Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines

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Abstract

The increasing presence of humanoid robot adoption has generated a change in explorative and exploitative routines. If the explorative routines provoke creativity and critical thinking which are delivered by humans, exploitative routines induce repetitive actions and mimic activities which are executed by humanoids. This has raised the need for a better balance between both routines involving an ambidextrous dynamic process. Here, product innovations play a relevant role in enhancing such balance and labour productivity. If, from the conceptual standpoint, this phenomenon has already been explored, there is still the need to empirically analyse it. We thus offer a meso-analysis of twenty-four countries located in Europe through the lens of the Service Robot Deployment (SRD) Model and the conceptual lens of organizational ambidexterity. By a regression methodology, the results show that humanoid robot adoption is still not affecting labour productivity which, by contrast, is positively and significantly connected with both radically new and marginally modified/unchanged production of innovative routines.
Our original contribution, which falls in the field of Artificial Intelligence, is that humanoids are not directly impacting labour productivity but indirectly through the generation of both new and marginally modified (or unchanged) routines. This situation persuades senior leaders to achieve a balance between exploitative and explorative product innovation routines.

Keywords: *artificial intelligence; labour productivity; contextual ambidexterity; International HRM; product innovation; explorative routines; exploitative routines.*

Introduction

As highlighted by the report entitled Industry 4.0 – Adoption Index (Research and Markets, 2020), humanoid adoption will be a step further into industry 4.0, introducing the new era of industry 5.0. This will induce an increasing shift of work by 2022 (World Economic Forum, 2018) thanks to the fact that companies can get benefits such as improving customer services in terms of time and costs, reducing information leakage and deception, and enhancing productivity (Wirtz & Zeithaml, 2018; Kumar et al., 2019).
These new technologies have been classified as artificial intelligences (AIs) since 1942 with the release of a new book entitled "Runaround" where a robot was confined by three laws: "(1) a robot may not injure a human being or, through inaction, allow a human being to come to harm; (2) a robot must obey the orders given to it by human beings except where such orders would conflict with the First Law; and (3) a robot must protect its own existence as long as such protection does not conflict

with the First or Second Laws" (Haenlein & Kaplan, 2019, p.6). A humanoid is recognised as an intelligent machine when an individual is not able to discriminate the machine from a human (Turing, 2009). In fact, the machine can have a physical or virtual presence in the form of a humanoid (Wirtz et al., 2018).

This has been also contextualized in a daily business working day where a humanoid is an artificial intelligence machine aimed at automatizing different levels of employees' activities, yielding both advantages (e.g., more agility to adjust a business model to fast market changes, more requests for fast and agile innovation, and more support for overcoming human constraints, among others) and challenges (e.g., more specialized skills and trainings, a growth in employability but also an increase in job loss) (Manyika, 2017).

Van Doon et al. (2017) introduced the concept of automated social presence, which refers to the duality of social presence (e.g., human-humanoids) that is perceived by customers. Besides, Wirtz et al. (2018) argue that humanoids can perform tasks in a limited range of situations with fewer emotional and cognitive skills. This so induces a more explorative analysis of the routines that are mostly delivered by humanoids. A company tends to modify routines when offering new products or when maintaining the same routines to exploit existing products (Alos – Simo et al., 2020). This reflects the dynamic process of ambidexterity which relies on the organizational capacity to make a balance between explorative and exploitative routines.

This has spurred our interest in exploring humanoid robot adoption along with explorative and exploitative routines in a product innovation and ambidextrous setting and addressing the research question of *how humanoid robot adoption is affecting labour productivity across the exploitative and explorative ambidextrous organizational routines?*

Hence, through the conceptual organizational ambidexterity lens (Stokes et al., 2019) we offer a meso-analysis (or country level analysis) by employing the Service Robot Deployment (SRD) Model (Wirtz et al., 2018; Paluch et al., 2020).

The model shows that "robots will be able to mimic superficial acting-type emotions to a high level, but deep acting and out-of-box thinking at a human level are not attainable in the foreseeable future" (Wirtz et al., 2018, p.913). In this regard, when the cognitive and emotional complexity is low, the task can be executed by humanoids; whereas, if such complexity is high, humans need to intervene. Humanoids can mainly perform routines ushering the emotional side of humans. As stated by Wirtz (2019), organizational ambidexterity can make the right balance between the adoption of new technologies with "the expected level of human touch" in the employees' work.

Then, in order to operationalize these concepts, we take into account the production of innovative enterprises, which can consist of either (or both) significantly new outputs with the employment of more cognitive and emotional tasks and incrementally modified/unchanged outputs with more mimicking tasks. We consider the former to be related to explorative routines and the latter related to exploitative routines (Pfeiffer, 2016). Furthermore, we have also investigated the effect of human-humanoid routines on labour productivity in a product innovation context. In fact, as documented by several empirical studies, labour productivity is usually (and positively) associated with product innovation (Brown & Guzmán, 2014, Crépon et al., 1998; Kurt & Kurt, 2015). This task is accomplished by means of a regression analysis that is carried out at the national (aggregate) level and takes into account a set of countries located in Europe.

This analysis enhances the current HRM literature which has offered systematic literature review (Lu et al., 2019; Ivanov et al., 2019) of conceptual or qualitative studies focused on the health (Beane, 2019; Green et al., 2016; Barrett *et al.*, 2012) and service industries (Čaić et al., 2019) and on the domain of human resource management (Tambe et al., 2019; Haenlein & Kaplan, 2019) with the organizational ambidexterity point of a view (Stoke et al., 2019) and individual outlook (Swart et al., 2019). However, a general halo of uncertainty still seems to linger about HRM practices and human-humanoid interactions, and how they affect the ambidextrous context of a company is not fully understood.

Besides, despite the advancements in the field of humanoids and AI, a large part of the existing research seems to be oriented to considering them as domains related to companies' processes and infrastructures only (Chauhan, 2018; Chaudhry et al., 2018). On the contrary, very few contributions have been provided that focus on the role of human resource management (HRM) practices in managing business automation and the decision making processes (Powell and Dent-Micallef, 1997; Haenlein & Kaplan, 2019; Tambe et al., 2019). Results show that humanoid robot adoption is still not affecting labour productivity which, by contrast, is positively and significantly connected with both radically new and marginally modified or unchanged products. Hence, our original contribution states the fact that AIs – with a focus on humanoids – are not impacting labour productivity very much. However, the latter is significantly connected to both explorative and exploitative routines.

Especially, the present study shows that there is still a need to explore new approaches without revolutionizing existing routines and knowledge (e.g., exploitative routines) (Malik et al., 2019a; O'Reilly & Tushman, 2008; Raisch et al., 2009; Tushman & O'Reilly, 1996).
This induces the second contribution which has a managerial connotation. So as to create a balance between explorative and exploitative routines, managers should introduce new rewards and empower a culture of trust and collaboration (Chang et al., 2009; Malik et al., 2019a). Employing a collaborative leadership evokes the third contribution which highlights the significance of prolonged orientation and socialization along with team-based design of labour productivity. In this regard, managers tend to adopt a culture of flexibility and adaptation (Simsek, 2009; Simsek et al., 2009).
Overall, humanoid robot adoption can enhance the effectiveness of HRM practices. These activities can be used by companies for screening candidates, employee engagement and re-engagement, and career development. Such collaborations can also be applied to HR policies, procedures, and the HR perspective, and they can enhance the effectiveness of HRM. This is to make sure they are employing individuals with the right skills in order to work towards the strategic objectives.

2. Literature review and hypotheses development

2.1. Humanoid robot adoption and labour productivity in a contextual ambidextrous (CA) product innovation setting.

The evolution of the Industry 4.0 has impacted the whole business world along with the macro-economic areas (e.g., political, economic, societal, and technological). In this scenario, companies – either multinationals or small to medium enterprises – are facing several challenges (Malik, 2019) which are inducing a different way of living, communicating, and working. This involves an ambidextrous approach which combines explorative and exploitive learning in three different ways. Generally speaking, researchers have divided organizational ambidexterity into three categories– namely structural, contextual ambidexterity, and co-evolutionary lock-in (Kang & Snell, 2009; O'Reilly & Tushman, 2004; Gibson & Birkinshaw, 2004; Jansen et al., 2008; Carmeli & Halevi, 2009; Burgelman, 2002).
Structural ambidexterity concerns the organizational environment of a company which seeks to exploit its strengths and explore new knowledge. This implicates an integration of all the business units into the core business along with an efficient allocation of resources (Gibson & Birkinshaw, 2004; Kang & Snell, 2009; O'Reilly & Tushman, 2004). Whereas contextual ambidexterity regards people working within a company and their skills and abilities to explore and exploit routines (Gibson & Birkinshaw, 2004). Co-evolutionary lock-in refers to the ability to connect the previous achievements of a company with the existing "product-market environment". Concerning HRM practices, a CA setting is mostly considered with an examination of employees' skills. In fact, in the scenario where humanoids are introduced into an organizational context, there is a common sense that humanoids will replace people and increase the job loss rate (Jarrahi, 2018). In fact, even though

the use of humanoids can improve product performance, it can also rather reduce employability (e.g., Keynes [1930] talked about "technological unemployment") and force the development of new skills (Davenport & Ronanki, 2018; Leontief,1952).
By contrast, Acemoglu and Restrepo (2017a;b) have recently shown that a robot does not shrink employment but can induce the need for highly skilled people (see also Graetz & Michaels, 2015). For instance, nowadays, there is a need for data scientists and analytics along with a clear understanding of what are the benefits of new technologies. A senior manager from a multinational company analysed by Scuotto and Mueller (2018) pointed out the significance of the benefits of using new technologies. People are reluctant to a change. They tend to conform to their routines – exploiting existing knowledge instead of exploring new knowledge.
Therefore, due to the presence of this reluctance to accept the "new", Davenport and Ronanki (2018) recommended first implementing a pilot project to introduce mechanical automation (or humanoids) and then "roll it out across the entire enterprise" (page 8). Besides, team-based designs need to be re-formed in the search for a more efficient balance between human and humanoids. In this regard, the SRD model better describes this interaction. It shows the involvement of cognitive and emotionally complex tasks which are performed by humans compared with the superficial mimicking actions which are better performed by humanoids. Humanoids usher in human action in their daily business practices (Wirtz et al., 2018; Paluch et al., 2020). This can generate more efficiency in HRM practices (see also Malik et al. 2019a) – "freeing up human workers to be more productive and creative" (Davenport and Ronanki, 2018; p. 10).
Kim et al. (2019) talk about "human–robot collaboration" (HRC) which is associated with robots assisting humans in performing their tasks. This intertwines human agility and machine power (Ajoudani et al., 2018) and enhances productivity (Acemoglu and Restrepo 2017a;b).

In this regard, we state the following:

H_1: Labour productivity is positively associated with humanoid robot adoption

2.2. Labour productivity and CA product innovation routines.

As stated by Acemoglu and Restrepo (2017a;b), humanoids can increase the level of labour productivity in a company, but there are also other external factors which influence productivity, such as interest rates, imports, and offshoring.
As far as labour productivity is concerned, several studies have documented its positive association with innovation. Although it is universally accepted that innovation increases firm performance by enhancing the productivity of capital, empirical evidence has been provided which shows that innovation increases the productivity of labour too. For instance, Brown & Guzmán (2014), by using a mixed analytical and empirical approach based on a Cobb-Douglas production function, find that innovation has a positive effect on labour productivity. In addition, Kurt & Kurt (2015), by applying panel causality and cointegration techniques, obtained a positive relationship between innovation and labour productivity. Finally, Crépon et al. (1998) developed a structural model that explains firms' productivity in terms of innovation output, finding that the former correlates positively with the latter (a review of papers that examine the relationship between product innovation and labour productivity can be found in Hall, 2011 and in Mohnen & Hall, 2013).
Innovation can have both explorative and exploitative features. Generally speaking, explorative product innovation refers to the development of radically new goods or services in order to meet the needs of emerging customers and markets (Benner & Tushman 2003); whereas exploitative product innovation entails the repetition and/or incremental refinement of an innovation that already exists (Alos-Simo et al., 2020; Piao & Zajac, 2016). This allows a company "to compete in mature technologies and markets efficiently, where control and incremental improvement are prized, and

also to compete in new technologies and markets where flexibility, autonomy, and experimentation are needed" (O'Reilly III & Tushman, 2013; p.324). In this circumstance, organizations move from a static and risk averse context to a more agile and ambidextrous environment, and employees are stimulated to "undertake cross-functional collaboration" (Fountaine et al., 2019). It has been demonstrated that ambidextrous companies also have high business performance (Campanella et al., 2016) along with the need of an effective senior team who can achieve a balance between exploitative and explorative routines (Halevi et al., 2015; Luo, et al., 2016).

In a nutshell, a company needs to be ambidextrous, and intertwine exploitative and explorative routines (March, 1991; Junni et al., 2013; 2015). These routines originate from a mix of practices such as sharing, acquiring, and absorbing new knowledge and combining it with the existing knowledge (Crossan et al., 1999; Scuotto & Mueller, 2018; Scuotto et al., 2017). Especially, exploration routines aim to bring new knowledge within a company; whereas, exploitative routines seek to employ existing domains to work on a daily basis (Galunic and Rodan, 1998; McGrath, 2001). Researchers have identified the characteristics of ambidexterity in employees' features, offering a variety of studies (Ahammad, Lee, Malul, & Shoham, 2015; Gibson & Birkinshaw, 2004; Patel et al. 2013). The influence of individuals on ambidextrous organizations is defined as contextual ambidexterity which leverages the skills and abilities of employees in order to combine exploitative and explorative routines (Gibson & Birkinshaw, 2004; Jansen et al., 2008; Kang & Snell, 2009; O'Reilly & Tushman, 2004). Basically, business units explore new ideas in a separate context from those that exploit routines (Tushman and O'Reilly, 1996). Along with those skills and abilities, employees' characteristics, such as educational background, career and goal orientation, "goal avoidance orientation", and cognitive features, leverage the capacity of being ambidextrous (Stokes et al., 2014; Jasmand et al., 2012; Ambos et al., 2008; Yu 2010).

Overall, there is a tendency to preserve existing knowledge and technologies (e.g., exploitative routines) rather than explore new ones. In fact, exploitative routines are enforced by previous achievements. People like to feel familiar with the environment rather take on the risk of the "unknown" (Ahuja and Morris Lampert, 2001; Schon &Argyris, 1996; Levinthal and March, 1993; March, 1991; McGrath, 2001). Exploitative routines serve as the root of a company. They induce a feeling of working in a comfortable zone. People seek to maintain those routines to be more productive (Cohendet & Llerena, 2003; Soosay & Hyland, 2008; Zollo & Winter, 2002).

Therefore, we declare the following:

H_2: Labour productivity is positively associated with exploitative product innovation routines

In product innovation, focusing on the domain of HRM practices with the application of new smart intelligence (e.g., humanoids), exploitative routines can be explicated in the sense of being less emotional and more related to mechanical tasks (Malik, 2019; Huang & Rust, 2018); whereas the need for critical thinking and more human actions can be associated with explorative product innovation. The efficient means to capitalize a on routine is to combine exploitative with explorative routines. Nelson and Winter (1982) define routines as predicable behaviour which should be combined with innovations along with a "culture of trust and empowerment" (Malik et al., (2019a). For instance, in allocating and using companies' resources, the balance between exploitation and exploration routines should come from a senior leader (Gibson & Birkinshaw, 2004; Nemanich & Vera, 2009) (Patel et al., 2013). Along with this, the occupancy time within a company can also impact the level of ambidexterity. In fact, people with a less occupancy time are more prone to generate ambidextrous outcomes (Ambos et al., 2008). Stressing the work of Stoke et al. (2014), career oriented employees are generally inclined to exploit existing routines and explore new ones. This has induced people to be job and assessment oriented (Jasmand et al., 2012) and flexible to market fluctuations. Basically, employees are more skilled to face environmental changes than before. Generally speaking, there are two forms of employees–namely, ambidextrous and goal oriented and "goal avoidance orientated" and ambidextrous. The latter limits the placement of explorative and exploitative routines within a company (Yu, 2010). Nevertheless, along with being goal-oriented, people are ambidextrous if they behave like they are driven by a sense of control and passion (Andriopoulos & Lewis 2009). Besides, from a cognitive viewpoint, those who are self-confident and open to the change are also favourable to ambidexterity. Alongside this, people characterized by analytical thinking and friendly behaviour are ambidextrous (Good & Michel 2013; Huang & Kim 2013). This also occurs when there is a high degree of commitment.

Indeed, it has been demonstrated that businesses' performance depends on employees' skills, commitment, and ability to spot opportunities (Ahammad et al., 2015; Appelbaum et al., 2000; Lepak, Liao, Chung, & Harden, 2006). Furthermore, it calls for the development of relationships based on agility, control, help, and trust (Kang & Snell, 2009; Ghoshal & Bartlett, 1994; Gibson & Birkinshaw, 2004) and triggers a renewal attitude in a company (Jensen et al., 2010). Although the exploitative routines can constrain innovation, explorative ones can encourage them (Stoke et al., 2017; Swart et al., 2019). On this basis, and also by focusing on explorative routines in product innovation (which, according to the extant literature, is one of the main determinants of labour productivity), we consider the following hypotheses:

H_3: Labour productivity is positively associated with explorative product innovation routines

3. Empirical analysis

3.1. *Research context*

We investigated the effect of the humanoid robot adoption on the productivity of labour in an ambidextrous product innovation setting. Specifically, our goal was to perform a meso (that is country level) analysis. Especially, we assessed the effect of the humanoid robot adoption on national (aggregate) labour productivity. In this respect, it is worth observing that the meso-perspective is often adopted in the literature, since several scholars (see, e.g., Hall, 2011 and Kurt and Kurt, 2015) have found it interesting to investigate the labour productivity of whole (national) economies and also human-humanoid interactions in the domain of HRM (Wirtz et al., 2018).

Therefore, since our goal was to investigate labour productivity and the extent to which it is influenced by humanoid adoption and innovation routines at the national level. We employed a regression model where we considered single countries as statistical units by using data as country-specific. In particular, we have taken into account the EU member countries as well as Norway (which is currently not an EU member). The choice of focusing on Europe was motivated by a number of different reasons. First, as recently documented by the International Federation of Robotics (IFR), the robot adoption in Europe has grown more than in America. Moreover, it has been noted that the use of robots is limited in developing countries (e.g., some African regions). Finally, we also excluded China because it is very different from Europe as far as the political, economic, cultural and labour systems are concerned (see, e.g., Luk & Preston, 2016, Zhongping, 2008). Moreover, it should also be pointed out that in recent years the industrial robotization in China has grown fast, but it has not reached explosive levels. For example, according to the International Federation of Robotics (IFR) in 2017, in China the number of robots in the manufacturing industry per 10,000 human employees was only 97, about one third of the number in Germany (see IFR – International Federation of Robotics. Welcome to the IFR Press Conference, 18 October 2018); whereas "The Robot Report" website (Demaitre, 2019), reports that in 2019 the number of robots per 10,000 human employees was "far behind that of other countries at 140". Additionally, as stated by Haenlein & Kaplan (2019), "While China and, to a certain extent, the United States try to limit the barriers for firms to use and explore AI, the European Union has gone the opposite direction with the introduction of the General Data

Protection Regulation (GDPR) that significantly limits the way in which personal information can be stored and processed" (p.12). Conversely, we include Norway because it is one of the most developed countries in Europe.

Furthermore, to measure explorative and exploitative product innovation routines, we consider the fact that a company is prone to modify routines to create a new product (explorative routines) or to maintain the same routines to exploit an existing product (exploitative routines) (Alos – Simo et al., 2020; Piao & Zajac, 2016). Those routines are also viewed through the lens of the SRD Model (Wirtz et al., 2018; Paluch et al., 2020) which describes humanoid tasks as mimicking activities with less of the critical thinking that is associated with humans. In both cases, humanoids are adopted as a support for the daily basic activities of employees (exploitative routines) or product generation (explorative routines). In a nutshell, explorative routines are considered to be more sophisticated and complex in terms of cognitive and emotional tasks; whereas, exploitative routines are recognised to be more for mimicking and repetitive tasks.

As already mentioned, the involvement of both routines calls for an ambidextrous organizational setting (O'Reilly III & Tushman, 2013).

3.2 *Data*

All the data were taken from Eurostat, the database of the Statistical office of the EU (see also the websites cited below). We initially collected data concerning the twenty-eight EU countries and Norway. However, the data for Belgium, Cyprus, Denmark, Greece, and Luxemburg were very incomplete, and thus these countries were excluded. So, we ended up with a dataset of twenty-four countries. For each one of the variables employed (which are described below), we considered the average of the data reported by Eurostat over the time-interval from 2014 to 2019, excluding those years in which data were not available (for some variables, data are only available on a single year).

3.3 *Model and variables*

We tested our hypotheses H_1, H_2, and H_3 by regression analysis. Since our goal is to assess whether labour productivity is associated with humanoid robot adoption, explorative product innovation, and exploitative product innovation routines, we used a baseline regression model (equation [1]) in which labour productivity was set as the dependent variable, whereas humanoid robot adoption, the amounts of explorative product innovation and exploitative product innovation routines were set as the independent variables. Furthermore, we added the following control variables: a variable related to work meaningfulness (namely the feeling of doing a useful job, see Nikolova, and Cnossen, 2020), the working time, and a variable connected with teamwork. These control variables were included because they could have an impact on labour productivity (see, e.g., Bailey et al., 2017; De Spiegelaere & Piasna, 2017; Long & Fang, 2013).

Dependent variable

Labour productivity (*LabProd*) per hour worked was computed by taking the ratio of the real output (the value of all goods and services produced less the value of any goods or services used in their creation) and the total number of hours worked. To have a percentage index, this ratio was further divided by the EU27 average in year 2020 and multiplied by 100 (data are taken from EUROSTAT - Labour productivity per person employed and hour worked).

Independent variables

Humanoid robot adoption (HumRob) is the use of humanoid robots for performing "human–robot collaboration" (HRC), i.e., accompanying human tasks, combining human agility and machine power (Ajoudani et al., 2018; Kim et al., 2019). Such adoption can generate "displacement" but also productivity improvement (Acemoglu and Restrepo 2017a;b).
The IFR classified robots in two main categories, *service* and *industrial* robots. Service robots perform jobs useful for humans, normally in non-manufacturing areas. They mimic and assist humans and usually accomplish tasks that require interaction with people. In contrast, industrial robots fully automate manufacturing tasks and have a limited interaction with people because they perform their tasks in clearly structured environments with external safe-guards.
To measure the humanoid interaction in our baseline regression model we considered service robots because they normally have a larger amount of interaction with people than industrial robots. Specifically, *HumRob* is calculated as the percentage of enterprises that use service robots. Nevertheless, robustness tests were also performed in which *HumRob* was computed based on industrial robots (see Section 4.1) (data are taken from EUROSTAT - 3D printing and robotics).

Explorative product innovation (*ProdInnExplor*) routines: We measure this by the turnover (per person) of innovative enterprises from new or significantly improved products that were new to the market. Precisely, we consider the product-innovative enterprises according to the 2016 Eurostat classification, i.e., the enterprises who introduced, during 2014-2016, "new or significantly improved goods and/or services with respect to their capabilities, user friendliness, components or sub-systems ", quoting from the Eurostat website https://ec.europa.eu/eurostat/cache/metadata/en/inn_cis10_esms.htm). Then, we considered the turnover of innovative enterprises from new or significantly improved products, i.e., the total amount of money that the above enterprises earned in the above three years from the sales of new or significantly improved products that were new to the market. Finally, to obtain the turnover per person, we divided the turnover by the country population (in year 2016). In this way, we obtained an aggregate measure of the radically new production of innovative enterprises, aimed at satisfying the needs of emerging customers and markets, i.e., a measure of the explorative product innovation at the country level.
(The data for the turnover were taken from EUROSTAT - Turnover of product innovative enterprises from new or significantly improved products by NACE Rev. 2 activity and size class. The data for the population were taken from EUROSTAT - Population change - Demographic balance and crude rates at national level).

Exploitative product innovation (*ProdInnExploit*) routines: We measured this by the turnover (per person) of innovative enterprises from only marginally changed or unchanged products. The calculation is analogous to that of *ProdInnExplor* with the only difference being that now we consider the sales of only marginally changed (or unchanged) products. In this way, we obtained an aggregate measure of the only marginally changed or unchanged production of innovative enterprises (i.e., the amount of repetition and/or incremental refinement of innovations that already exist), i.e., a measure of the exploitative product innovation at the country level.
(The data for the turnover were taken from EUROSTAT - Turnover of product innovative enterprises from new or significantly improved products by NACE Rev. 2 activity and size class. The data for the population were taken from EUROSTAT - Population change - Demographic balance and crude rates at national level).

Control variables

As we already mentioned, we controlled for some additional characteristics related to work which could impact labour productivity (see, e.g., Bailey et al., 2017, De Spiegelaere & Piasna, 2017, Long and Fang, 2013):

Feeling of doing a useful work (*UsefulWork*) is the percentage of employed persons who that think that they do useful work.
(Data were taken from EUROSTAT - Employed persons thinking that they do useful work by sex and age)

Working time (TimeWork): This is hours worked in a week. It is the average number of hours worked in a week by a person with full employment. It also includes extra hours, either paid or unpaid.
(Data were taken from EUROSTAT - Hours worked per week of full-time employment)

Team working (TeamWork): This is the attitude towards working in team. It is measured by the percentage of enterprises that consider teamwork as one of the main skills needed for the enterprise development.
(Data are taken from EUROSTAT - Main skills needed for the development of the enterprise by type of skill and size class)

For the reader's convenience, all of the variables employed are listed in Table 1.

Table 1 goes here

3.3 *Baseline regression*

First of all, we used the following baseline regression model:

$$LabProd = \beta_0 + \beta_1 HumRob + \beta_2 ProdInnExplor + \beta_3 ProdInnExploit + \beta_4 UsefulWork + \beta_5 TimeWork + \beta_6 TimeWork + \varepsilon \quad (1)$$

where the β coefficients are computed by standard OLS estimation. By computing the so-called VIF (variance inflation factors), we found that there is no multi-collinearity issue (the mean VIF is equal to 1.77, the largest one is equal to 2.93). Moreover, to test the statistical significance of the computed coefficients, we used Huber-White robust standard error estimation (corrected for heteroskedasticity, see Huber, 1967 and White, 1980).

4. Findings

Descriptive statistics for all the variables of model (1) are shown in Table 2. As we may observe, *LabProd* has a rather large variability among the EU countries, since its values range from 45.67 to 168.85. The variables related to the humanoids' interaction and to product innovation show a large variability too. Specifically, *HumRob* ranges from 3.00 to 11.00, *ProdInnExplor* ranges from 0.07 to 10.86, and *ProdInnExploit* ranges from 0.84 to 33.54 (*ProdInnExploit* also has a large standard deviation, 10.44).

Table 2 goes here

Table 3 reports the Pearson's correlations among the variables in model (1). In particular, labour productivity shows a positive and relatively large, albeit not significant, correlation with the humanoids interaction (0.3681) and a positive and large correlation with both explorative product innovation (0.7370) and exploitative product innovation (0.9290).

Table 3 goes here

The results of the regression analysis are reported in Table 4. First of all, we may observe that the regression is statistically significant, as the p-value associated with the F-statistics is smaller than 0.01. Moreover, the proportion of the variance of the dependent variable that the regression is able to predict is rather high, since the adjusted R^2 is equal to 0.829.

As we may observe in Table 4, the coefficients of both *ProdInnExplor* and *ProdInnExploit* are positive and significant (at the 0.01 level), which indicates that labour productivity is positively associated with both explorative and exploitative product innovation. Instead, the coefficient of *HumRob* is not significant (p-value > 0.1), which suggests that humanoid interaction does not affect labour productivity. Therefore, among our research hypotheses H_1, H_2 and H_3, only H_2 and H_3 are supported by the empirical evidence; whereas H_1 is not supported.

Finally, as far as the control variables are concerned, labour productivity is not significantly associated with any of them.

Table 4 goes here

4.1 *Robustness tests*

We performed some robustness tests to corroborate the results of the baseline regression model (1). First of all, we re-estimated the model using the standard OLS standard error estimator (without correction for heteroscedasticity), and the results obtained are very similar to those obtained previously. Specifically, *HumRob* is still not significant, whereas *ProdInnExplor* and *ProdInnExploit* are positive and significant (at the 0.05 and 0.01 levels, respectively).

Moreover, we used an econometric specification that generalizes the linear regression (1) and allows for error distributions other than Gaussian. In particular, we employed a generalized linear model (GLM) with the same variables as in (1) and a logarithmic link function (see, e.g., Agresti, 2015). The family function was chosen to be the inverse-Gaussian because, after considering several different kinds of family functions (the Gamma and the power function), we found that the inverse-

Gaussian provides the smallest Bayesian information criterion (BIC). The results provided by the GLM, which are reported in Table 5, confirm those of the baseline model (1) because *HumRob* is still not significant whereas *ProdInnExplor* and *ProdInnExploit* are still positive and significant (at the 0.05 0.01 level, respectively). By comparison of Tables 4 and 5, we may see that the GLM yields a relevant improvement with respect to the baseline model, as far as the goodness-of-fit is concerned, since the BIC decreases from 156.306 to -35.330.

Table 5 goes here

Moreover, we also estimated some regression models alternative to the baseline specification (1) in which we used new or additional variables. Specifically, we considered one variable related to the adoption of industrial robots:

Industrial robots (IndRob): the percentage of enterprises that use industrial robots (data taken from EUROSTAT - 3D printing and robotics) and other two variables related to work (at the country level)

Working from home (WorkHome): the percentage of employed persons that at least in some circumstance worked from home (data taken from EUROSTAT - Employed persons working from home as a percentage of the total employment, by sex, age and professional status)

Second job (SecondJob): the percentage of employed persons who have more than one job (data taken from EUROSTAT - Percentage of employed adults having a second job by sex, age groups, number of children and age of the youngest child.

Then, as a further robustness test, we replaced *HumRob* with *IndRob* so that the humanoids' interaction is measured by the percentage of enterprises that use industrial robots. That is, we estimated the following model:

$$LabProd \;=\; \beta_0 + \beta_1 IndRob + \beta_2 ProdInnExplor + \beta_3 ProdInnExploit + \beta_4 UsefulWork$$

$$+ \beta_5 TimeWork + \beta_6 TimeWork + \varepsilon.$$

The results (which we did not tabulate in order to save space) are perfectly analogous to those yielded by model (1). *IndRob* is still not significant, whereas *ProdInnExplor* and *ProdInnExploit* are still positive and significant, both at the 0.01 level (analogous results would also be obtained if we added *IndRob* in the baseline model (1) as a further regressor instead of simply replacing *HumRob*).
Furthermore, in the baseline model (1) we also included *WorkHome* and *SecondJob* among the regressors:

$$LabProd \;=\; \beta_0 + \beta_1 HumRob + \beta_2 ProdInnExplor + \beta_3 ProdInnExploit + \beta_4 UsefulWork$$

$$+ \beta_5 TimeWork + \beta_6 TimeWork + \beta_7 WorkHome + \beta_8\, SecondJob + \varepsilon.$$

The results (again, we did not tabulate them in order to save space) are similar to those obtained using model (1). *HumRob* is still not significant, whereas *ProdInnExplor* and *ProdInnExploit* are still positive and significant at the 0.05 and 0.01 levels, respectively.

Thus, in summary, all of the robustness tests performed confirmed the results of the baseline regression model (1).

5. Discussion

As we summarized in Table 6, the empirical evidence indicates that humanoid robot adoption does not impact labour productivity at meso-level. By contrast, labour productivity is positively and significantly associated with exploitative and explorative routines of product innovators.
The positive effect of product innovation on labour productivity, even at the national level, has already been highlighted in previous work (Crépon et al., 1998; Kurt & Kurt, 2015). However, our empirical analysis also shows that the production of radically new outputs is not the only routine that impacts labour productivity at the country level. In fact, we found that the exploitation (i.e., repetition or marginal modification) of existing products made by innovative enterprises is positively associated with labour productivity as well. This is consistent with more general theories according to which exploitative routines are still capable of improving firms' performance (Malik et al., 2019a; O'Reilly & Tushman, 2008; Raisch et al., 2009; Tushman & O'Reilly, 1996).
Innovation can have both explorative and exploitative features, even if the concepts of exploration and exploitation can lead to different definitions and interpretations (see, e.g., Li et al., 2008). According to Benner & Tusthman (2003), we can regard explorative product innovation routines as those related to the development of radically new goods or services in order to meet the needs of emerging customers and markets. Whereas, in line with Alos-Simo et al. (2020) and Piao and Zajac's (2016) study, exploitative product innovation routines entail repetition and/or incremental refinement of innovations that already exist. This induces an ambidextrous organizational environment aimed at being adaptable to future changes (March, 1991; Junni et al., 2013; 2015). As emerged, the present research has enlarged the debate on humanoid robot adoption in the domain of HRM practices. Looking at this phenomenon from a positive lens (Wilson et al., 2017; Baughin, 2018), there is a need of employing "trainers, explainers, and sustainers" as the new job categories and, accordingly, new HRM practices should be developed so that the use of humanoids can cogitate and absorb new skills (Russell & Norvig, 1996). This is very useful for a long term business orientation (Ramona & Anca, 2013; Armstrong, 2009). Moreover, Malik (2019) also examines the effect of the revolution of Industry 4.0 on HRM. He considers a positive value in employing a mechanical automation for labour productivity. Additionally, we highlight the relevance of explorative and exploitative routines that have emerged from the use of robots.

Table 6 goes here.

Tambe et al. (2019) affirm that the most complex task is to generate a consensus among employees in interacting with such machines. It asks for a randomized decision making process because humanoids are not able to make fair and valuable decisions even if nowadays some robots can accomplish cognitive and emotional tasks (Čaić et al., 2019; Avery, 2019; Huang and Rust, 2018). Yet, they are very effective in undertaking repetitive activities that are usually defined as routines (Lacity & Willcocks, 2016; Davenport, 2017).
This can usher employees into offering faster and more efficient service (Benmark & Venkatachari, 2016) and dedicating more time to customers' care (Barrett et al., 2012). Yet, humanoids also support data collection and analysis even though this also increases the need for more technologically skilled people (Beck & Libert, 2017). Nevertheless, there are many studies which discuss the negative effects that stem from the new era of AI with a focus on humanoids. Bearne (2019) talks about shadow learning which emphasizes the lack of learning opportunities and actions and diminishes the development of a critical thinking. Indeed, Green et al. (2016) have already enforced the need for

specialised training. Barrett et al. (2012) noticed the increasing level of frustration among employees and the reduction of autonomy. Alongside this, Beane and Orlikowski (2015) highlight that humanoids can negatively influence work coordination. Other scholars also state that their intelligence will generate a massive level of unemployment (Acemoglu and Restrepo, 2017; Akerkar and Salomons, 2017). Despite that, our study enforces the positive outcomes derived from humanoid robots' adoption in the organizational ambidexterity context. In fact, such adoption is still not affecting labour productivity which, by contrast, is positively and significantly connected with both radically new and marginally modified/unchanged production of innovative routines. In this way, organizations make technological advancement; whereas employees have "the expected level of the human touch" (see Wirtz, 2019).

5.1 Production and managerial implications

From the managerial standpoint, this has relevant implications that concern those employees who are reluctant to changes but prefer to work in an existing domain. In fact, a pervasive sense of relying on previous achievements persists, and, as stated by Stokes et al. (2014), people are less prone to change their status quo if they are living in a wealthy condition. Nevertheless, the conservative features of these employees can be profitably exploited as well, because managers can assign them exploitative production tasks, which, according to our findings, would be beneficial to labour productivity.

Yet, explorative and exploitative routines can be separate (Malik et al., 2019a), and senior leaders can pursue both of them and find a suitable balance between them (Gibson & Birkinshaw, 2004; Nemanich & Vera, 2009). The exploitative routines involve the development of creativity and critical thinking (Simsek, 2009; Simsek et al., 2009; Good & Michel, 2013; Huang & Kim, 2013). Jasmand et al. (2012) highlight that employees are job and assessment oriented, and they are flexible and responsive to market changes (see also Ambos et al., 2008). Nevertheless, our findings enforce the presence of "goal avoidance orientation" people. This has resulted in constraining contextual ambidexterity (Yu 2010). Indeed, it is widely argued that explorative and exploitative routines should coexist in an innovative environment, and the present study confirms this.

Employees are often characterized as being less agile, passionate, self-confident, and open to those who are ambidextrous (Andriopoulos & Lewis 2009; Good & Michel 2013; Huang & Kim 2013). Overall, people tend to preserve exploitative routines, and they are averse to innovations. Working in a comfortable zone in which everything is known and familiar is still considered primary.

Employees should be able to know the relationship between cause and effect in different situations (Ahuja and Morris Lampert, 2001; Schon &Argyris, 1996; Levinthal and March, 1993; March, 1991; McGrath, 2001). This also affects labour productivity (Cohendet & Llerena, 2003; Soosay & Hyland, 2008; Zollo & Winter, 2002). To this aim, it is crucial that HRM "recruits, trains, motivates, and rewards their employees so as to contribute to business growth" (Sission, 1994, in Kelleher and Perrett, 2001, p.423).

As stated by Levinthal & March (1993) and subsequently by Malik (2019), reluctance creates 'exploration traps'. People desire to justify action and forecast potential outcomes. Nevertheless, referring to Davenport and Ronanki (2018), it is possible to let employees accept new intelligent technologies by introducing a pilot test first and then rolling it out into the whole company. This would gradually gain a sense of acceptance into the organizational environment. Hence, if humanoid robot adoption is still at its infancy, there is a need for better managerial understanding of how to implement it and dramatically improve human resource management.

6. **Conclusions**

The present research contributes to the existing HRM and management literature by investigating the effect of humanoids' interaction on labour productivity and enforcing the persistent relevance of explorative and exploitative routines in product innovation.
Companies are making efforts to be versatile and adapt to the Industry 4.0 revolution. From a managerial point of view, senior leaders need to intervene to promote the most efficient routines and get the optimal balance among them in an ambidextrous setting. In particular, according to our findings, product innovative companies should pursue explorative innovation by developing significantly new goods and services that fulfil the needs of emerging customers and markets (Benner & Tushman 2003) as well as exploitative innovation by engaging in the repetition and/or the incremental refinement of innovations that already exist (Alos-Simo et al., 2020; Piao & Zajac, 2016). More in general, this would encourage new research on the role of senior leaders in an ambidextrous context that incorporates the transforming effect of Industry 4.0 (Malik, 2019). For instance, new rewards or a gradual acceptance can be evaluated as a means for embracing AI introduction into a company (Chang et al., 2009; Davenport & Ronanki, 2018).
Furthermore, there is a general sense of fear and reluctance towards the use of humanoids. The present paper analyses the effect of humanoid interaction on labour productivity, finding no significant association between them. Differently, investigating how robot automatization impacts other firm dimensions (e.g., production costs, product quality and design, process organization and control) could be another interesting line of research. Showing the benefits that stem from robotics (Scuotto & Mueller, 2018) can be an alternative solution for AIs' embracement and acceptance. Qualitative research can be employed because a deep investigation on this new phenomenon is requested. In fact, this theme is so new that new studies are welcome in order to extend our research to different countries or business scenarios (such as family businesses). Alongside this, new analyses can address the need for highly skilled people and how to recruit and engage with them.
To conclude, exploiting the existing domain lingers, and the current business scenario provokes the demand for renewal and a transformative attitude. The research supports a positive opinion of human robot adoption that has the potential to improve human resource management.

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Table 1. Variables' name, description and use

Variable name	**Description**	**Use**
LaborProd	Labour Productivity per hour worked	Baseline regression model
HumRob	Humanoids interaction	Baseline regression model
ProdInnExplor	Explorative product innovation	Baseline regression model
ProdInnExploit	Explorative product innovation	Baseline regression model
UsefulWork	Employees who consider their job useful	Baseline regression model
TimeWork	Time worked	Baseline regression model
TeamWork	Importance of working in team	Baseline regression model
IndRob	Enterprises employing industrial robots	Robustness test
SecondJob	People doing a second job	Robustness test
WorkHome	Employees working from home	Robustness test

Table 2. Descriptive Statistics.

	Mean	**St.Dev**	**Min**	**Max**
LaborProd	91.67	32.97	45.67	168.85
HumRob	5.95	2.46	3.00	11.00
ProdInnExplor	1.97	2.14	0.07	10.86
ProdInnExploit	12.81	10.44	0.84	33.54
UsefulWork	85.36	5.05	75.30	95.90
TimeWork	41.19	1.11	38.97	44.21
TeamWork	43.39	12.05	23.20	72.90

Table 3. Pearson's correlations, ** and * denote significance at the 5% and 1% levels, respectively.**

	LaborProd	*HumRob*	*ProdInn Explor*	*ProdInn Exploit*	*UsefulWork*	*TimeWork*	*TeamWork*
LaborProd	1						
HumRob	0.3681	1					
ProdInn Explor	0.7370***	0.5616**	1				
ProdInn Exploit	0.9290***	0.2667	0.6141***	1			
UsefulWork	0.2640 0.1230	0.2640	0.2640	0.2640	1		
TimeWork	-0.2945	-0.1038	-0.0881	-0.2947	-0.0946	1	
TeamWork	-0.1632	-0.0695	0.0596	-0.1967	-0.0133	0.1454	1

Table 4. Regression results, * denote significance at the 1% level.**

Variable	***β***
Constant	60.250
HumRob	0.667
ProdInnExplor	10.530***
ProdInnExploit	1.579***
UsefulWork	0.444
TimeWork	-0.898
TeamWork	-0.309
F-stat	20.20***
R^2	0.886
Adjusted R^2	0.829
AIC	149.695
BIC	156.306

Table 5. GLM results, ** and * denote significance at the 5% and 1% levels, respectively.**

Variable	***β***
Constant	4.252***
HumRob	0.012
ProdInnExplor	0.132**
ProdInnExploit	0.018***
UsefulWork	0.003
TimeWork	-0.012
TeamWork	-0.002
Deviance	0.003
AIC	15.842
BIC	-35.330

Table 6. Hypotheses tested.

Hypothesis	***Evidence***
H_1: Labour productivity is positively associated with humanoid robot adoption	Not supported by data
H_2: Labour productivity is positively associated with exploitative product innovation	Supported by data
H_3: Labour productivity is positively associated with explorative product innovation	Supported by data