegre, 2022; Wei, Liu, & Herndon, 2011), our results partially disconfirm this, suggesting that it depends on the organizational context in which it operates. In particular, in highly digitalized context can exert negative backfires effects.

Finally, by investigating the triple relationship HPWS, digital technology and employee empowerment, we also reply to the emerging call which encourage to further explore to the interplay between HRM and technology by considering organizational contextual factors (Kim et al., 2021), being one of the first contributions in this regard.

3.5.2 Managerial implications

This study's results are worth of attention because they are grounded on a large-scale dataset and contribute to fill important gaps in the literature which have not been addressed yet, especially at the empirical level. Our findings highlight important implications for managers. First of all, our data demonstrate that organizations that make large use of HPWS are more likely to introduce new radical innovation within their organization. Therefore, to develop radical innovation managers should implement HPWS in order to provide workers with abilities, motivation and opportunities to develop both product and process innovation since these kinds of practices enable workers to better understand and analyze the innovation process. In particular, the results show that those companies that implement HPWS of practices are better able to succeed in a generation of radial innovation. Since radical innovation require high degree of skills, knowledge and risk, managers are encouraged to enable their workforce with the necessary capabilities and motivation and opportunity to undergo to the radical innovation process. Hence, they could achieve this by equipping their workforce with the necessary degree of HPWS in order to foster workers creativity and entrepreneurial motivation, by enhancing the organizational innovative output.

Second, managers should also rely on digital technologies in enhancing the radical innovative outcome of companies since our findings demonstrate that digital technologies release a very high contribution in the generation of both radical product and process innovation, in line with prior studies (Bresciani, Huarng, Malhotra, & Ferraris, 2021). Therefore, digital technologies are a good ally for managers and the for the innovation process itself. However, our results show that it possible to have negative effects, especially when managers decide to couple digital technology with a decentralization of the decision-making power. In fact, the findings show that managers should be cautious in this combination, because an excessive use of decentralization in high technological context can have backfires effects on the HRM practices targeted to boost the generation of radical innovations. In fact, a cocktail of high level of both digital technologies and employee empowerment could be harmful for HPWS since they can reduce their positive effect toward both types of radical innovation. Therefore, we suggest managers to balance the use of decentralization with respect to the level of technological presence in the workplace. In particular, if they desire to reach a stronger innovative output, our results show that they have to make large use of HPWP combined with high levels of digital technologies, but low levels of decentralization.

3.5.3 Limitations and future research suggestions

The current work presents some limitations. First, the dataset. Although it is a large-scale survey, it presents limitation in the construction of the variables since they are coded with different scales; moreover, although it offers the benefit of greater generalizability, it does not provide extensive question batteries for the measurement of specific concepts. For instance, we did not have reliable constructs for measuring the level of skills in the workplace, while there is a vast number of articles which highlight that digital technologies are strongly associated with high need of skills in the workplace (Ciarli et al., 2021; Dixon et al., 2021; Kim et al., 2021; Smids et al., 2020; Vrontis, et al., 2021), especially when developing radical innovations (Oltra et al., 2022). Hence, this is a potential limitation of this study and considering this aspect is important in order to provide additional evidence in support of our findings. Therefore, we strongly encourage future research to analyze three-way interaction among skills, digital technologies and HRM practices on radical innovation. Another limitation which opens avenues for further research is the dependent variable. We measured radical innovation by not considering the classification of radical innovations (i.e. new to the firm vs new to the market) and our results might differ depending on the level of newness of the innovation. Therefore, we encourage further investigation toward this direction. A third limitation is the European framework. Although we provided support of our hypotheses, significant differences in the relation patterns of the models may occur when considering single countries since in Europe there are great differences in the innovation performance across EU member states. Therefore, the results might differ depending on the country/countries which are considered. This issue definitely deserves further investigation.

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Annex 3

Annex 3.1 ANOVA for the main variables of the model

Construct	Robust F-test Brown-Forsythe	No innovations (N. 11,909)	Product inn. (N. 2,450)	Process inn. (N. 2,198)	Differences *
HPWS	153.124 (p=.000)	M=-1.82 (10.03)	M=-.14 (9.60)	M=1.76 (9.35)	Process>product + no inn.
TECH	348.571 (p=.000)	M=-.28 (.97)	M=.16 (1.06)	M=.24 (1.08)	Process>product + no inn.**
EMPL_EMP	90.309 (p=.000)	M=-.06 (.99)	M=.07 (.95)	M=.23 (.96)	Process>product + no inn.

The dependent variable was created by merging the product and process innovation variables; 5,030 cases were dropped since we considered companies that introduced only a product or process innovation but not both.
HPWS, TECH and EMP_EMP are standardized values. M (mean), (sd)
*Games-Howell post hoc test. ANOVA is run by not applying the dataset weights. ** at 0.1 confidence interval

Annex 3.2 Average Marginal effects of the models

	Model 1		Model 2	
	dy/dx	S.E.	dy/dx	S.E.
HPWS	.0075***	.0007	.0096***	.0006
Controls	Yes		Yes	

	Model 3		Model 4	
	dy/dx	S.E.	dy/dx	S.E.
TECHxHPWS	.0009	.0006	.0003	.0006
TECH	.0910***	.0064	.0925***	.0059
HPWS	.0047***	.0007	.0068***	.0065
Controls	Yes		Yes	

	Model 5		Model 6	
	dy/dx	S.E.	dy/dx	S.E.
HPWSxTECHxEMPL_EMP	-.0012*	.0005	-.0018***	0.0005
EMPL_EMPxTECH	-.0012	.0067	.0033	.0062
HPWSxEMPL_EMP	-.0004	.0006	-.0012.	.0006
HPWSxTECH	.0013*	.0007	.0009	.0006
EMPL_EMP	.0304***	.0070	.0437***	.0066
TECH	.0936***	.0067	.0947***	.0062
HPWS	.0039***	.0008	.0058***	.0007
Controls	Yes		Yes	

Annex 3.3 Model's variable and measures

HPWS		
Description	*Item scale*	*Variable*
Training and learning		
How many employees have participated in training sessions at other locations? (% of employees)	1-7	Formal and informal Training
How many employees have received on-the-job training? (% of employees)	1-7	
How important are the following reasons for providing training to employees?		
Allowing employees to acquire skills they need to do job rotation	1-4	Training purpose
Increasing the capacity of employees to articulate ideas	1-4	
How many employees are in jobs that require continuous training? (% of employees)	1-7	Skill-enhancing job diffusion
Recruitment		
When recruiting new employees, how important is that the candidate has the skills required to do the job?	0-1	Skilled employee recruitment
When recruiting new employees, how important is that the candidate has the educational qualification that are required?	0-1	
Reward		
How many employees at this establishment received the following types of variable pay? (% of employees)		
Payment by results	1-7	Variable pay schemes intensity
Individual performance	1-7	
Team performance	1-7	
Establishment performance	1-7	
How often are the following practices used to motivate employees: offering monetary rewards	1-4	Monetary lever
Performance appraisal		
To be evaluated positively, how important is it that employees show the following behavior?		
Helping colleagues without being asked	1-4	Performance appraisal
Making suggestions for improving the way things are done in the company	1-4	
Intrinsic motivational practices		
How often are the following practices used to motivate employees?		
Communicating a strong mission and vision, providing meaning to our work	1-4	
Providing interesting and stimulating work	1-4	
Providing opportunities for training and development	1-4	

(Continued)

	Information sharing	
Does this establishment make use of suggestion schemes?	Yes/No	Suggestion program
Which of the following practices are used to involve employees in how work is organized?		
Meetings between employees and manager	1-3	Knowledge-sharing
Meetings open to all employees	1-3	
Dissemination of information	1-3	
Discussions with employees on-line	1-3	
	Job design	
For how many employees in this establishment does their job include finding solutions to unfamiliar problems? (% of employees)	1-7	Work time discretion and problem solving
For how many employees does their job include independently organizing their own time? (% of employees)	1-7	
Which of these two statements best describes the general approach to management? Managers control employees or employees can autonomously carry out their tasks	0-1	Work method discretion
	Digital Technologies	
How many employees use personal computers or laptops? (% of employees)	1-7	Computer use
Does this establishment use robots?	Yes/No	Robots
Does this establishment use data analytics to improve the process of production?	Yes/No	Data analytics
Does this establishment use data analytics to monitor employee performance?	Yes/No	
	Employee empowerment	
In your opinion to what extent have employees directly influenced management decisions in the following areas?		
The organization and efficiency of work processes	1-4	
Dismissals	1-4	
Training and skill development	1-4	
Working time arrangements	1-4	
Payment schemes	1-4	
	Radical innovation	
Since the beginning of 2016, has this establishment introduced?		
Any new or significantly changed product or services: *New to the market*		Product innovation
New to the establishment but not to the market		
Any new or significantly changed process: *New to the market* *New to the establishment but not to the market*		Process innovation

(Continued)

Control variables	
How many people work in this establishment?	Size
Since what year has this establishment been carrying out this activity?	Years
Establishment's main activity category	Sector
How important is to regulary developing new product, services or processes?	Strategy
How competitive the market is?	Market competitiveness
Country of the establishment	Country