UNIVERSITÀ CATTOLICA del Sacro Cuore

**DIPARTIMENTO DI POLITICA ECONOMICA**

# AI Worker Management technologies in traditional industries

Claudia Collodoro

Lucrezia Fanti

Jacopo Staccioli

Maria Enrica Virgillito

Quaderno n. 56/ January 2026

VP VITA E PENSIERO

Università Cattolica del Sacro Cuore

DIPARTIMENTO DI POLITICA ECONOMICA

# AI Worker Management technologies in traditional industries

Claudia Collodoro

Lucrezia Fanti

Jacopo Staccioli

Maria Enrica Virgillito

Working Paper n. 56 - January 2026

VP VITA E PENSIERO

*Claudia Collodoro, Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy*

✉ claudia.collodoro@unicatt.it

*Lucrezia Fanti, Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy − Institute of Economics, Sant'Anna School of Advanced Studies, Pisa, Italy*

✉ lucrezia.fanti@unicatt.it

*Jacopo Staccioli, Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy − Institute of Economics, Sant'Anna School of Advanced Studies, Pisa, Italy*

✉ jacopo.staccioli@unicatt.it

*Maria Enrica Virgillito, Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy − Institute of Economics, Sant'Anna School of Advanced Studies, Pisa, Italy*

✉ mariaenrica.virgillito@unicatt.it

Dipartimento di Politica Economica
Università Cattolica del Sacro Cuore – Largo A. Gemelli 1 – 20123 Milano
Tel. 02-7234.2921

✉ dip.politicaeconomica@unicatt.it

https://dipartimenti.unicatt.it/politica_economica



ISBN digital edition (PDF): 978-88-343-6217-4

www.vitaepensiero.it

**Abstract**

This work provides a comprehensive large-scale analysis of artificial intelligence-based worker management (AIWM) systems from an industry-wide exposure perspective focusing on traditional industries. We begin by examining the knowledge production underlying these workforce management tools and leverage technology patent-classification to identify their dynamics and specific features. For this purpose, we use patent data retrieved from Orbis Intellectual Property covering the years 1975 to 2022, considering patents filed with both the EPO and the USPTO. Furthermore, to identify patents related to AIWM heuristics, we retrieve their full text from Google Patents and conduct a textual analysis using a dependency parsing algorithm. Finally, using the dictionary of human tasks provided by O*NET, we construct a measure of exposure to AIWM systems for individual human tasks and occupations. Linking the technological and labour market domains, we find that the professions most exposed to AIWM systems are those at the top of organisational hierarchies.

**JEL classification:** O14, O33.

**Keywords:** Artificial Intelligence Worker Management, Sector-level Analysis, Patenting Activity, Techno-organisational Change.

## 1 Introduction

Artificial intelligence-based worker management (AIWM) technologies are technological artefacts designed to algorithmically and automatically control the workplace division of labour. These technologies encompass work management systems that monitor operations at workstations and, through data collection, rapidly process the information needed for semi-automated decisions or to support decision-makers' choices (EU-OSHA, 2022a). In other words, these AI-powered digital devices differ from similar tools in that they automate decision-making processes, either wholly or in part. Regardless of whether it is technically feasible or legally permissible to make decisions fully autonomous from human intervention, the automation of data collection and processing, already widespread and now enhanced by AI algorithms, warrants careful reflection.

In recent years, the deployment of AI worker management tools has been greatly accelerated by the outbreak of the COVID-19 pandemic and the subsequent surge in remote work (Allyn, 2020; Adams-Prassl, 2022). Moreover, while those tools are often hailed as enhancing efficiency and performance, they risk placing a heavy burden on working conditions, leading to various health risks such as burnout, work-related stress, and psychosocial harm (Urzì Brancati and Curtarelli, 2021; Urzì Brancati et al., 2022). Despite the controversies briefly mentioned, the technology itself is neither inherently good nor bad (Aloisi and De Stefano, 2022). In fact, the use of such tools could be beneficial in the workplace if there were greater awareness of how they function and stronger involvement of workers and their representatives in managing their introduction (Mateescu and Nguyen, 2019; Gallagher et al., 2025). In principle, these systems could serve as instruments for tasks upgrading and potentially expand workers' roles within the workplace if employees are reassigned to more complex, non-automatable activities. However, existing case-study evidence indicates that many applications of these systems tend to amplify worker risks rather than mitigate them. These technologies are therefore redefining the employer-employee relationship, expanding managerial prerogatives, and making workforce control increasingly pervasive. In this sense, they display several elements of continuity with the broader digitisation of production processes observed in recent years.

The scientific literature in this domain is largely grounded in qualitative analyses that examine in detail the effects of algorithm-driven management systems on organisational structures and working conditions (see, among others, Wood, 2021; Woodcock, 2022; Rani et al., 2024). Complementing this body of work, several studies use cross-sectional survey data to map both the degree of advancement in the adoption of such systems and their psychosocial implications, whether at the workplace level (Urzì Brancati and Curtarelli, 2021) or at the level of individual workers (Fernández-Macías et al., 2023). Moreover, recent OECD employer surveys provide cross-national comparisons of the implementation of such systems, offering insights into how their diffusion and impacts vary across institutional and socio-economic contexts (Milanez et al., 2025). In contrast, this paper conducts a large-scale quantitative analysis to address the following questions. (i) How does the development of AIWM technologies differ across specific sectors and who are the major actors in each field? (ii) Are there sector-specific patterns in the heterogeneous applications of AIWM tools? (iii) Does the position of a sector, either upstream or downstream, affect the rate and trajectory of technological development? (iv) Which human tasks and occupations are most exposed to AIWM?

We study AIWM technologies by analysing detailed patent data across four distinct industrial sectors, which, for the sake of brevity, we hereafter refer to as *traditional* sectors (Lippert et al., 2023). By this term, we denote highly labour-intensive industries whose production processes are strongly standardised and digitalised, and which do not involve forms of work organisation mediated by digital platforms. Accordingly, we examine a technologically advanced manufacturing sector, namely automotive (NACE 29), alongside three service segments that are closely interrelated with industrial production and market operations. Specifically, these include logistics and transportation services (NACE 52 and 53), as well as business-oriented services such as employment activities (NACE 78) and administrative and support services (NACE 82). Together, these sectors form a representative sample of archetypal high-technology manufacturing and key service domains that provide essential infrastructure, coordination, and organisational support to the broader economy. Moreover, as demonstrated by EU-OSHA (2022b), AIWM systems are increasingly diffusing into industries where production processes are already highly standardised. In addition, the four sectors under investigation represent a non-negligible share of employment, amounting to roughly 11% of overall jobs in the United States.[1]

The rationale for further examining the dynamics of patenting activity in these sectors is grounded in technological specificities and heterogeneity in sectoral knowledge-production trends, as well as in the occupational structures characterizing these sectors. Furthermore, we focus on these specific sectors by drawing on the growing body of qualitative studies identifying them as key traditional industries where algorithmic management practices are already widespread. In this context, the adoption of AI-enhanced digital tools is expected to affect an increasing number of workers who already face work intensification and a general decline in job quality. Transcending the scope of digital platforms, the automation of decision-making processes in traditional jobs is also expected to trigger a reconfiguration of organisational hierarchies. The extent and direction of this hierarchical reconfiguration are likely to depend on stakeholder participation in managing adoption and use, as well as on the progress of social dialogue. An other motivation concerns the varying degrees of involvement of these four sectors in the production of technological knowledge. Indeed, the automotive sector is a technological frontier industry, often both a developer and adopter of technologies essential to its production processes, whereas the same cannot be said for the other sectors (NACE 52 and 53, 78, and 82). In contrast, logistics, employment, and business support services can more readily be viewed as target industries for ICT companies. Moreover, these sectors are characterized by a high incidence of standardized blue-collar and white-collar occupations. Considering the occupational composition of these sectors in the North American context, we observe that workers employed in transportation and moving activities, administrative and office support roles, and production-related occupations are overrepresented relative to the overall occupational structure. Notably, these same occupations are those most likely to be targeted and managed through algorithmic management systems. Thus, the growing number of workers likely to be exposed to such management systems, along with the reconfiguration of organisational hierarchies and the diverse applications of these technologies in traditional industries, motivated us to begin our investigation with these sectors. Thus, the paper contributes to bridging the gap between case-based evidence on algorithmic management and quantitative measures of technological exposure.

To this purpose, we provide quantitative information on the innovative activity and potential applications of AIWM technologies. In this regard, we identify not only the most relevant actors in terms of innovative activities, but also advance the characterisation of the scope of application and knowledge base embedded in these technologies. After identifying the technology of interest through the Cooperative Patent Classification (CPC), we analyse the textual content of patents to identify functions associated with worker activities and tasks. Our methodology broadly builds on the work of Staccioli and Virgillito (2025).

To conduct this empirical analysis, we construct a new dataset beginning with sector-level patent data from Orbis-IP, which we then match with the full text of patents available in Google Patents. In this way, starting from the universe of patents related to each industry, we gradually narrow our focus on the AIWM technologies. Technologies are initially screened based on CPC codes and subsequently examined through textual analysis. Drawing on information from O*NET, we implement a cosine-similarity approach to identify the tasks most

[1]Authors' calculations based on data from the Occupational Employment and Wage Statistics (OEWS), U.S. Bureau of Labor Statistics.

exposed to AIWM technologies. We then replicate the analysis at the occupational level. We anticipate that these workforce management systems will have a stronger impact on occupations characterised by a high degree of *routinisation*. In line with the digitalisation processes of the past decade, we further expect manual jobs to be increasingly governed by management algorithms through centralised organisational and control practices. Conversely, the other side of the coin concerns occupations responsible for operating these management systems. As highlighted in the existing literature, the exposure of *middle-management* roles to AIWM algorithms appears equally pervasive. These digitally enabled solutions, enhanced by artificial intelligence and equipped with data-driven learning capabilities, are designed to optimise and, in some cases, automate non-strategic organisational decision-making processes traditionally performed by intermediate positions within organisational hierarchies.

On this basis, we examine whether and how knowledge production for AIWM systems takes place within the aforementioned sectors, outlining their various scopes of application and potential impacts on different occupations. Finally, by analysing the U.S. employment structure, we provide insights into the size of the workforce exposed to AIWM systems, disaggregated by occupational category and federal state.

Using our patent identification strategy, we identify algorithms primarily designed to manage work processes, evaluate workers and enable real-time monitoring. With little differentiation across sectors, these inventions aim at efficiently juggling work processes and optimally matching workers to specific job tasks to enhance corporate performance. When we subsequently conduct the similarity analysis with work actions, we consistently identify job tasks related to the streamlining of organisational and decision-making processes, as well as the enhancement of coordination across different functions. These dimensions closely reflect the heuristics of AI-based workplace management systems, even when aggregated at the occupational level. According to our findings, the occupational groups most exposed to algorithmic management systems include production, engineering, and specialist health. This result is consistent with the existing literature on the subject, while also suggesting distinct implications for each of these occupational categories. For workers in subordinate or lower hierarchical positions within firms, high levels of exposure are likely to translate into greater subjection to algorithmic management tools, often accompanied by limited decision-making autonomy. By contrast, in the case of engineering professions, such exposure may primarily reflect their involvement in the design and development of the systems themselves. Furthermore, with reference to the occupational structure of the US, our analysis indicates that workers most exposed to AI-based workplace management systems are geographically concentrated in the so-called *Rust Belt* region, encompassing the industrial areas surrounding the Great Lakes. This spatial distribution reflects the historical legacy of a strong manufacturing base in these states.

Hence, the present work contributes to the emerging quantitative literature on algorithmic management by (i) mapping the production of AIWM technologies across traditional industries, (ii) identifying their impact on workers' tasks and occupations, and (iii) distinguishing between developer and user exposure, thereby clarifying the heterogeneous effects of AIWM systems on the workforce.

The remainder of the paper is organised as follows. Section 2 reviews the extant literature on the subject. Section 3 presents the methodology of our empirical analysis, whose findings are described in Section 4. Results are further discussed in Section 5, alongside concluding remarks.

## 2 *Literature Review*

According to the definition provided by the European Agency for Safety and Health at Work (EU-OSHA, 2022b), "AI-based worker management [...] refers to a worker management system that gathers data, often in real time, from the workplace, workers, the work they do and the (digital) tools they use for their work, which is then fed into an AI-based system that makes automated or semi-automated decisions [...] on worker management related questions". From this report, we can identify at least two key aspects of AIWM tools. On the one hand, there is a clear continuity with the digitalisation process that has transformed workplaces, particularly over the last decades. This technological development entails transforming work process information into digital format (Cirillo et al., 2021; Krzywdzinski, 2021; Cirillo et al., 2023) enabled by the introduction of interconnected smart devices and sensors for data collection, such as *wearable devices* (see, among others, Krzywdzinski et al., 2022; Caria et al., 2023), and data analytics tools. In parallel with the expansion of digital infrastructure (Calvino and Fontanelli, 2023), the advent of software algorithms has facilitated the emergence of data-driven approaches to workforce management (Lee et al., 2015). On the other hand, the novelty introduced by AIWM technologies lies in (i) varying degrees of autonomous decision-making authority and (ii) predictive capabilities regarding the work process (such as task and shift allocation) and workers' performance.

Autonomy in decision-making is what characterises AIWM algorithms. These algorithms are used to automate managerial functions, although at present AIWM tools primarily complement managerial work across various functional areas of business operations (from recruitment and hiring to the coordination of work activities). Such "intelligent" algorithms are equipped with sensors that allow them to interact in real time with their environment, continuously readjusting and reorienting tasks in line with employers' interests (Kresge, 2020). The discretion and autonomy of the workforce are therefore likely to be eroded, potentially leading to a reconfiguration of the employer-employee relationship within productive organisations. Consequently, the progressive withdrawal of workers from organisational control ultimately expropriates them of their knowledge of the production process (Kellogg et al., 2020). The resulting degradation of labour is particularly evident in warehouses (Massimo, 2020), where, due to "chaotic storage", retail workers are entirely directed by algorithms and stripped of their autonomy (Delfanti, 2021). Evidence of this progressive loss of autonomy is also found in Cox and Oosterwijk (2024). Analysing regular workplaces across Scandinavian countries, the authors discuss how the use of algorithmic management tools is reshaping the balance of power between employers and employees. Furthermore, alongside the reconfiguration of decision-making authority, there are risks related to the expansion of pervasive control and the possibility of real-time performance monitoring. The availability of such granular data, used for ranking workers, further enables predictions about their future performance. Evidence of these practices is also highlighted in the ILO report on *Algorithmic Management Practices in Regular Workplaces* (Rani et al., 2024). In the inquiry, Rani et al. (2024) note that "A smaller proportion of companies are also using data analytics and AI to make real-time predictions and conduct scenario evaluations".

The widespread use of software algorithms capable of collecting and processing large amounts of data and optimising resource use has been observed since the 1990s. As briefly mentioned earlier, the use of algorithmic management finds its first found full realisation in digital platforms, which form the foundation of the platform-mediated gig economy (Kenney and Zysman, 2016; Garcia Calvo et al., 2023).[2] Alongside the ever-increasing number of platform workers worldwide,[3] we now observe the deployment of the same software algorithms in traditional production organisations. Logistics, retail, call centres, service industries, and healthcare facilities are among the traditional sectors most affected by the adoption of these intelligent algorithms (EU-OSHA, 2022b).

The proliferation of digital devices and algorithmic management in traditional sectors has led some scholars to question the possible *platformisation* of regular workplaces. Among others, González Vázquez et al. (2024) associate the forms of worker management and monitoring increasingly observed in traditional sectors with extensions of those characteristic of digital work platforms. What all industries have in common is that

[2] A large body of literature documents the rapid recent development of digital platforms, both in terms of business models (ranging from open source to freemium, among others) and application sectors (from housing to transport, as well as education and care services).

[3] See official surveys presented in the ILO (2024) report "Realizing decent work in the platform economy".

the implementation of algorithmic management systems requires extensive and widespread use of digital tools (Calvino and Fontanelli, 2023), such as wearable technologies (Krzywdzinski et al., 2024) and the Internet of Things (Urzì Brancati et al., 2022). In line with the digitalisation process, Baiocco et al. (2022) identify the centralisation of knowledge and control, along with the redefinition of tasks and roles, as two key channels through which the introduction of algorithmic management affects traditional workplaces. However, it is worth noting that the rate of deployment and the scope of application of these systems vary widely across sectors (Mateescu and Nguyen, 2019). In addition, the scope of management algorithms in regular workplaces slightly differs from that in digital platforms, as they must interact with pre-existing rules and organisational schemes. This heterogeneity generally depends on sectoral specificities and more specifically on the techno-organisational capabilities of individual workplaces. Furthermore, algorithmic management practices in traditional jobs enhance the decision-making process rather than fully automate it (Wood, 2021). As highlighted by Lippert et al. (2023), algorithmic management in manufacturing and warehousing is primarily used to complement managerial tasks along the organisational hierarchies and is highly context-dependent.

Through a field analysis in the logistics sector, Krzywdzinski et al. (2025) aim to broaden the control-resistance perspective that dominates the debate on the digitisation of traditional sectors and, more specifically, the spread of algorithmic management practices. According to the authors, the use of such tools creates opportunities for cross-functional collaboration between different technical profiles (from data analysts to process engineers) and the workforce. In this way, the implementation of management algorithms can enhance workflow efficiency and improve ergonomic aspects, rather than exacerbating pervasive control of the workforce. Furthermore, Krzywdzinski et al. (2025) point out that this worker-friendly approach to the use of intelligent algorithms is closely related to the German regulatory framework on which their analysis is based. By contrast, Mateescu and Nguyen (2019) take the opposite view, stating that "features of algorithmic management expand the scope, scale, and purpose of surveillance and data collection".

Furthermore, the use of intelligent algorithms is becoming increasingly widespread also in human resource management. The process of identifying and selecting candidates' résumés is now frequently carried out through the use of AI algorithms. At this stage of the selection process, employers may therefore delegate a substantial portion of decision-making to algorithmic management tools. While this automation has improved the efficiency of HRM tasks, the use of such algorithms often ends up reproducing racial and gender biases or stereotypes. As noted by Mujtaba and Mahapatra (2019), "Amazon ended its AI-based candidate evaluation tool because it was shown to discriminate against female candidates". In other words, algorithmic management of the workforce is increasingly enabling employers to sort, target, discriminate against, and ultimately punish workers. Beyond its immediate implications for workers, the systematic collection of workforce data within proprietary platforms has itself become a highly profitable enterprise for software developers and service providers (Mateescu, 2023). These actors are now positioned to reshape organisational structures and managerial practices in ways that extend far beyond traditional forms of supervision. At the same time, such developments pose serious risks to workers' privacy and raise critical questions regarding the ownership, governance and ethical use of those data. The candidate assessment phase is also increasingly being entrusted to AI-based algorithms, which reduce the time of video and telephone interviews and ultimately accelerate the overall recruitment process (Jarrahi et al., 2021). Nevertheless, some studies emphasise how AI-augmented tools can improve recruitment practices, as "The application compares the interviewed applicants to the top talent employees in the company and finally suggest the best applicants to recruiters" (Johansson and Herranen, 2019). Moreover, hiring and firing decisions are sometimes based on performance rankings generated by AIWM tools that meticulously monitor the work process. Such algorithmic management of human resources is likely to significantly increase workplace stress and ultimately deteriorate the overall quality of work. This is particularly

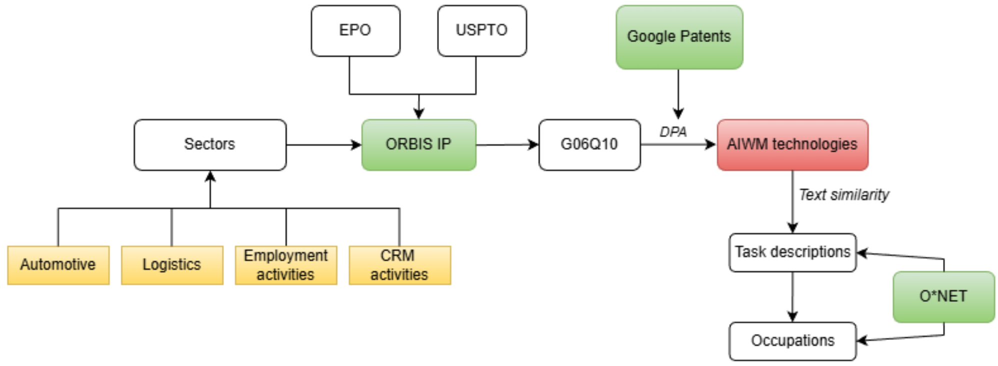



Figure 1: Workflow of our methodology. Green boxes denote data sources. Yellow blocks refer to the analysed sectors. Red frame for the final set of patents comprising the AIWM technologies.

evident in logistics and warehousing, where the accelerated pace of work is often deemed incompatible with basic human needs, as illustrated by the waves of protests in Amazon's warehouses (Dzieza, 2020). While most existing studies rely on qualitative or case-based evidence, the present paper aims to provide a quantitative mapping of the specific industries outlined above, assessing the extent to which AI-based workplace management (AIWM) technologies have diffused across these sectors and and the degree to which the employed workforce is exposed to their implementation.

## 3 *Data and Methodology*

The present methodological section builds upon the approach proposed by Staccioli and Virgillito (2025). The methodology relies on multiple data sources: Orbis Intellectual Property provides firm-level patent information; patent texts have been retrieved from Google Patents; and O*NET offers detailed descriptions of human tasks, allowing the information to be aggregated to the occupational level. Finally, data on the occupational composition of the US labour force and its geographical distribution are drawn from the Occupational Employment and Wage Statistics (OEWS) compiled by the US Bureau of Labor Statistics. The combined use of these databases enables us to construct three key groups of indicators: (i) patent shares, (ii) cosine similarity by task, and (iii) exposure by occupation and state.

The workflow of this sectoral-level analysis is illustrated in Fig. 1. It summarises the databases used (green boxes) and the sectoral dimension of patenting activity in algorithmic management technologies (yellow blocks); the red frame identifies the final subset of patents that incorporate AIWM heuristics. Adopting this sectoral perspective, we begin our inquiry with data from Orbis-IP, which enable us to identify firms operating within each individual industry. From this database, we obtain information on patents filed with the European Patent Office (EPO) and the United States Patents and Trademarks Office (USPTO) between 1975 and 2022. We then leverage the Cooperative Patent Classification (CPC), assigned by the patent authority to describe the technological domain of the invention, focussing on class `G06Q`, which refers to "information and communication technology [ICT] specially adapted for administrative, commercial, financial, managerial or supervisory purposes; systems or methods adapted for administrative, commercial, financial, managerial or supervisory purposes".

To identify AIWM technologies, we perform a textual analysis by scanning the full text of the patents using a dependency parsing algorithm (see Appendix A.2 for details). In line with previous studies (Rughi et al., 2025), we move beyond the simple identification of patents based uniquely on the co-occurrence of relevant keywords at the sentence level. Instead, we employ a dependency parsing algorithm to capture the

$$
\underbrace{\begin{bmatrix} \textit{`administer'} \\ \textit{`assess'} \\ \textit{`control'} \\ \textit{`direct'} \\ \textit{`evaluate'} \\ \textit{`manage'} \\ \textit{`monitor'} \\ \textit{`predict'} \\ \textit{`rate'} \\ \textit{`record'} \\ \textit{`surveil'} \\ \textit{`track'} \end{bmatrix}}_{\text{verbal predicate}} \times \underbrace{\begin{bmatrix} \textit{`employee'} \\ \textit{`human'} \\ \textit{`labor'} \\ \textit{`manpower'} \\ \textit{`operator'} \\ \textit{`person'} \\ \textit{`technician'} \\ \textit{`worker'} \\ \textit{`workforce'} \end{bmatrix}}_{\text{direct object}} \times \underbrace{\begin{bmatrix} \textit{`action'} & \textit{`function'} \\ \textit{`behavior'} & \textit{`hazard'} \\ \textit{`biometric'} & \textit{`health'} \\ \textit{`compliance'} & \textit{`intensity'} \\ \textit{`efficiency'} & \textit{`keystroke'} \\ \textit{`emotion'} & \textit{`location'} \\ \textit{`facial'} & \textit{`mistake'} \\ \textit{`performance'} & \textit{`posture'} \\ \textit{`productivity'} & \textit{`risk'} \\ \textit{`safety'} & \textit{`screen'} \\ \textit{`stress'} & \textit{`task'} \\ \textit{`voice'} & \textit{`wellbeing'} \end{bmatrix}}_{\text{object attribute}}
$$

Figure 2: Triplets of keywords for the AIWM text query.

underlying semantic structure. This approach allows to more effectively filter out *false positives*, i.e. patents that contain the relevant keywords but fail to embed AIWM heuristics (examples are provided in the Appendix). We specifically look for triplets of specific keywords at the sentence levels.

Listed in Fig. 2, they consist of verbal predicates, direct objects and additional attributes that refer to systems and software designed to automating managerial prerogatives, ranging from directing and controlling work to enhancing production process and workflows. For example, we include predicate such as *monitor*, *direct*, or *rate*, which refer directly to *workers* or the *workforce* and are associated with attributes such as *compliance* or *productivity*. Following the EU-OSHA (2022b) report, we identify three main scopes for these technologies: (i) increasing workforce and workflow efficiency and productivity, (ii) improving the decision-making process, and (iii) enhancing workers' health, safety, and well-being. As already noted by Staccioli and Virgillito (2025), the first two scopes of application may partially overlap.

Once the pool of patents related to algorithmic management technologies is obtained, we link their full text with task-related information from O*NET. Using cosine similarity (see Appendix A.3 for further details), we obtain a quantitative measure of the exposure of AIWM technologies to individual tasks. Subsequently, O*NET enables the aggregation of 19,281 tasks to the level of 923 SOC2018 occupations, allowing us to measure exposure across organisational hierarchies. Furthermore, we use cosine similarity values to weight the share of workers most exposed to these new systems relative to the US occupational structure. The OEWS database provides detailed information on the number of employees by full-digit occupation, industrial sector of employment (up to the 5-digit NAICS level), and geographical location. We therefore analyse workforce exposure to AIWM technologies across the 22 2-digit occupational categories and US states.

This study adopts a methodological framework designed at elucidate the potential repercussions of AIWM systems development on employment dynamics. Although the analysis of intellectual property does not offer direct evidence of the adoption or diffusion of the technologies under scrutiny, it nonetheless yields analytically valuable insights into the technological trajectories shaping the sectors concerned. By moving from a comprehensive mapping of the sector-level patent universe to a systematic assessment of occupational exposure, the approach enables a nuanced examination of both the convergences and the divergences in the scopes of application of these systems across sectors.

| | | Automotive | Logistics | Employment act. | Business Support act. |
|---|---|---|---|---|---|
| # | overall | 606,826 | 21,548 | 2,204 | 351,676 |
| # | G06Q10 | 4,756 | 1,547 | 222 | 6,877 |
| % | G06Q10 | 0.78% | 7.18% | 10.07% | 1.96% |
| # | AIWM | 88 | 24 | 23 | 141 |
| % | AIWM | 0.014% | 0.1% | 0.98% | 0.04% |

Table 1: Summary of patent magnitudes in levels (#) and percentage (%) for each of the target sectors.

## 4 *Results*

In this section, we present the results of the empirical analysis. Specifically: (i) in the first part, we use industry-level patent data and, by exploiting CPC codes, identify patents related to algorithmic management technologies and map the main companies active in the four sectors under study; (ii) in the second part, we present the results of textual and similarity analyses, ultimately providing a quantitative measure of the degree of exposure of of tasks and occupations to AIWM technologies; (iii) in the final part, we report evidence on the exposure of the US employment structure to AIWM systems.

### 4.1 Sectoral trends and actors

To identify the patents included in the analysis, we begin by selecting the firms active in each of the four sectors and retrieving their corresponding BvD (Bureau van Dijk) identification numbers as assigned by Orbis. Using Orbis IP, we then collect the patents in which these BvD codes appear as *applicants*, restricting the dataset to applications filed with the EPO and USPTO. Consistent with Damioli et al. (2021), we use the BvD codes of *applicants* to link patent-level with firm-level information. To avoid double counting, we rely on *patent family* identifiers throughout the analysis. We also identify the global ultimate owners to account for corporate ownership structures. For instance, the patent titled *Method of Rating Employee Performance* (`US6853975B1`, also discussed below) is included in our dataset because its applicant is the Ford Motor Company, a holding active in the automotive sector; the same logic applies to all other observations. Applying this identification strategy, Tab. 1 presents sector-level descriptive statistics. The table reports information on the entire universe of patents associated with each industry and on the subset of patents specifically related to algorithmic management. More precisely, we first examine the total number of patents in each sector (column "# patents"), then the absolute and relative shares of patents classified under the technological category `G06Q10`, and finally those patents containing AIWM heuristics as identified through textual analysis.

With regard to industry-specific dynamics, the most intense patenting activity is observed among firms operating in the automotive manufacturing sector and in business services. In automotive, a substantial share of patenting concerns propulsion systems, engines, and, more recently, electrical systems designed to support the sector's ecological transition (Agostini and Caviggioli, 2015; Mazzei et al., 2023). In business services, as we will discuss further below, much of the patenting activity concerns inventions related to payment methods and system architectures. Consequently, although patenting activity in these domains is considerably broader than in the other sectors under analysis, the share of algorithmic management systems remains rather limited. In particular, only 0.78% and 1.96% of patents fall within our first restriction (6-digit CPC code `G06Q10`), which refers to ICT systems designed for management purposes, in the automotive and business services sectors, respectively. Moreover, the textual analysis yields a share of patents incorporating AIWM heuristics amounting to 0.014% for NACE 29 and 0.04% for NACE 82 (see columns (i) and (iv) in Tab. 1). By contrast, in logistics and

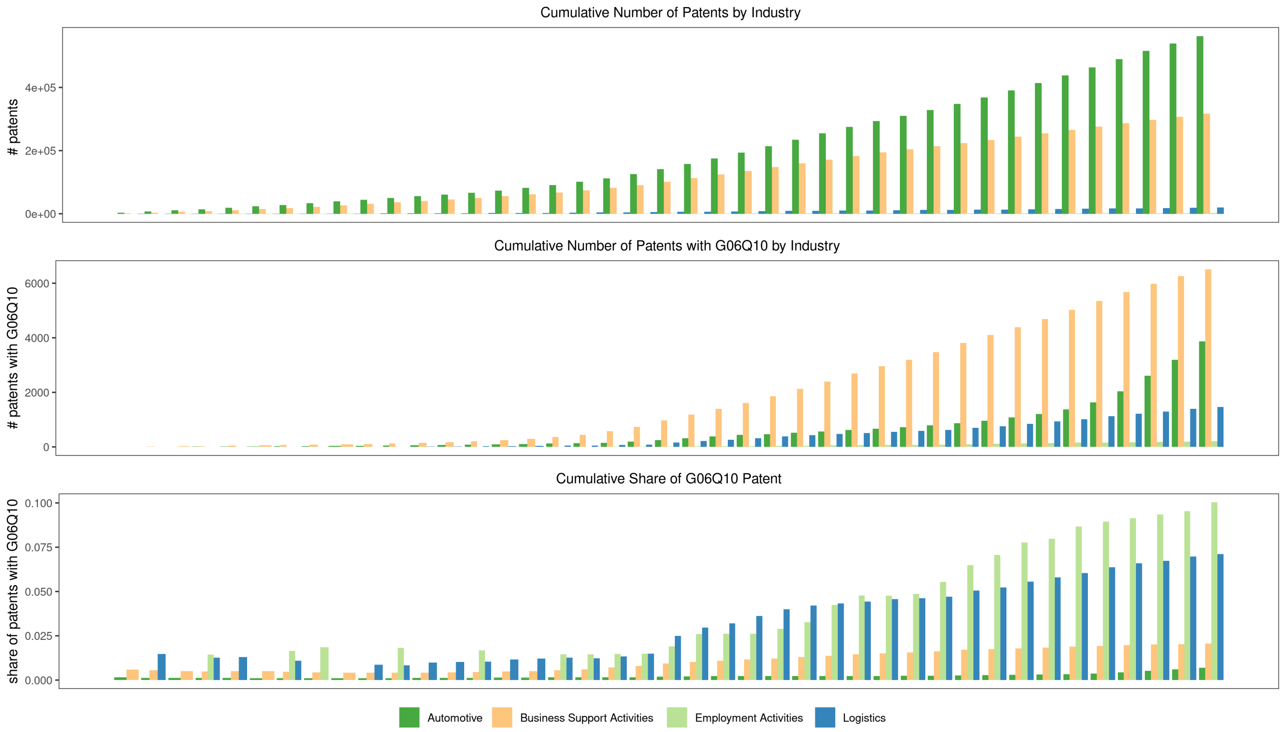



Figure 3: Time evolution of patenting activity in each of the target sectors, considering the cumulative number of all patents (top), the cumulative number of `G06Q10` patents (middle), and the share of the latter over the former (bottom).

employment services we observe a generally more modest level of patenting activity overall (first row, columns (ii) and (iii) in Tab. 1). However, these sectors display slightly higher shares of patents when the subsequent restrictions for the identification of AIWM heuristics are applied. Specifically, we find that approximately 7.18% of patents in logistics and 10.07% in employment services carry a 6-digit CPC code equal to `G06Q10`, while 0.1% and 0.98% encompass AIWM heuristics.

Figs. 3 illustrate the temporal dynamics of patenting activity in each individual sector. As noted in several other sources (WIPO, 2024), we observe a substantial increase in patenting activity in recent years, particularly since 2000. In line with the information provided by the descriptive statistics, the automotive sector is, in absolute terms and over the analysed time-span, the most active in patenting (dark green in the chart). During the period considered, the number of patents increased from fewer than 5,000 in the 1980s to more than 20,000 in 2020. Business support activities follows in terms of volume, showing an increase from around 2,000 patents in 1980 to about 10,000 in 2020 (yellow bars). In absolute terms, patenting activity in logistics and employment services is significantly more modest and stable: the former increases from approximately 500 patents in the 1990s to around 700 in 2020, while the latter remains nearly unchanged at around 50 patents per year over the period considered (blue and light green in the plot). The upper row of Fig. 3 reports the cumulative absolute number of patents by industry. In the next two rows of Fig. 3, we observe, in both cumulative absolute and relative terms, a pronounced upward trajectory in patents with at least one CPC code assigned to the technology class `G06Q10`. The analysis indicates that, in cumulative absolute terms, business support activities account for the largest number of `G06Q10` patents, whereas in cumulative relative terms, employment services display the highest share of `G06Q10`. Specifically, the number of patents in business support activities increased substantially, rising from approximately 200 in the 1990s to more than 7,000 by 2020. In relative terms, this corresponds to an increase from just above 0.5% in 1990 to around 2.05% in 2020. In the employment services sector, the absolute number of patents in `G06Q10` was relatively limited at the outset of the observation period;

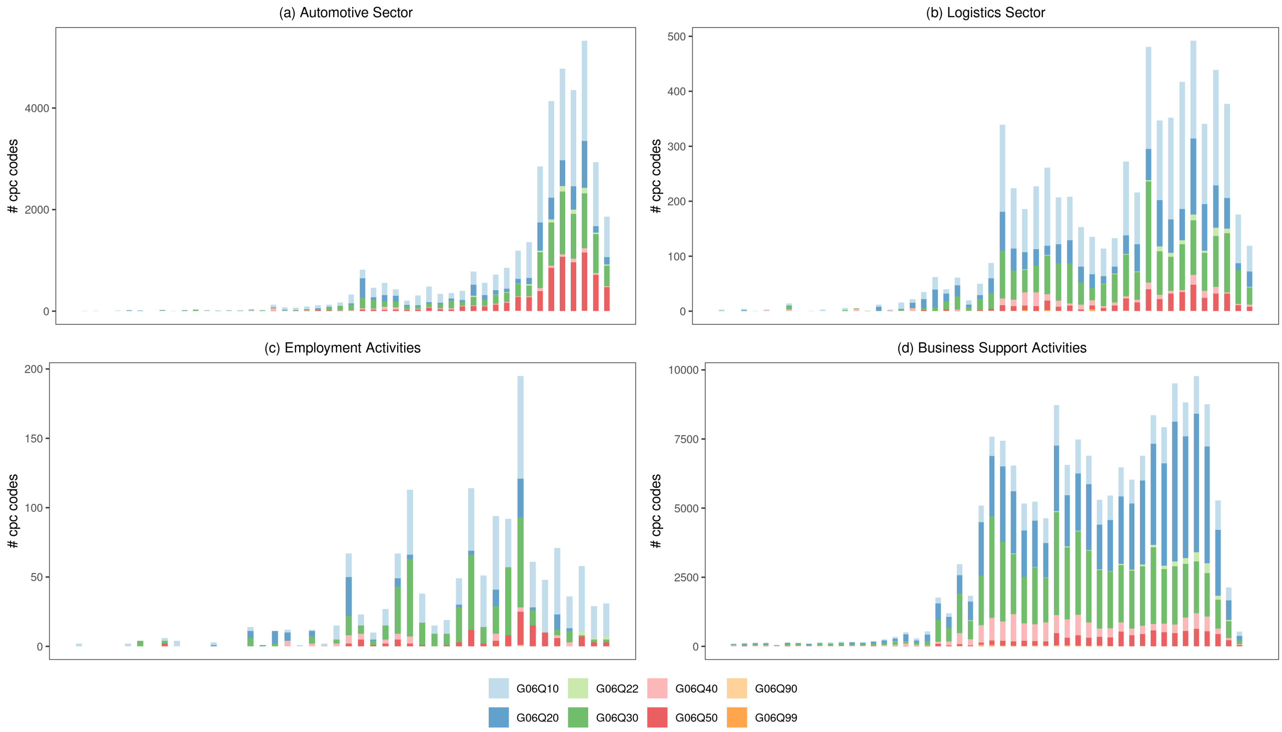



Figure 4: Breakdown of CPC group `G06Q` per year and sector under study.

however, patenting activity has increased markedly over time. Specifically, the number of patents increased from fewer than 20 in the 1990s to just over 250 by 2015. In relative terms, the technological class `G06Q10` corresponds to approximately 10.82% of the cumulative share. In the automotive industry, we observe a substantial increase in the absolute number of patents classified under `G06Q10`, rising from fewer than 100 in the 1990s to about 5,000 in 2020. This upward trend is also reflected in relative terms, with the share expanding from below 0.1% to just above 0.8%. Overall, this corresponds to a cumulative growth rate of approximately 7% in the `G06Q10` technological subclass. Turning to the logistics sector, we again observe an increase in absolute terms, from fewer than 50 patents classified under `G06Q10` in the 1990s to more than 1,500 around 2020. In percentage terms, the share increased from below 2% of total patenting activity in the early 2000s to just under 7% in recent years. This translates into a cumulative growth rate of roughly 2.5%.

Overall, the data point to a sustained increase in patenting activity across the sectors under investigation, a pattern that persists even when the scope of the analysis is restricted to algorithmic management systems. This finding further indicates a progressively stronger involvement of firms in the automotive, logistics and employment services sectors, underscoring not only their growing engagement with these technologies but also the broader strategic relevance of this domain for the future development of these industries.

In addition, Fig. 4 presents the breakdown of `G06Q` into the main technological subclasses across the four sectors under study. This highlights that the `G06Q10` subclass, recognised in the literature as the technological category characterising AIWM technologies, constitutes a highly relevant technical subcategory. In the automotive industry, more than 40% of `G06Q` patents fall under `G06Q10`, the subclass related to ICTs and processing systems or methods specially adapted for "Administration; Management" (panel (a) of Fig. 4). In the logistics sector (panel (b)), the breakdown by technological subclasses shows that `G06Q10` accounts for more than 44%, followed by `G06Q30` at approximately 25% and `G06Q20` at around 18%, corresponding respectively to the subcategories related to "commerce" and "payment architectures, schemes, or protocols". Panel (c) displays the breakdown of `G06Q` within the employment activities sector. Approximately 48% of the technological subclasses fall under `G06Q10`. This is followed by `G06Q30`, accounting for around 30%, and `G06Q20`, which rep-

| # G06Q | Company | Country | % portfolio |
|---|---|---|---|
| 1,874 | Toyota Motor Corporation | JP | 4.58% |
| 782 | Honda Motor | JP | 2.86% |
| 500 | Hyundai Motor Company | KR | 2.40% |
| 499 | Ford Global Technologies | US | 3.12% |
| 361 | Honeywell International | US | 2.05% |
| 268 | Robert Bosch | DE | 0.58% |
| 197 | GM Global Technology Operations | US | 1.81% |
| 158 | Ford Motor Company | US | 1.81% |
| 136 | Toyota Motor Engineering & Manufacturing North America | US | 26.25% |
| 133 | Denso Corporation | JP | 0.53% |

Table 2: Top 10 companies in the automotive sector by number of `G06Q` patents. The last column reports the percentage of `G06Q` patents in their portfolio.

resents just under 10%. Finally, in the business support activities sector (panel (d)), `G06Q10` subclass accounts for about 15% of patents with a 4-digit CPC in the `G06Q` category. The largest shares of technical subclasses in this sector correspond to `G06Q20` and `G06Q30`, accounting for approximately 38% and 32%, respectively.

This overview allows us to examine the specific characteristics of each sector in greater detail. Within the broader technological class `G06Q`, systems and methods serve a wide range of purposes, from management and supervision to commercial and financial applications. A more detailed breakdown of the technological content of the identified patents enables us to detect the differing scopes of application of the underlying inventions across industries. For instance, in the employment services sector, most patents fall within subclass `G06Q10`, which explicitly encompasses algorithmic management systems. This is consistent with the sector's structural need to automate the organisation and supervision of the workforce. By contrast, business support services exhibit a significant concentration of patents in the subclass related to payment systems and architectures. The other sectors under consideration, logistics and automotive, although displaying somewhat lower percentages, nevertheless show a substantial share of patents in subclass `G06Q10`, again reflecting the importance of algorithmic management technologies for enabling workforce direction and evaluation.

Still relying on CPC codes, Appendix A.1 reports the 4-digit co-occurrence analysis among technology subcategories differentiating by industry. This type of analysis is used to identify which technological subcategories constitute the invention underlying a given patent. In other words, when `G06Q` co-occurs with, for example, `G06F` (*Electric Digital Data Processing*) or `H04L` (*Transmission of Digital Information*), we can infer that the patented invention relates to systems, methods or software that span and integrate multiple technological subfields. Two central insights emerge from this investigation (see Fig. 8). First, the co-occurrence of 4-digit technological categories appears to be relatively homogeneous across industries. Indeed, the most frequent co-occurrences involve technological classes associated with digital knowledge domains. This leads to the second key point: AIWM algorithms are enabled by digital systems, and this finding underscores their continuity with earlier digital devices, positioning them as an incremental trajectory within the broader digital paradigm.

In addition, below we present a ranking of the top 10 companies in each sector that are active in patenting ICT systems specially adapted for different purposes. In other words, we report the share of `G06Q` patents relative to the entire patent portfolio of the top ten corporations. Regarding the automotive sector (Tab. 2), the top ten corporations are primarily large vehicle manufacturers from key countries in this industry. The ranking also includes two major component producers, namely Bosch and Denso. The geographical distribution shows

| # G06Q | Company | Country | % portfolio |
|---|---|---|---|
| 335 | United Parcel Service | US | 6.50% |
| 156 | Maplebear | US | 13.60% |
| 137 | United States Postal Service | US | 5.20% |
| 99 | Deutsche Post | DE | 2.60% |
| 30 | Wing Aviation | US | 11.40% |
| 25 | Fedex | US | 4.10% |
| 21 | Omnitracs | US | 3.30% |
| 19 | California Research | US | 0.66% |
| 18 | Jungheinrich | DE | 0.36% |
| 13 | Grubhub | US | 86.60% |

Table 3: Top 10 companies in the logistics sector by number of G06Q patents. The last column reports the percentage of G06Q patents in their portfolio.

| # G06Q | Company | Country | % portfolio |
|---|---|---|---|
| 29 | TTEC holdings | US | 63.04% |
| 21 | MyJobMatcher | US | 63.64% |
| 19 | Recruit Holdings | JP | 82.61% |
| 6 | Monster Worldwide | US | 75.00% |
| 6 | PT&T | NL | 8.82% |
| 6 | On Time Staffing | US | 66.67% |
| 5 | Toyo Engineering Corporation | JP | 2.54% |
| 5 | Volt Information Sciences | US | 71.43% |
| 5 | Profiles International | US | 83.33% |
| 5 | VisuaLimits | US | 62.50% |

Table 4: Top 10 companies in the employment activities sector by number of G06Q patents. The last column reports the percentage of G06Q patents in their portfolio.

a strong concentration in countries hosting major automotive brands and component manufacturers, such as the US, Japan, South Korea, and Germany.

Tab. 3 presents the top ten logistics corporations. Among those companies are national postal service entities, such as United States Postal Service or Deutsche Post, as well as major logistics firms such as UPS and FedEx. The widespread enthusiasm for the use of AI systems is also evident on the websites of these logistics companies. For instance, the Omnitracs webpage[4] refers to the use of such algorithms for predictive analytics, emphasising their benefits in terms of performance optimisation. In addition, as highlighted by the literature review conducted by Chen et al. (2024), the deployment of artificial intelligence–driven systems to improve decision-making processes, optimise transport, and manage warehouses is a key factor enabling companies to achieve their environmental sustainability goals in the logistics sector. Nevertheless, as will be discussed in greater detail in sub-section 4.2, AIWM patents in this field frequently concern systems for evaluating and rewarding the workforce based on performance.

Tab. 4 presents data on companies engaged employment activities. The portfolios of these companies exhibit a relatively large share G06Q patents. Furthermore, the top companies in terms of patenting activity are concentrated in only a small number of countries. As stated on the official websites of some of these corporations, their mission is to revolutionise the hiring process “with guided interview questions, automated

[4]https://www.omnitracs.com/omnitracs-predictive-analytics

| # G06Q | Company | Country | % portfolio |
|---:|---|:---:|---:|
| 2,841 | MasterCard Technologies | US | 81.80% |
| 1,009 | eBay | US | 56.49% |
| 406 | Advanced New Technology | GB | 53.21% |
| 152 | Rovi Guides | US | 12.42% |
| 142 | Fair Isaac Corporation | US | 57.72% |
| 132 | Western Union | US | 73.74% |
| 91 | Excalibur IP | US | 38.89% |
| 87 | Worldpay | US | 95.60% |
| 65 | Stripe | US | 72.20% |
| 65 | West Technology Group | US | 26.97% |

Table 5: Top 10 companies in the business support activities sector by number of `G06Q` patents. The last column reports the percentage of `G06Q` patents in their portfolio.

real-time scoring and transcriptions, and comprehensive participant analytics"[5].

Finally, Tab. 5 lists the largest firms in the business support activities sector, which are heavily concentrated in anglophone countries. A significant share of `G06Q` patents is observed in this sector. Nevertheless, as shown by the sectoral breakdown of the technology category `G06Q` (panel (d) in Fig. 4), many of these patents fall into subclass `G06Q20`, which refers to "payment architectures, schemes or protocols". This helps explain the presence of Mastercard Technologies as the leading company in the sector.

To sum up, examining different traditional sectors allows us to detect similarities and divergences. We observe analogous dynamics in the rise of patenting activity, although with varying degrees of intensity. In essence, this trend reflects a general and growing interest among economic actors in equipping themselves with workforce management tools. This aspect is particularly relevant, as the development of knowledge for such workforce management systems occurs outside the high-tech sectors, suggesting a direct interest in their use by firms operating in traditional industries. In other words, patenting activity on AIWM devices by a car manufacturer, for example, may lead us to speculate about the firm's specific interest in adopting such algorithmic systems.[6] Conversely, sectoral differentiation becomes evident when examining the breakdown of technological subclasses of `G06Q` (see Fig. 4). The definition of this technical category, "ICT specially adapted for administrative, commercial, financial, managerial or supervisory purposes", already highlights the breadth of its potential applications. Accordingly, we observe a substantial prevalence of the technological subclass `G06Q10` in the automotive (NACE 29), logistics (NACE 52 & 53), and employment activities sectors (NACE 78), whereas subclasses `G06Q20` and `G06Q30` feature prominently in the business support activities industry (NACE 82). While in the former sectors `G06Q10` captures administration and management activities and is widely recognised in the literature as characteristic of AIWM systems, the technological subcategories in NACE 82 reflect industrial specialisation primarily related to e-commerce and payment architectures. In addition, we identify the main patent holders in each sector and show that they are heavily concentrated in the US and the UK. However, there are also major players in Europe (notably Germany and the Netherlands), as well as in Japan and South Korea.

[5] My Job Matcher Inc. (https://job.com/). Similar examples include Recruit Holdings (https://recruit-holdings.com/en/) and On Time Staffing Inc. (https://www.ontimestaffing.com/).

[6] It is, however, beyond the scope of this work to infer actual technology adoption from companies' patenting activity, except on a purely speculative basis.

## 4.2 Text and cosine similarity analysis

In this section, we refine the identification of AIWM patents using text analysis. Starting from the set of `G06Q` patents, we apply a dependency parsing algorithm to the full patent text (i.e. the concatenation of title, abstract, description, and claims) to identify those exhibiting the AIWM heuristics presented above (i.e. *boost labour efficiency/productivity*, *improve decision-making process*, and *enhance workers' health, safety and well-being*).[7] In what follows, we present selected extracts while maintaining a sectoral-level perspective.

**Automotive:** (i) "user interface is used to optimize workplace performance by automatically assigning and/or scheduling the appropriate tasks for the appropriate employee at the appropriate time (e.g. based on one or more relationships determined as between detected criteria such as employee skills, availability, experience, history, and/or the like)." [US20240112122A1]

(ii) "provides a method of rating employee performance which is completely automated and performed electronically via an intranet and electronic message system." [US6853975B1]

**Logistics:** "systems and methods for evaluating and compensating employees based on performance. In particular, systems and methods consistent with the present invention provide tools for establishing performance expectations, obtaining feedback on individual and organizational performance, linking individual contributions to organizational success." [US7991641B2]

**employment activities:** (i) "There is provided a method of automatically determining a compatibility quality score for selecting at least one candidate from a plurality of candidates suitable for a job role, using a machine learning model." [US20220180326A1]

(ii) "system and methods for extracting timing and emotional content from recorded audio in order to automate screening decisions for hiring candidates by processing candidate audio responses to predict candidate alignment for given job position." [US20140297551A1]

**business support activities:** "by automatically identifying employees and agents who may be available to work during the surge and offering them incentives to work during the surge, an employer or administrator is released from the difficult task of finding available employees and agents and convincing them to work during a predicted surge." [US20210081968A1]

Most of the identified patents fall into the first two AIWM heuristics: increasing workforce/workflow productivity, and enhancing decision-making processes. The patents reported in the automotive and logistics sectors, assigned respectively to Ford and the US Postal Service (Tabs. 2 and 3), include rating systems and concern the automation of reward procedures based on individual worker performance. In the fields of employment services and business support activities, the identified technologies concern performance optimisation through the efficient matching of tasks and competencies, both in recruitment processes and in the organisation of work shifts. Among the various capabilities of AIWM systems, their predictive capacity also emerges from some extracts (e.g. *"predict candidate alignment for given job position"*). Finally, in the area of employment agencies, the extraction of *emotional content* from candidates' interviews appears among the attributes and scopes of application of AIWM technologies.[8]

At this stage, having identified the patents containing AIWM heuristics through textual analysis, we now present the procedures and results of the text similarity investigation. It is worth noting that for the 276 patents

[7] Methodological details are provided in Appendix A.2.

[8] With regard to the activities carried out by HR managers, this aspect is also highlighted by Moore et al. (2018) and Todolí-Signes (2019).

identified through textual analysis, we retain their full text.[9] This allows us to employ a technique commonly used in natural language processing to weight the relevance of a term within a document relative to a collection of documents. The intuition behind this approach, known as *term frequency-inverse document frequency* (tf-idf henceforth), is that a word recurring frequently in a document but not in the collection as a whole is relevant and should therefore be emphasised. Conversely, terms recurring frequently in both the individual document and the entire text collection are less distinctive and should therefore be downweighted. In other words, the value of this relevance measure increases with the term's frequency in the document and decreases with its frequency in the collection as a whole. We thus apply the tf-idf technique on both patent texts and human task descriptions to construct a similarity matrix consisting of all possible task-patent pairs (further details are provided in Appendix A.3).

After assessing the relevance of individual terms within their respective textual bodies, the cosine similarity measure captures the degree of proximity between the two corpora. In our case, we compare, on the one hand, the full text of patents and, on the other, the description of tasks performed by the workforce. The former contains, among other information, the scopes of application of AIWM technologies, while the latter details the human tasks that constitute occupations. Thus, this similarity measure enables us to quantify the degree of exposure of human activities to AIWM systems.

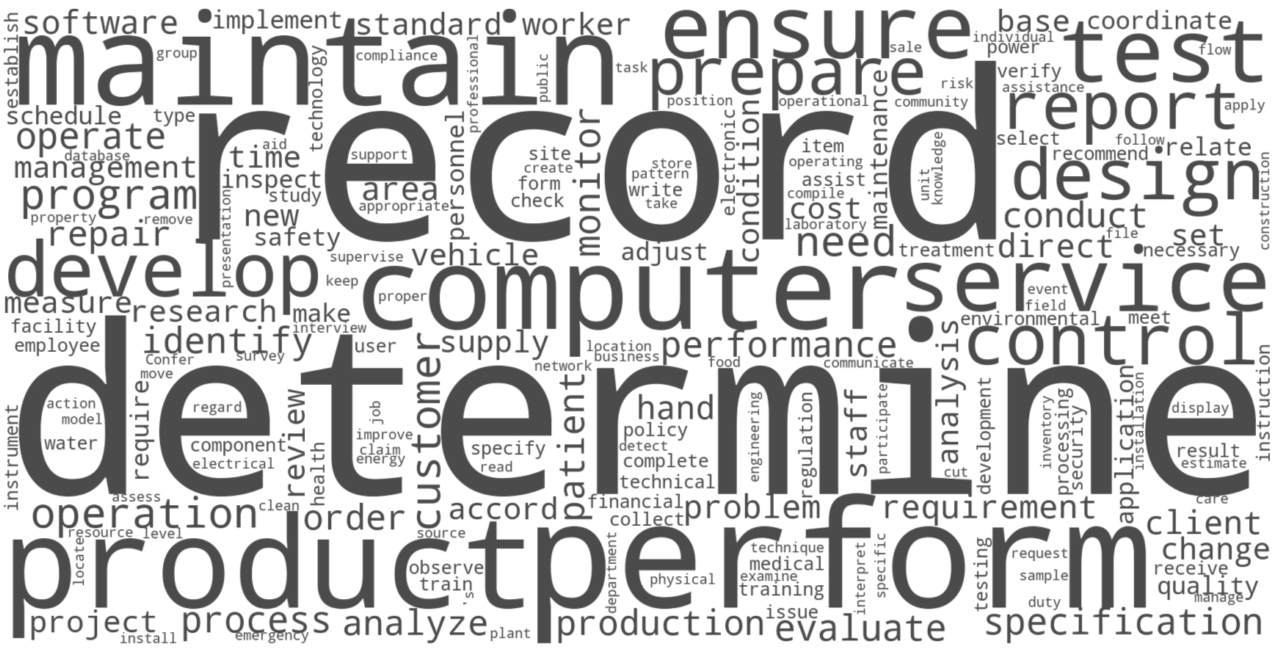



Figure 5: Word cloud of human task descriptions for all sectors. Each word is weighted by the cosine similarity of the underlying task.

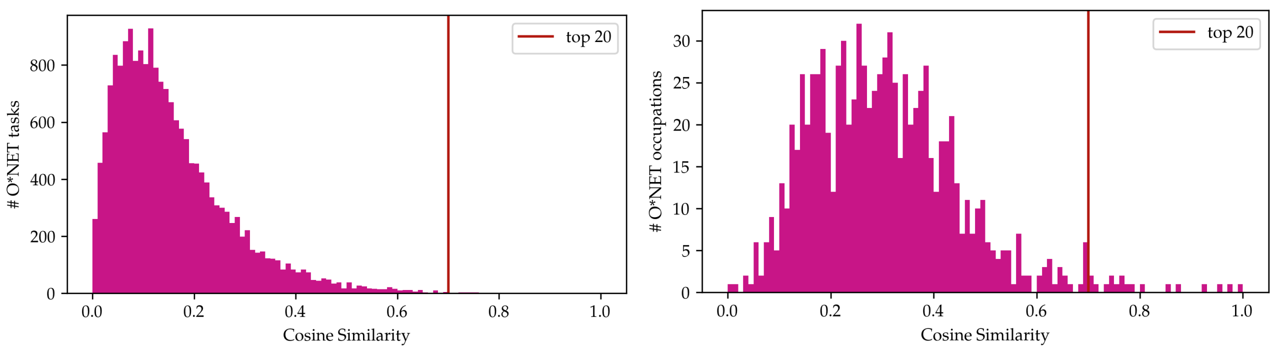
The word cloud in Fig. 5 displays the most recurrent terms in human task texts re-weighted by their corresponding cosine similarity values. Before extracting the group of characterising lemmas, English stop words are removed, along with highly inflated terms such as *system, method, information, machine, activity, device, work* and *tool*. The character size of the headwords highlights their relevance and reflects the terms exhibiting a higher degree of proximity between AIWM devices and human tasks. We group these terms according to the three AIWM heuristics discussed earlier. Words such as *coordinate, design, determine, develop, maintain*, and *repair* can be associated with processes aimed at improving workforce productivity, while *control, direct, perform, program, record*, and *test* are more likely to fall under the heuristic of improving decision-making

[9] In the remainder of the analysis, we consider the entire patent corpus without maintaining the categorisation into different sectors. Hence, these 276 patents come from the automotive, logistics, employment and business support activities sectors.

| Rank | SOC | Occupation | Similarity |
|---|---|---|---|
| 1 | 51 | Production Occupations | 1.00 |
| 2 | 17 | Architecture and Engineering Occupations | 0.72 |
| 3 | 29 | Healthcare Practitioners and Technical Occupations | 0.70 |
| 4 | 19 | Life, Physical, and Social Science Occupations | 0.61 |
| 5 | 43 | Office and Administrative Support Occupations | 0.59 |
| 6 | 11 | Management Occupations | 0.59 |
| 7 | 15 | Computer and Mathematical Occupations | 0.59 |
| 8 | 13 | Business and Financial Operations Occupations | 0.52 |
| 9 | 49 | Installation, Maintenance, and Repair Occupations | 0.46 |
| 10 | 53 | Transportation and Material Moving Occupations | 0.46 |
| 11 | 47 | Construction and Extraction Occupations | 0.42 |
| 12 | 25 | Educational Instruction and Library Occupations | 0.40 |
| 13 | 27 | Arts, Design, Entertainment, Sports, and Media Occupations | 0.34 |
| 14 | 33 | Protective Service Occupations | 0.18 |
| 15 | 39 | Personal Care and Service Occupations | 0.18 |
| 16 | 41 | Sales and Related Occupations | 0.18 |
| 17 | 31 | Healthcare Support Occupations | 0.11 |
| 18 | 21 | Community and Social Service Occupations | 0.08 |
| 19 | 35 | Food Preparation and Serving Related Occupations | 0.08 |
| 20 | 45 | Farming, Fishing, and Forestry Occupations | 0.03 |
| 21 | 23 | Legal Occupations | 0.00 |
| 22 | 37 | Building and Grounds Cleaning and Maintenance Occupations | 0.00 |

Table 6: 2-digit occupations by (rescaled) cosine similarity.

processes. However, as already noted, these two broad areas of application have blurred boundaries and often overlap. Other terms, such as *analyse, evaluate, identify, monitor, project*, and *process* appear more closely related to procedures for defining production standards and detecting errors, lying between the two applications discussed. Finally, albeit in smaller fonts, terms such as *quality, risk, safety*, and *security* can be linked to applications targeting health and worker well-being.




(a) Task level.

(b) Occupations level.

Figure 6: Frequency distribution of cosine similarity values at the task level (a) and aggregated at the occupation level (b). The vertical line isolates to its right the 20 highest values of cosine similarity.

Fig. 6 presents the distributions of the cosine similarity measure for both tasks and occupations. The distribution of the 19,281 O*NET tasks (left-hand panel of Fig. 6a), is highly skewed. The red line shows that only the first 20 human functions exhibit a cosine similarity measure exceeding 0.7.[10] The most exposed tasks range from "Direct and coordinate operational, management, and supportive services of one or a number of postal facilities" to "Program and use computers to store, process and analyse data".

However, this classification of human activities risks being scarcely informative, as it does not indicate the centrality of each task within its occupation. As discussed in more detail in Appendix A.3, each human function is assigned a *core* or *supplemental* label that characterises its degree of centrality. It is possible that tasks show-

[10]The first 20 tasks scaled according to cosine similarity measure are listed in Tab. 8 of the Appendix.

ing a high degree of proximity to AIWM systems are not central to their respective occupations. Therefore, we aggregate the exposure measure at the 2-digit occupation level, appropriately weighting individual human activities and rescaling the similarity index to range from 0 to 1.[11] As shown in Tab. 6, *production occupations* rank first, indicating the highest exposure to AIWM systems. These are followed by *engineering occupations* (SOC code 17), with *managerial occupations* (SOC code 11) appearing in sixth position. In general, the eight most exposed occupations involve activities related either to defining procedures and workflows for standardising production processes or to applying them within *production occupations*. Moreover, occupations ranked from second to eighth are typically positioned at the upper levels of organisational hierarchies. Indeed, technical, engineering, and managerial occupations dominate the ranking. This result is consistent with our expectations, as AIWM systems are designed to improve production efficiency and enhance decision-making processes, namely the activities typically undertaken by these professionals. For the remaining occupational categories, the similarity index declines rapidly, reaching 0 for legal and building/grounds cleaning occupations.

The present analysis does not allow us to determine whether the AIWM tools may replace or complement the work of these professional categories, a question on which we therefore remain agnostic. However, for occupations with a cosine similarity greater than 0.5, we cautiously suggest that technical-managerial occupations are exposed primarily as developers and users of these systems, whereas production occupations are more susceptible to their application in day-to-day work activities.

Finally, we report the distribution of the cosine similarity measure for the 923 full-digit occupations in Fig. 6b. This histogram, although less skewed than its counterpart for tasks, shows that substantial exposure among highly disaggregated occupations is relatively rare. Therefore, these technical tools for workforce management affect only a small portion of the overall employment structure. The vast majority of occupations, in fact, fall within exposure levels between 0.1 and 0.4. The red line leaves to its right the 20 occupations most exposed to AIWM systems, each exhibiting a proximity measure above 0.7.

In sum, we identify the human tasks and occupations most exposed to AIWM systems. Specifically, the tasks most vulnerable to AIWM algorithms involve management, coordination, and record-keeping activities, which are typically performed by high-level professionals within the organisational production hierarchy. This is clearly illustrated by the word cloud (see Fig. 5), in which terms such as *record, determine, control*, and *evaluate* prominently appear. In addition, aggregating from tasks to occupations shows that specialists, managers, and analysts are the occupational categories most exposed to AIWM systems.[12] Finally, considering the ranking of occupations with the highest cosine similarity (Tab. 6), we observe that the top two positions are occupied by *production occupations* and *architecture and engineering occupations*, respectively. Based on these findings, we may advance the hypothesis that production occupations are those most directly targeted by AIWM tools, whereas the high exposure of engineers and managers reflects both their involvement in developing the underlying algorithms and their role in facilitating workforce coordination. This pattern indicates that exposure is not homogeneous across occupational hierarchies but follows two distinct mechanisms. On the one hand, *developer exposure* concerns technical and managerial occupations involved in designing, calibrating, and operating AIWM systems. On the other hand, *user exposure* applies to production and service workers whose activities are increasingly monitored and guided by these systems. This distinction helps to clarify the heterogeneous meaning of *exposure* in the context of algorithmic management.

[11] Appendix A.3 provides tables of the top 20 full-digit occupations by cosine similarity differentiated across the four surveyed sectors.

[12] This is particularly evident from the full-digit occupation rankings in Appendix A.3.1.

| Rank | SOC | Occupation | # empl. | % empl. | # weighted | % weighted |
|---|---|---|---|---|---|---|
| 1 | 51 | Production | 2,513,960 | 1.65% | 2,513,960 | 1.65% |
| 2 | 53 | Transportation and Material Moving | 5,115,370 | 3.35% | 2,356,232 | 1.54% |
| 3 | 43 | Office and Administrative Support | 3,064,190 | 2.01% | 1,808,747 | 1.18% |
| 4 | 49 | Installation, Maintenance, and Repair | 1,396,480 | 0.91% | 646,542 | 0.42% |
| 5 | 13 | Business and Financial Operations | 1,001,780 | 0.66% | 517,642 | 0.34% |
| 6 | 11 | Management | 757,890 | 0.5% | 446,974 | 0.29% |
| 7 | 29 | Healthcare Practitioners and Technical | 439,170 | 0.29% | 307,835 | 0.2% |
| 8 | 15 | Computer and Mathematical | 456,340 | 0.3% | 268,199 | 0.18% |
| 9 | 17 | Architecture and Engineering | 186,620 | 0.12% | 134,284 | 0.09% |
| 10 | 47 | Construction and Extraction | 295,140 | 0.19% | 122,699 | 0.08% |
| 11 | 41 | Sales and Related | 551,640 | 0.36% | 97,222 | 0.06% |
| 12 | 25 | Educational Instruction and Library | 109,920 | 0.07% | 44,450 | 0.03% |
| 13 | 39 | Personal Care and Service | 230,420 | 0.15% | 41,220 | 0.03% |
| 14 | 27 | Arts, Design, Entertainment, Sports, and Media | 111,660 | 0.07% | 38,127 | 0.02% |
| 15 | 19 | Life, Physical, and Social Science | 61,300 | 0.04% | 37,457 | 0.02% |
| 16 | 31 | Healthcare Support | 252,740 | 0.17% | 27,515 | 0.02% |
| 17 | 33 | Protective Service | 126,880 | 0.08% | 23,138 | 0.02% |
| 18 | 35 | Food Preparation and Serving Related | 153,430 | 0.1% | 11,777 | 0.01% |
| 19 | 21 | Community and Social Service | 31,480 | 0.02% | 2,473 | 0.0% |
| 20 | 45 | Farming, Fishing, and Forestry | 14,080 | 0.01% | 375 | 0.0% |
| 21 | 23 | Legal | 19,520 | 0.01% | 16 | 0.0% |
| 22 | 37 | Building and Grounds Cleaning and Maintenance | 321,870 | 0.21% | 0 | 0.0% |

Table 7: "# empl." refers to the overall level of employment by 2-digit occupation in automotive, logistics, employment and business support activities sectors. "# weighed" represents the level of employment in the traditional sectors covered by this survey, adjusted according to the (rescaled) cosine similarity index. Percentages are both computed with respect to total US employment.

### 4.3 Employment exposure in the US context

Having presented the results on the degree of exposure to AIWM systems across the entire occupational structure, it is useful to place this information in a real employment context. To do so, we use OEWS survey data retrieved from the Bureau of Labour Statistics, which reflect the occupational landscape of North America.

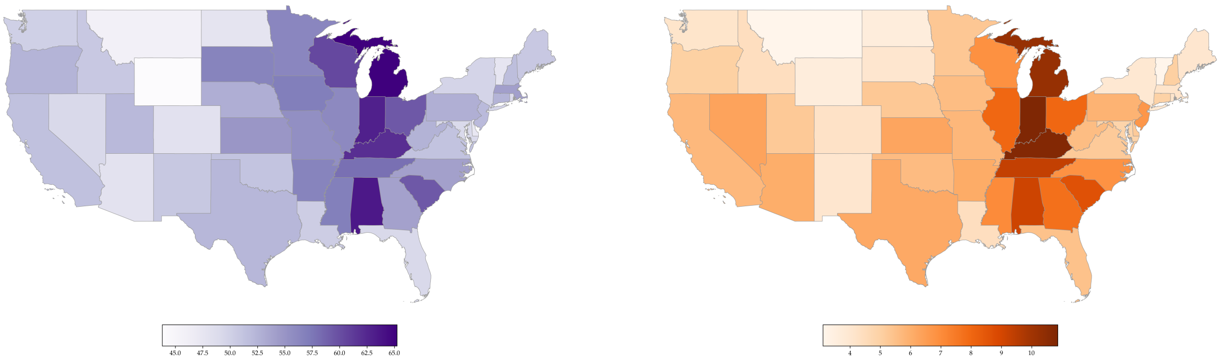
The first column of Tab. 7 reports the total number of employees by occupational category in the automotive, logistics, employment, and business support services sectors. The next column provides the share of these employees relative to the total number of North American workers (over 150 million according to the survey). As shown, among the four sectors analysed, the highest percentage corresponds to workers in *Transportation and Material Moving Occupations*, at 3.35% (also the largest category in absolute terms), followed by those in administrative support activities, at 2.01%. These are followed by workers employed in manufacturing occupations, who represent 1.65%. Considered alone, this information provides a snapshot of the sectoral specialisation of US employment. Since our objective is to capture the scale of employment potentially affected by AIWM systems, we rescale the number of employees in each occupation by their corresponding cosine similarity value (Tab. 6). Accordingly, the third column (which determines the ranking) reports employment weighted by exposure to AIWM technologies, while the last column expresses the same information in percentage terms relative to total US employment. After rescaling, employment in production occupations remains unchanged (as their similarity measure equals 1), whereas the twenty-second category contains no employee because its similarity is null. As a result, the dispersion in employment across categories decreases.

In a second step, we incorporate information on the geographical distribution of North American employees. In this context, we define *exposed* workers as those obtained by weighting the workforce by the similarity measure.[13] Thus, Fig. 7 displays, respectively, the percentage of people exposed to AIWM relative to employment in the four industries considered (panel 7a) and relative to total US employment by state (plot 7b). Shades of purple and orange range from light for the lowest percentages to dark for the highest levels of AIWM

[13]In the weighting process, we use the cosine similarity measure computed for the twenty-two 2 digit occupations.

exposure (noting that the scales differ considerably). The upper panel shows that the Rust Belt, i.e. the Great Lakes region in the Northeast, has the highest exposure to workforce management algorithms, with between 55% and 65% of employees in the four industries of interest. Alabama also appears in dark purple. The lighter-coloured states, including Wyoming in white, still show non-negligible exposure levels of around 40% of the workforce. This confirms that the sectors initially identified as targets of the AIWM tools are highly exposed in terms of the share of the (potentially) affected workforce. Fig. 7b, by contrast, shows exposure relative to total US employment. Again, the most exposed states are located in the Rust Belt, with peaks in Kentucky and high levels also in Tennessee, Alabama and South Carolina. In this case, however, the share of exposed workers ranges between 4 and 13%. States with lighter shadings, such as Montana or New Mexico, exhibit even lower percentages.

Both maps show that the workforce exposed to AIWM is largely concentrated in the Northeastern states. This pattern is consistent with the fact that production occupations are the most exposed to AIWM systems (cosine similarity equal to 1) and that these states' production specialisation is closely tied to manufacturing activities, particularly the automotive sector in Michigan. Thus, by rescaling employment using cosine similarity, states whose occupational structures are strongly characterised by *productive occupations* (over 2.5 million in the four industries considered) clearly emerge. The workforce in transportation and materials handling (SOC code 53, with over 5 million employees in the 4 sectors studied) is more evenly distributed across North American states and exhibits more moderate exposure to AIWM (cosine similarity equal to 0.72). Florida, Texas, and Nevada emerge as states with relatively high scaled exposure in SOC 53 (around 2% relative to total US employment), although this share becomes substantially diluted once exposure is aggregated occupations across at the state level. Finally, more than 3 million employees in SOC 43 exhibit an even lower degree of exposure (cosine similarity of 0.59) and are very evenly distributed across the US. Overall, the picture reveals a strong concentration of exposure driven primarily by the manufacturing professions.




(a) Sectors under study.

(b) Overall employment.

Figure 7: Percentage of the most exposed employees in each US state with respect to the four sectors under study (a) and for overall employment (b). Darker shades denote higher exposure values.

## 5 *Discussion and Conclusion*

"Artificial intelligence (AI) is already part of our lives – it is not science fiction" (EC, 2018). This is how the European Commission's April 2018 report, "Artificial Intelligence for Europe", begins. Since then, we have witnessed the articulation of a roadmap for the technological development of the European Union, which identifies digital technologies and, more recently, artificial intelligence as the driving force behind the revival of the EU economy.[14] The recent competitiveness strategy plan (Draghi, 2024), which provides a detailed comparison between European and US technological performance, shows that despite Europe's lag in the high-tech sector, it hosts 13% of global AI economic activity, ranking third after the US and China. This finding, together with the recognition of the strategic importance of AI, contributes in the report to defining a coordinated development strategy at the European level. As the report states, "AI will revolutionise several industries in which Europe specialises and will be crucial for EU companies' ability to remain leaders in their sector". While this may offer considerable advantages across sectors (i.e. in healthcare for early disease diagnosis, in preventive maintenance of industrial machinery, and in analysing the supply and consumption of energy from renewable sources Delponte, 2018), it also entails significant potential risks.

Certainly, the growing diffusion of AI systems in workplace contexts has revived the long-standing and topical debate on the impact of new technologies on employment and job displacement. In this regard, the annual survey on European attitudes towards technological change conducted by the IE Center for the Governance of Change (CGC) reflects this concern and reports a significant increase (from 58% to 68%) in the share of EU citizens favouring stricter legislative regulation of new technologies to protect jobs.[15] Alongside job loss anxiety, the deterioration in the quality of work (Berg and Gmyrek, 2023) and the effects of these devices on production organisation and workers' control are equally alarming. In addition, the high levels of discrimination resulting from the use of AI algorithms require serious attention. AI systems are trained on vast amounts of data that reflect existing social inequalities and thus reproduce and amplify them along lines of race, class, and gender (Juego et al., 2024). Milner and Traub (2021) define *algorithmic racism* as the practice that "reproduce[s] and spread[s] racial disparities, shifting power and control from Black and brown people and communities". Intersecting gender and racial dimensions, the report *Systematic Prejudices* by the International Research Centre on Artificial Intelligence (UNESCO, 2024), shows that AI systems and Large Language Models (LLMs) continually reintroduce gender stereotypes and thereby exacerbate dynamics of social marginalisation. The crystallisation of inequalities is also evident in the production processes underlying AI systems. Indeed, alongside the advanced work of highly specialised technicians and engineers in the Global North, labour-intensive data-labelling and sorting activities have led to the proliferation of micro-jobs often located in low-income countries in the Global South (Tubaro and Casilli, 2019; Tubaro et al., 2020). Therefore, next to the opportunities offered by AI systems, there are growing concerns about their impact on the world of work, both in terms of potential job losses and the progressive deterioration of job quality. This technological dynamic, intertwined with existing socio-economic inequalities, risks giving rise to potential dystopian scenarios linked to the possible emergence of "techno-feudalism" (Dosi and Virgillito, 2019).

Specifically, the recent introduction of artificial intelligence-based systems for managing workers have aroused considerable interest, both for the technological transformation they promise and for the risks that inevitably accompany their pervasive diffusion (see the OSH reports by the European Agency for Safety and Health at Work, EU-OSHA, 2022b; EU-OSHA, 2022a). Increased workplace monitoring and control, the rising incidence of psychophysical stress, and the general deterioration of employment conditions are alarmingly affecting a growing number of workers. Among the most widely examined factors in the economic literature to explain this decline in working conditions is technological change.

On this ground, in this paper we lay the foundation for a novel line of inquiry by conducting a large-scale analysis of AIWM systems within traditional yet highly digitalised industries. Starting from a descriptive analysis of patenting activity, we categorise technical attributes, fields and scopes of application, and the actors

[14]The *European approach to artificial intelligence* document provides an overview of the evolution of the EU legislative framework and resources for enhancing research and industrial capacity: https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence.

[15]See the 2023 edition of *European Tech Insights*: https://www.ie.edu/cgc/news-and-events/news/european-tech-insights-2023/

involved in the production of knowledge for AI-augmented worker management devices in the four sectors of interest. In this way, we examine the dynamics of knowledge production on AIWM systems in the automotive, logistics, employment, and business services domains, which, albeit to varying degrees, all exhibit growing patenting activity in these algorithms. The refinement strategy entails focusing on patents classified under CPC `G06Q10` and applying a dependency-parsing algorithm to identify those that incorporate AIWM heuristics. We then progress in our work by using a cosine similarity analysis to assess the degree of proximity between patents and the textual corpus of job tasks and contents provided by the O*NET dictionary of occupations. By adopting this approach, we are able to quantify the exposure of distinct occupational categories to AIWM systems without presupposing whether these technologies substitute for or complement human activities. To better grasp the meaning of the exposure index, we present the absolute and relative number of employees potentially exposed to AIWM devices within the North American occupational structure. Finally, we provide their geographical distribution across the US (see Fig. 7) and show that the highly exposed occupations are those in the upper part of the hierarchical distribution, following production occupations.

Our results show that AIWM-related patenting is indeed growing in traditional industries, particularly in automotive and logistics, and that workforce exposure is highest among production, engineering, and managerial occupations. Moreover, this dual pattern of developer and user exposure highlights that algorithmic management extends beyond low-skill automation and increasingly permeates decision-making roles.

Given the wide impact these devices are expected to generate within the production organisations of traditional sectors, we recommend introducing legislative instruments to protect workers. We consider that public policies can promote the responsible use of these technologies for the benefit of society as a whole. In this sense, we follow the suggestions provided by Bernhardt and Hinkley (2024). On the basis of the US Executive Orders on AI, the authors recommend core principles to guide government action so as to ensure that the introduction of new technological devices benefits both public- and private-sector workers.[16] These recommendations, organised into five macro areas, range from adopting robust sets of worker technology rights to promoting worker-centred technological development and calling for investment in applied research on the impacts of these technologies.[17]

Within the European context, the adoption of Regulation (EU) 2024/1689 represents the first comprehensive legislative framework worldwide specifically aimed at governing artificial intelligence systems. The Regulation seeks to ensure the development and deployment of AI in a human-centred, responsible, and trustworthy manner, while at the same time serving as a key reference point for strengthening the protection of workers, as well as of citizens more broadly. A further significant aspect concerns the extraterritorial scope of the Regulation, which applies also to organisations and operators established outside the European Union whenever they place AI systems on the EU market or deploy them within the Union (Cristofolini, 2024). The Regulation is grounded in a risk-based approach, which entails progressively more restrictive normative requirements as the potential harms associated with specific applications increase. This approach is intended to strike a delicate balance between fostering technological innovation within the EU and safeguarding fundamental rights and safety. However, the adoption of a risk-based framework also gives rise to regulatory gaps. These shortcomings give rise to significant challenges, including the substantial degree of autonomy afforded to companies developing so-called intelligent algorithms, as well as the resulting power asymmetries within work contexts (Cristofolini, 2024; Özkiziltan and Landini, 2025). Thus, greater involvement of all stakeholders is essential, with a particular focus on ensuring the meaningful participation of the most vulnerable individuals directly

[16] A continuously updated collection of American legislative interventions grouped by regulatory notions is available here: https://laborcenter.berkeley.edu/tech-and-work-policy-guide/. See also Khan and Bernhardt (2025).

[17] Further details are provided here by the UC Berkley Labour Center: https://laborcenter.berkeley.edu/what-workers-and-unions-stand-to-gain-from-recent-executive-orders-on-artificial-intelligence/.

affected by the use of such technological tools. There is an urgent need to strengthen social dialogue and to require transparent communication concerning the implementation of workforce management systems in the workplace.

The contribution of this work lies in providing a sectoral investigation using a general-to-specific analytical approach that maps technology characteristics to workforce exposure to AIWM systems. From this perspective, we observe that corporations in sectors of varying maturity and technological advancement are also contributing to the production of knowledge for workforce management devices. This evidence, on the one hand, calls for further investigation into sectoral specificities and dynamics and, on the other, suggests that the companies patenting these technologies may themselves be interested in their adoption.

The main limitation of this work lies in the lack of additional empirical evidence on the sectoral-level adoption of AIWM systems. Future extensions of this study shall include fieldwork analyses or survey data, which are essential for understanding the potential and risks associated with the introduction of these AI-enhanced digital systems into manufacturing workplaces. In addition, we plan to conduct an in-depth investigation of the employment services sector, given growing concerns about intersectional discriminatory practices in selection and recruitment activities. Finally, we aim to enrich the analysis complementing it with qualitative information from engineers and developers of such systems, as well as from workers and trade union organisations, all of whom are fully involved in the process that is poised to reconfigure organisational and production hierarchies.

*Acknowledgements*

Maria Enrica Virgillito acknowledges the support from the Italian Ministry of University and Research, PRIN 2022 project 2022Z78M8J: "DIGITWORK – The Digital Transition and the World of Work: Labour markets, Organizations, Job quality and Industrial Relations.

The authors wish to acknowledge the participants of the 3rd International Conference on Disruptive Technology (2025) in Leeds for their insightful and valuable comments.

*References*


Adams-Prassl, Jeremias (2022). 'Regulating algorithms at work: Lessons for a 'European approach to artificial intelligence''. In: *European Labour Law Journal* 13(1), pp. 30–50. DOI: 10.1177/20319525211062558.

Agostini, Lara and Federico Caviggioli (2015). 'R & D collaboration in the automotive innovation environment: An analysis of co-patenting activities'. In: *Management Decision* 53(6), pp. 1224–1246. DOI: 10.1108/MD-06-2014-0407.

Allyn, Bobby (2020). *Your Boss Is Watching You: Work-From-Home Boom Leads To More Surveillance*. NPR. URL: https://www.npr.org/2020/05/13/854014403/.

Aloisi, Antonio and Valerio De Stefano (2022). *Your Boss Is an Algorithm: Artificial Intelligence, Platform Work and Labour*. Hart Publishing.

Baiocco, Sara, Enrique Fernández-Macías, Uma Rani and Annarosa Pesole (2022). *The Algorithmic Management of work and its implications in different contexts*. Background paper 9. European Commission.

Berg, Janine and Pawel Gmyrek (2023). 'Automation hits the knowledge worker: ChatGPT and the future of work'. In: *UN multi-stakeholder forum on science, technology and innovation for the SDGs (STI Forum)*.

Bernhardt, Annette and Sara Hinkley (2024). *What Workers and Unions Stand to Gain from Recent Executive Orders on Artificial Intelligence*. UC Berkeley Labor Center. URL: https://laborcenter.berkeley.edu/what-workers-and-unions-stand-to-gain-from-recent-executive-orders-on-artificial-intelligence/.

Calvino, Flavio and Luca Fontanelli (2023). *A portrait of AI adopters across countries*. Science, Technology and Industry Working Papers 2. OECD.

Caria, Sara, Francesco Garibaldo and Matteo Rinaldini (2023). 'Shadowing Industry 4.0: an empirical study of digitalisation in a German/Italian automotive firm'. In: *International Journal of Automotive Technology and Management* 23(2-3), pp. 303–321. DOI: 10.1504/IJATM.2023.133361.

Chen, Wenwen, Yangchongyi Men, Noelia Fuster, Celia Osorio and Angel A Juan (2024). 'Artificial Intelligence in Logistics Optimization with Sustainable Criteria: A Review'. In: *Sustainability* 16(21), 9145. DOI: 10.3390/su16219145.

Cirillo, Valeria, Lucrezia Fanti, Andrea Mina and Andrea Ricci (2023). 'The adoption of digital technologies: Investment, skills, work organisation'. In: *Structural Change and Economic Dynamics* 66, pp. 89–105. DOI: 10.1016/j.strueco.2023.04.011.

Cirillo, Valeria, Matteo Rinaldini, Jacopo Staccioli and Maria Enrica Virgillito (2021). 'Technology vs. workers: the case of Italy's Industry 4.0 factories'. In: *Structural Change and Economic Dynamics* 56, pp. 166–183. DOI: 10.1016/j.strueco.2020.09.007.

Cox, Theo and Gerard Rinse Oosterwijk (2024). *Algorithmic Management in the Workplace: Case Studies on the Impact of Algorithmic Technologies in Seven Sectors in the Nordics*. Policy Study. Foundation for European Progressive Studies (FEPS). URL: https://feps-europe.eu/wp-content/uploads/2024/09/Algorithmic-management-in-traditional-workplaces.pdf.

Cristofolini, Chiara (2024). 'Navigating the impact of AI systems in the workplace: strengths and loopholes of the EU AI Act from a labour perspective'. In: *Italian Labour Law e-Journal* 17(1), pp. 75–103.

Damioli, Giacomo, Vincent Van Roy and Daniel Vertesy (2021). 'The impact of artificial intelligence on labor productivity'. In: *Eurasian Business Review* 11(1), pp. 1–25. DOI: 10.1007/s40821-020-00172-8.

Damioli, Giacomo, Vincent Van Roy, Daniel Vertesy and Marco Vivarelli (2024). *Is artificial intelligence generating a new paradigm?: Evidence from the emerging phase*. Discussion Paper 17183. IZA Institute of Labor

Economics. URL: https://www.iza.org/publications/dp/17183/is-artificial-intelligence-generating-a-new-paradigm-evidence-from-the-emerging-phase.

Delfanti, Alessandro (2021). 'Machinic dispossession and augmented despotism: Digital work in an Amazon warehouse'. In: *New Media & Society* 23(1), pp. 39–55. DOI: 10.1177/1461444819891613.

Delponte, Laura (2018). *European Artificial Intelligence (AI) leadership, the path for an integrated vision*. Study. European Parliament. URL: https://www.europarl.europa.eu/thinktank/en/document/IPOL_STU(2018)626074.

Dosi, Giovanni and Maria Enrica Virgillito (2019). 'Whither the evolution of the contemporary social fabric? New technologies and old socio-economic trends'. In: *International Labour Review* 158(4), pp. 593–625. DOI: 10.1111/ilr.12145.

Draghi, Mario (2024). *The Draghi report: A competitiveness strategy for Europe (Part A)*. European Commission. URL: https://commission.europa.eu/topics/eu-competitiveness/draghi-report_en.

Dzieza, Josh (2020). *How hard will the robots make us work*. The Verge. URL: https://www.theverge.com/2020/2/27/21155254.

EC (2018). *Artificial Intelligence for Europe*. Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions on Artificial Intelligence for Europe. European Commission. URL: https://digital-strategy.ec.europa.eu/en/library/communication-artificial-intelligence-europe.

EU-OSHA (2022a). *Artificial intelligence for worker management: an overview*. Report. European Agency for Safety and Health at Work. URL: https://healthy-workplaces.osha.europa.eu/en/publications/artificial-intelligence-worker-management-overview.

EU-OSHA (2022b). *Artificial intelligence for worker management: mapping definitions, uses and implications*. Policy Brief. European Agency for Safety and Health at Work. URL: https://healthy-workplaces.osha.europa.eu/en/publications/artificial-intelligence-worker-management-mapping-definitions-uses-and-implications.

Fernández-Macías, Enrique, Cesira Urzì Brancati, Sally Wright and Annarosa Pesole (2023). *The platformisation of work: Evidence from the JRC Algorithmic Management and Platform Work survey (AMPWork)*. Science for Policy Report. European Commission.

Gallagher, Cailean, Karen Gregory and Boyan Karabaliev (2025). 'Digital worker inquiry and the critical potential of participatory worker data science for on-demand platform workers'. In: *New Technology, Work and Employment* 40(1), pp. 20–40. DOI: 10.1111/ntwe.12286.

Garcia Calvo, Angela, Martin Kenney and John Zysman (2023). 'Understanding work in the online platform economy: the narrow, the broad, and the systemic perspectives'. In: *Industrial and Corporate Change* 32(4), pp. 795–814. DOI: 10.1093/icc/dtad005.

González Vázquez, Ignacio, Maurizio Curtarelli, Ioannis Anyfantis, Emmanuelle Brun and Annick Starren (2024). *Digitalisation and workers wellbeing: The impact of digital technologies on work-related psychosocial risks*. JRC Working Papers Series on Labour, Education and Technology 3. European Commission.

ILO (2024). *Realizing decent work in the platform economy*. Report. International Labour Office. URL: https://www.ilo.org/resource/conference-paper/ilc/113/realizing-decent-work-platform-economy.

Jarrahi, Mohammad Hossein, Gemma Newlands, Min Kyung Lee, Christine T. Wolf, Eliscia Kinder and Will Sutherland (2021). 'Algorithmic management in a work context'. In: *Big Data & Society* 8(2). DOI: 10.1177/20539517211020332.

Johansson, Jennifer and Senja Herranen (2019). *The application of artificial intelligence (AI) in human resource management: Current state of AI and its impact on the traditional recruitment process*. Student thesis. Jönköping International Business School, Jönköping University. URL: https://urn.kb.se/resolve?urn=urn:nbn:se:hj:diva-44323.

Juego, Bonn, Tereza Østbø Kuldova and Gerard Rinse Oosterwij (2024). *Algorithms by and for the workers: Towards a fair, democratic and humane digitalisation of the workplace*. Policy Study. Foundation for European Progressive Studies (FEPS). URL: https://feps-europe.eu/publication/algorithms-by-and-for-the-workers/.

Jurafsky, Daniel and James H. Martin (2025). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. Third Edition draft. URL: https://web.stanford.edu/~jurafsky/slp3/.

Kellogg, Katherine C., Melissa A. Valentine and Angèle Christin (2020). 'Algorithms at work: The new contested terrain of control'. In: *Academy of Management Annals* 14(1), pp. 366–410. DOI: 10.5465/annals.2018.0174.

Kenney, Martin and John Zysman (2016). 'The rise of the platform economy'. In: *Issues in Science and Technology* 32(3), pp. 61–69. URL: https://issues.org/rise-platform-economy-big-data-work/.

Khan, Mishal and Annette Bernhardt (2025). *The Current Landscape of Tech and Work Policy in the U.S.: A Guide to Key Laws, Bills, and Concepts*. UC Berkeley Labor Center. URL: https://laborcenter.berkeley.edu/tech-and-work-policy-guide/.

Kresge, Lisa (2020). *Data and algorithms in the workplace: a primer on new technologies*. Working Paper. UC Berkeley Labor Center. URL: https://laborcenter.berkeley.edu/working-paper-data-and-algorithms-in-the-workplace-a-primer-on-new-technologies/.

Krzywdzinski, Martin (2021). 'Automation, digitalization, and changes in occupational structures in the automobile industry in Germany, Japan, and the United States: a brief history from the early 1990s until 2018'. In: *Industrial and Corporate Change* 30(3), pp. 499–535. DOI: 10.1093/icc/dtab019.

Krzywdzinski, Martin, Maren Evers and Christine Gerber (2024). 'Control and Flexibility: The Use of Wearable Devices in Capital- and Labor-Intensive Work Processes'. In: *ILR Review* 77(4), pp. 506–534. DOI: 10.1177/00197939241258206.

Krzywdzinski, Martin, Sabine Pfeiffer, Maren Evers and Christine Gerber (2022). *Measuring work and workers: Wearables and digital assistance systems in manufacturing and logistics*. Discussion Paper. WZB Berlin Social Science Center.

Krzywdzinski, Martin, Daniel Schneiß and Andrea Sperling (2025). 'Between control and participation: The politics of algorithmic management'. In: *New Technology, Work and Employment* 40(1), pp. 60–80. DOI: 10.1111/ntwe.12293.

Lee, Min Kyung, Daniel Kusbit, Evan Metsky and Laura Dabbish (2015). 'Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers'. In: *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pp. 1603–1612. DOI: 10.1145/2702123.2702548.

Lippert, Isabell, Kathrin Kirchner and Martin Wiener (2023). 'Context matters: the use of algorithmic management mechanisms in platform, hybrid, and traditional work contexts'. In: *Proceedings of the 56th Hawaii International Conference on System Sciences*, pp. 5282–5291. URL: https://scholarspace.manoa.hawaii.edu/items/763fba5d-cbd8-46af-b4d1-65cc62d0a2b4.

Massimo, Francesco S. (2020). 'A struggle for bodies and souls: Amazon management and union strategies in France and Italy'. In: *Amazon in the Global Economy*. Ed. by Jake Alimahomed-Wilson and Ellen Reese. Pluto Books, pp. 129–144.

Mateescu, Alexandra (2023). *Challenging Worker Datafication*. Explainer. Data & Society. URL: https://datasociety.net/library/challenging-worker-datafication/.

Mateescu, Alexandra and Aiha Nguyen (2019). *Algorithmic Management in the Workplace*. Explainer. Data & Society. URL: https://datasociety.net/library/explainer-algorithmic-management-in-the-workplace/.

Mazzei, Julia, Tommaso Rughi and Maria Enrica Virgillito (2023). 'Knowing brown and inventing green? Incremental and radical innovative activities in the automotive sector'. In: *Industry and Innovation* 30(7), pp. 824–863. DOI: 10.1080/13662716.2023.2230159.

Milanez, Anna, Annikka Lemmens and Carla Ruggiu (2025). *Algorithmic management in the workplace: New evidence from an OECD employer survey*. Artificial Intelligence Papers 31. OECD.

Milner, Yeshimabeit and Amy Traub (2021). *Data Capitalism and Algorithmic Racism*. Research. Dēmos. URL: https://www.demos.org/research/data-capitalism-and-algorithmic-racism.

Montobbio, Fabio, Jacopo Staccioli, Maria Enrica Virgillito and Marco Vivarelli (2024). 'Labour-saving automation: A direct measure of occupational exposure'. In: *World Economy* 47(1), pp. 332–361. DOI: 10.1111/twec.13522.

Moore, Phoebe V., Pav Akhtar and Martin Upchurch (2018). 'Digitalisation of Work and Resistance'. In: *Humans and Machines at Work: Dynamics of Virtual Work*. Ed. by P. Moore, M. Upchurch and X. Whittaker. Springer, pp. 17–44. DOI: 10.1007/978-3-319-58232-0_2.

Mujtaba, Dena F and Nihar R Mahapatra (2019). 'Ethical considerations in AI-based recruitment'. In: *2019 IEEE International Symposium on Technology and Society (ISTAS)*. URL: https://ieeexplore.ieee.org/document/8937920.

Özkiziltan, Didem and Fabio Landini (2025). 'Trustworthy and human-centric? The new governance of workplace AI technologies under the EU's Artificial Intelligence Act'. In: *Transfer: European Review of Labour and Research*.

Rani, Uma, Annarosa Pesole and Ignacio González Vázquez (2024). *Algorithmic Management practices in regular workplaces: case studies in logistics and healthcare*. Report. European Commission. URL: https://www.ilo.org/publications/algorithmic-management-practices-regular-workplaces-case-studies-logistics.

Rughi, Tommaso, Jacopo Staccioli and Maria Enrica Virgillito (2025). 'Labour-saving heuristics in green patents: A natural language processing analysis'. In: *Ecological Economics* 230, 108497. DOI: 10.1016/j.ecolecon.2024.108497.

Staccioli, Jacopo and Maria Enrica Virgillito (2025). 'Will your boss be an algorithm? A patent-based analysis of artificial intelligence worker management technologies and labour exposure'. In: *Eurasian Business Review*. Forthcoming. DOI: 10.1007/s40821-025-00317-7.

Todolí-Signes, Adrián (2019). 'Algorithms, artificial intelligence and automated decisions concerning workers and the risks of discrimination: the necessary collective governance of data protection'. In: *Transfer: European Review of Labour and Research* 25(4), pp. 465–481. DOI: 10.1177/1024258919876416.

Tubaro, Paola, Antonio A Casilli and Marion Coville (2020). 'The trainer, the verifier, the imitator: Three ways in which human platform workers support artificial intelligence'. In: *Big Data & Society* 7(1). DOI: 10.1177/2053951720919776.

Tubaro, Paola and Antonio A. Casilli (2019). 'Micro-work, artificial intelligence and the automotive industry'. In: *Journal of Industrial and Business Economics* 46, pp. 333–345. DOI: 10.1007/s40812-019-00121-1.

UNESCO, IRCAI (2024). *Challenging systematic prejudices: an Investigation into Gender Bias in Large Language Models*. Report CI/DIT/2024/GP/01. UNESCO and International Research Centre on Artificial Intelligence. URL: https://unesdoc.unesco.org/ark:/48223/pf0000388971.

Urzì Brancati, Cesira and Maurizio Curtarelli (2021). *Digital tools for worker management and psycho-social risks in the workplace: Evidence from the ESENER survey*. JRC Working Papers Series on Labour, education and Technology 12. European Commission. URL: https://publications.jrc.ec.europa.eu/repository/handle/JRC125714.

Urzì Brancati, Maria Cesira, Maurizio Curtarelli, Sara Riso and Sara Baiocco (2022). *How digital technology is reshaping the art of management*. JRC Working Papers Series on Labour, Education and Technology 5. European Commission. URL: https://publications.jrc.ec.europa.eu/repository/handle/JRC130808.

WIPO (2024). *World Intellectual Property Indicators 2024*. Report. World Intellectual Property Organization. DOI: https://doi.org/10.34667/tind.50133.

Wood, Alex J. (2021). *Algorithmic Management: Consequences for Work Organisation and Working Conditions*. JRC Working Papers Series on Labour, Education and Technology 7. European Commission.

Woodcock, Jamie (2022). 'Artificial intelligence at work: The problem of managerial control from call centers to transport platforms'. In: *Frontiers in Artificial Intelligence* 5, 888817. DOI: 10.3389/frai.2022.888817.

# A Appendix

## A.1 Technological co-occurrence analysis

In this subsection, we present the results of the co-occurrence analysis based on patents' CPC codes. This exercise covers patents filed over the entire period under study (1976-2022). Sectoral-level information in Fig. 8 provides an overview of the 4-digit technology subcategories that complement the scope of technical subclass `G06Q`. Across all four sectors, we observe a strong continuity with the digital knowledge base:[18] `G06F` refers to electric digital data processing; `H04L` and `H04W` to the wireless communication of digital information; `G06N` and `G06K` to computing arrangements and graphical data reading.

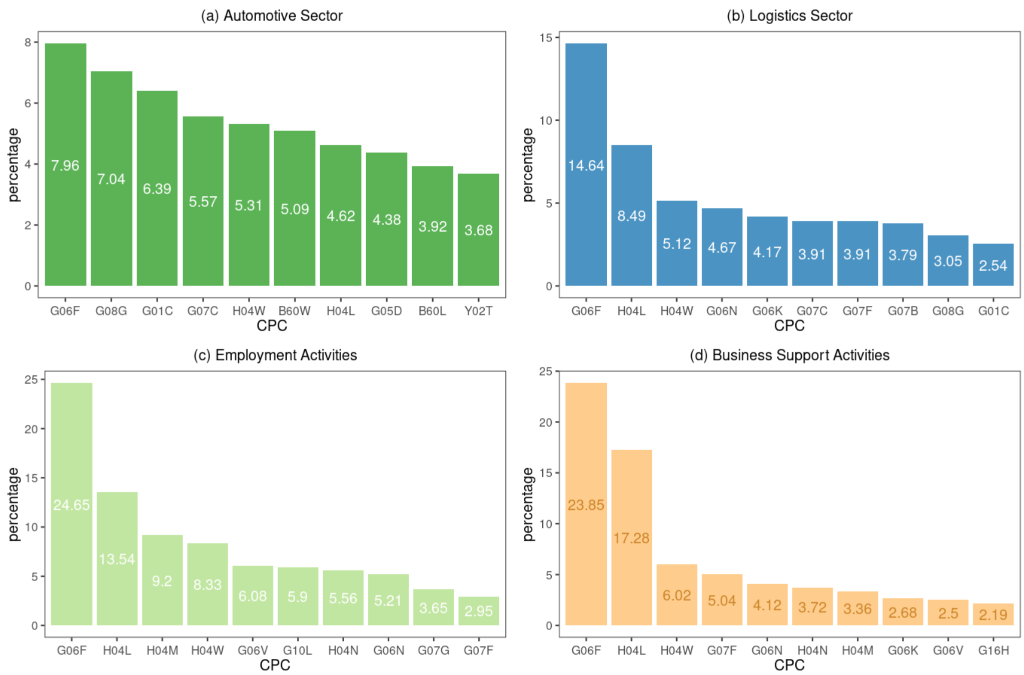



Figure 8: Co-occurrence of `G06Q` with other 4-digit CPC codes for patents in each sector under study.

## A.2 Natural language processing and dependency parsing

To identify patents that contain AIWM heuristics, we conduct three successive steps of textual analysis after restricting our focus to patents classified under CPC `G06Q10`. First, we preprocess the entire patent corpus as follows: we (i) tokenise the full-text obtaining a list of sentences, (ii) apply the same procedure to obtain a list of words, (iii) remove stop-words (such as “a”, “the”, “if”),[19] which carry little informative content, and (iv) reduce each lemma to its morphological root using a stemming algorithm.

Second, we perform a multi-word co-occurrence query on patents' full-text, comprising *title, abstract, description,* and *claims*. By means of keyword search, we single out sentences containing a combination of *predicate, object,* and *attribute* from the list of triplets (see Fig. 2), and flag a patent as *potentially AIWM* accordingly. Notably, this algorithm does not require keyword to be adjacent to one another; in other words, keywords can appear in any order in the text and need not follow one another. The procedure flags a patent as *potential AIWM* if it finds at least one triplet in any of its sentences. However, this co-occurrence method does

[18] To deepen the discussion, see Damioli et al. (2024).

[19] We employ the list of stop-words identified in the Natural Language Toolkit (`nltk`) Python library.

not control for the syntactic structure of sentences, which may lead to *false positives*. An example is given in the following excerpt:

*"in other words, the method of the invention may be executed by enhancing the* ***function****ality of a* ***control****lable braking system, that may be any system known to a* ***person*** *skilled in the art that allows for selectively braking down certain wheels of the vehicle, such as an esp system for example, featured by a state-of-the-art vehicle.", EP3524493B1*

In this case, we see that the occurrence of a triplet fails to correctly identify the targeted AIWM heuristics. Thus, as a third step, we apply a dependency parsing algorithm to account for the syntactic structure of sentences (Jurafsky and Martin, 2025).[20] This procedure enables patents to be flagged not only on the basis of detected triplets, but also by enforcing that the syntactic structure corresponds to one of the following patterns, where arrows denote syntactic linkages.

BASELINE: predicate $\longrightarrow$ attribute $\longrightarrow$ object;

PATTERN I: predicate $\longleftarrow$ attribute $\longrightarrow$ object;

PATTERN II: predicate $\longrightarrow$ object $\longrightarrow$ attribute;

PATTERN III: object $\longrightarrow$ attribute $\longrightarrow$ predicate;

PATTERN IV: object $\longrightarrow$ predicate $\longrightarrow$ attribute.

[20]The development of this second methodological phase draws significant inspiration from the work of Rughi et al. (2025).

## A.3 Computing the cosine similarity measure

In developing part of the following analysis, we draw substantial inspiration from the methodology proposed in Montobbio et al. (2024).

To link information on the technological content of AIWM tools to occupations, we draw on the O*NET database. As already noted, O*NET provides a highly granular dictionary of 19,281 human tasks that can be aggregated up to the occupation level. Thus, to compare the 276 identified AIWM patents with the 19,281 human activities, we first implement a preprocessing phase necessary to identify the morphological root of words (so-called *stemming*). Once the headwords are identified, we convert the two textual corpora into frequency vectors of the underlying common words. The text of each patent and each task is thus transformed into a vector whose elements represent the frequency with which each word appears. All the vectors belong to the same vector space, as they share the same dimensionality defined by the unique vocabulary of the corpora. Finally, the degree of proximity between each patent-task pair corresponds to the cosine of the angle between their respective vectors.

Below we provide more specific definitions to clarify the procedures for computing word frequencies and measuring cosine similarity.

As briefly noted, vector entries represent the frequency of terms within a document. Instead of using raw frequencies, we use the so-called *term frequency-inverse document frequency* (tf-idf) technique. The rationale behind this approach is to associate each term a relevance that is directly proportional to its (raw) frequency within the document (tf) and inversely proportional to its occurrence in the entire corpus (idf).

*Definition 1*: Let $D$ denote a collection of documents $d$, each composed of a set of terms from a dictionary $T$. The tf-idf measure of a term $t$ appearing in document $d$ is defined as:

$$\text{tf-idf}(t,d,D) := \text{tf}(t,d)\cdot \text{idf}(t,D), \quad \forall d \in D, \forall t \in T$$

$$\text{tf}(t,d) := 1_d(t) = \begin{cases} 1 & \text{if } t \in d \\ 0 & \text{otherwise} \end{cases}, \quad \forall d \in D, \forall t \in T$$

$$\text{idf}(t,D) := \log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right), \quad \forall t \in T$$

In this case, we construct two *document-term* matrices, one for AIWM patents and the other for human tasks. Each row contains a vector of word frequencies, while the columns represent the dictionary of common terms. Therefore, our first matrix, $D^{AIWM}$, has dimension $276x6,867$, whereas the second, $D^{TASK}$, has dimension $19,281x6,867$, where 6,867 denotes the number of unique words in the joint corpora after removing stop-words.

Finally, the degree of proximity between the two text corpora corresponds to the cosine between each pair of row vectors from $D^{AIWM}$ and $D^{TASK}$. Formally, the cosine similarity between two vectors $X,Y \in \mathbb{R}$ is defined as

$$\cos(X,Y) := \frac{X\cdot Y}{||X||||Y||} = \frac{\sum_{t=1}^{|T|} x_t y_t}{\sqrt{\sum_{t=1}^{|T|} x_t^2}\sqrt{\sum_{t=1}^{|T|} y_t^2}} = D^{AIWM}\cdot (D^{TASK})'$$

where $x_t$ and $y_t$ denote the components of vectors $X$ and $Y$, respectively, and $\|\cdot\|$ denotes the Euclidean norm. Furthermore, since the values resulting from tf-idf are non-negative, it holds that $cos(X,Y) \in [0,1]$, i.e. cosine similarity values range between 0 and 1.

A cosine similarity matrix collects all possible patent-task pairs and therefore has 276 rows and the 19,281 columns. To identify the exposure level of human activities, we group the observations by task, sum them, sort them in descending order, and finally normalise the results to the range between 0 and 1. The final outcome of this procedure is reported in Tab. 8.

In addition, when aggregating from tasks to occupations, the O*NET dictionary characterises the former according to their centrality within the latter, labelling them as *core* if they are pivotal to the work activity or as *supplemental* otherwise.[21] We provide an example to briefly clarify this aspect. In the occupation *Chief Executives*, task 8823 "Direct or coordinate an organisation's financial or budget activities to fund operations, maximise investments, or increase efficiency" is classified as *core*, whereas task 8849 "Attend and participate in meetings of municipal councils or council committees" is classified as *supplemental*. Thus, when aggregating to the occupation level, we weight the measure of task similarity as follows:

$$\begin{aligned} core &: \frac{2/3}{\text{\# tasks in the occupation}} \\ supplemental &: \frac{1/3}{\text{\# tasks in the occupation}} \end{aligned}$$

It is necessary to rescale our weighting scheme by the denominator, since occupations may be composed of different numbers of underlying tasks.

Below we present summary tables of rankings based on the normalised values of the cosine similarity measure for tasks (all sectors) and, in sub-section A.3.1, for full-digit occupations at the sector level.

The ranking of the top 20 human tasks most exposed to AIWM systems is reported in Tab. 8. Direction and control activities, which are typical of *middle management* functions within productive organisations, stand out. These are followed by planning and evaluation activities, which are likewise generally the prerogative of intermediate technical figures within organisational hierarchies.

[21] In the O*NET documentation, the criteria for this labelling procedure, namely the dimensions of *importance*, *relevance*, and *frequency* of tasks within occupations, are detailed: https://www.onetcenter.org/dictionary/29.1/excel/task_statements.html.

| Rank | Task ID | Task description | Similarity |
|---|---|---|---|
| 1 | 11944 | Set up and operate computer-controlled machines or robots to perform one or more machine functions on metal or plastic workpieces | 1.00 |
| 2 | 5261 | Direct and coordinate operational, management, and supportive services of one or a number of postal facilities | 0.93 |
| 3 | 11034 | Audition performers for one or more dance parts | 0.93 |
| 4 | 17681 | Determine efficient and cost-effective methods of moving goods from one location to another | 0.88 |
| 5 | 5161 | Compare information or figures on one record against same data on other records, or with original copy, to detect errors | 0.87 |
| 6 | 9493 | Direct activities of one or more workers who assist in preparing and serving meals | 0.87 |
| 7 | 11641 | Enter information into computers to copy programs from one electronic component to another or to draw, modify, or store schematics | 0.85 |
| 8 | 9238 | Enter into record-keeping systems appropriate data needed to create new title records or to update existing ones | 0.83 |
| 9 | 11338 | Transport mail from one work station to another | 0.83 |
| 10 | 5320 | Perform risk assessments and execute tests of data processing system to ensure functioning of data processing activities and security measures | 0.81 |
| 11 | 174 | Program and use computers to store, process, and analyze data | 0.81 |
| 12 | 13536 | Use mechanical applicators that spread compounds and embed tape in one operation | 0.80 |
| 13 | 12317 | Regulate equipment operations and conditions, such as water levels, based on instrument data or from computers | 0.77 |
| 14 | 21747 | Configure information systems to incorporate principles of least functionality and least access | 0.76 |
| 15 | 21434 | Maintain claim files, such as records of settled claims and an inventory of claims requiring detailed analysis | 0.76 |
| 16 | 10887 | Operate and calibrate computer systems and devices to comply with test requirements and to perform data acquisition and analysis | 0.76 |
| 17 | 19624 | Direct installation or operation of environmental monitoring devices or supervise related data collection programs | 0.76 |
| 18 | 12796 | Record operating data such as products and quantities pumped, gauge readings, and operating times, manually or using computers | 0.75 |
| 19 | 9389 | Select materials and components to be used, based on device design | 0.75 |
| 20 | 807 | Use data entry devices, such as optical scanners, to input data into computers for revision or editing | 0.74 |

Table 8: Top 20 tasks by (rescaled) cosine similarity considering all four sectors under study.

### A.3.1 Full-digit occupation exposure

Here, adopting a sector-level perspective, we provide tables ranking the full-digit occupations most exposed to AIWM systems. As we observe, the top occupations in each sector are engineers, managers or specialists in data management and networking systems. With specific reference to the employment services sector, the occupations with the greatest exposure are human resources specialists, talent directors, and human factors engineers. All these roles are expected to be significantly enhanced by the diffusion of worker-profiling tools.

| Rank | SOC | Occupation | Similarity |
|---|---|---|---|
| 1 | 17-2072.01 | Radio Frequency Identification Device Specialists | 1.00 |
| 2 | 15-1243.01 | Data Warehousing Specialists | 0.95 |
| 3 | 15-2051.02 | Clinical Data Managers | 0.93 |
| 4 | 15-1212.00 | Information Security Analysts | 0.84 |
| 5 | 15-1244.00 | Network and Computer Systems Administrators | 0.80 |
| 6 | 19-2099.01 | Remote Sensing Scientists and Technologists | 0.79 |
| 7 | 17-2041.00 | Chemical Engineers | 0.78 |
| 8 | 53-1043.00 | First-Line Supervisors of Material-Moving Machine and Vehicle Operators | 0.77 |
| 9 | 17-3021.00 | Aerospace Engineering and Operations Technologists and Technicians | 0.77 |
| 10 | 15-2041.00 | Statisticians | 0.76 |
| 11 | 47-2231.00 | Solar Photovoltaic Installers | 0.75 |
| 12 | 13-1032.00 | Insurance Appraisers, Auto Damage | 0.72 |
| 13 | 13-1031.00 | Claims Adjusters, Examiners, and Investigators | 0.69 |
| 14 | 51-8012.00 | Power Distributors and Dispatchers | 0.69 |
| 15 | 17-2141.02 | Automotive Engineers | 0.69 |
| 16 | 43-9111.00 | Statistical Assistants | 0.69 |
| 17 | 53-6021.00 | Parking Attendants | 0.68 |
| 18 | 51-8031.00 | Water and Wastewater Treatment Plant and System Operators | 0.68 |
| 19 | 51-9161.00 | Computer Numerically Controlled Tool Operators | 0.68 |
| 20 | 17-1022.01 | Geodetic Surveyors | 0.68 |
| 21 | 15-1211.00 | Computer Systems Analysts | 0.68 |
| 22 | 11-9199.09 | Wind Energy Operations Managers | 0.67 |
| 23 | 15-1231.00 | Computer Network Support Specialists | 0.67 |
| 24 | 15-1251.00 | Computer Programmers | 0.67 |
| 25 | 43-5032.00 | Dispatchers, Except Police, Fire, and Ambulance | 0.67 |
| 26 | 15-1232.00 | Computer User Support Specialists | 0.66 |
| 27 | 11-9111.00 | Medical and Health Services Managers | 0.66 |
| 28 | 49-2011.00 | Computer, Automated Teller, and Office Machine Repairers | 0.66 |
| 29 | 15-1241.01 | Telecommunications Engineering Specialists | 0.66 |
| 30 | 17-2061.00 | Computer Hardware Engineers | 0.65 |

Table 9: Automotive: top 30 full-digit occupations by (rescaled) cosine similarity.

| Rank | SOC | Occupation | Similarity |
|---|---|---|---|
| 1 | 15-2051.02 | Clinical Data Managers | 1.00 |
| 2 | 13-1031.00 | Claims Adjusters, Examiners, and Investigators | 0.95 |
| 3 | 15-1243.01 | Data Warehousing Specialists | 0.93 |
| 4 | 15-1212.00 | Information Security Analysts | 0.93 |
| 5 | 15-1244.00 | Network and Computer Systems Administrators | 0.90 |
| 6 | 17-2072.01 | Radio Frequency Identification Device Specialists | 0.89 |
| 7 | 15-2041.00 | Statisticians | 0.85 |
| 8 | 11-9199.09 | Wind Energy Operations Managers | 0.81 |
| 9 | 43-5021.00 | Couriers and Messengers | 0.81 |
| 10 | 43-9041.00 | Insurance Claims and Policy Processing Clerks | 0.81 |
| 11 | 43-9021.00 | Data Entry Keyers | 0.81 |
| 12 | 41-2021.00 | Counter and Rental Clerks | 0.80 |
| 13 | 17-2041.00 | Chemical Engineers | 0.80 |
| 14 | 15-1231.00 | Computer Network Support Specialists | 0.78 |
| 15 | 43-3011.00 | Bill and Account Collectors | 0.77 |
| 16 | 11-9111.00 | Medical and Health Services Managers | 0.76 |
| 17 | 43-9111.00 | Statistical Assistants | 0.76 |
| 18 | 47-2231.00 | Solar Photovoltaic Installers | 0.74 |
| 19 | 19-2099.01 | Remote Sensing Scientists and Technologists | 0.74 |
| 20 | 43-5032.00 | Dispatchers, Except Police, Fire, and Ambulance | 0.72 |
| 21 | 15-1211.00 | Computer Systems Analysts | 0.72 |
| 22 | 49-2011.00 | Computer, Automated Teller, and Office Machine Repairers | 0.72 |
| 23 | 51-1011.00 | First-Line Supervisors of Production and Operating Workers | 0.72 |
| 24 | 41-2022.00 | Parts Salespersons | 0.71 |
| 25 | 17-3021.00 | Aerospace Engineering and Operations Technologists and Technicians | 0.71 |
| 26 | 15-1232.00 | Computer User Support Specialists | 0.71 |
| 27 | 15-1299.03 | Document Management Specialists | 0.71 |
| 28 | 15-1241.01 | Telecommunications Engineering Specialists | 0.71 |
| 29 | 15-1251.00 | Computer Programmers | 0.70 |
| 30 | 13-2041.00 | Credit Analysts | 0.70 |

Table 10: Logistics: top 30 full digit occupations by (rescaled) cosine similarity.

| Rank | SOC | Occupation | Similarity |
|---|---|---|---|
| 1 | 13-1071.00 | Human Resources Specialists | 1.00 |
| 2 | 27-2012.04 | Talent Directors | 0.85 |
| 3 | 15-1211.00 | Computer Systems Analysts | 0.81 |
| 4 | 17-2112.01 | Human Factors Engineers and Ergonomists | 0.79 |
| 5 | 27-2041.00 | Music Directors and Composers | 0.76 |
| 6 | 15-1232.00 | Computer User Support Specialists | 0.75 |
| 7 | 15-2041.00 | Statisticians | 0.74 |
| 8 | 43-4161.00 | Human Resources Assistants, Except Payroll and Timekeeping | 0.73 |
| 9 | 51-1011.00 | First-Line Supervisors of Production and Operating Workers | 0.73 |
| 10 | 15-1231.00 | Computer Network Support Specialists | 0.72 |
| 11 | 19-3032.00 | Industrial-Organizational Psychologists | 0.72 |
| 12 | 15-1244.00 | Network and Computer Systems Administrators | 0.72 |
| 13 | 15-1242.00 | Database Administrators | 0.71 |
| 14 | 15-1299.02 | Geographic Information Systems Technologists and Technicians | 0.71 |
| 15 | 17-2061.00 | Computer Hardware Engineers | 0.71 |
| 16 | 15-2051.02 | Clinical Data Managers | 0.70 |
| 17 | 21-1015.00 | Rehabilitation Counselors | 0.69 |
| 18 | 17-2041.00 | Chemical Engineers | 0.68 |
| 19 | 15-1212.00 | Information Security Analysts | 0.68 |
| 20 | 15-1243.00 | Database Architects | 0.68 |
| 21 | 13-1031.00 | Claims Adjusters, Examiners, and Investigators | 0.68 |
| 22 | 17-2072.01 | Radio Frequency Identification Device Specialists | 0.66 |
| 23 | 53-1042.00 | First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand | 0.66 |
| 24 | 11-3131.00 | Training and Development Managers | 0.66 |
| 25 | 15-1243.01 | Data Warehousing Specialists | 0.66 |
| 26 | 49-1011.00 | First-Line Supervisors of Mechanics, Installers, and Repairers | 0.62 |
| 27 | 15-1299.03 | Document Management Specialists | 0.62 |
| 28 | 15-1251.00 | Computer Programmers | 0.62 |
| 29 | 43-9041.00 | Insurance Claims and Policy Processing Clerks | 0.61 |
| 30 | 11-3121.00 | Human Resources Managers | 0.60 |

Table 11: Employment activities: top 30 full digit occupations by (rescaled) cosine similarity.

| Rank | SOC | Occupation | Similarity |
|---|---|---|---|
| 1 | 15-2051.02 | Clinical Data Managers | 1.00 |
| 2 | 15-1243.01 | Data Warehousing Specialists | 0.95 |
| 3 | 15-1212.00 | Information Security Analysts | 0.92 |
| 4 | 15-2041.00 | Statisticians | 0.90 |
| 5 | 17-2072.01 | Radio Frequency Identification Device Specialists | 0.89 |
| 6 | 15-1244.00 | Network and Computer Systems Administrators | 0.83 |
| 7 | 15-1231.00 | Computer Network Support Specialists | 0.83 |
| 8 | 15-1299.03 | Document Management Specialists | 0.81 |
| 9 | 43-9111.00 | Statistical Assistants | 0.78 |
| 10 | 13-1031.00 | Claims Adjusters, Examiners, and Investigators | 0.77 |
| 11 | 15-1211.00 | Computer Systems Analysts | 0.77 |
| 12 | 15-1299.02 | Geographic Information Systems Technologists and Technicians | 0.77 |
| 13 | 19-2099.01 | Remote Sensing Scientists and Technologists | 0.76 |
| 14 | 15-1232.00 | Computer User Support Specialists | 0.73 |
| 15 | 15-1242.00 | Database Administrators | 0.71 |
| 16 | 43-9041.00 | Insurance Claims and Policy Processing Clerks | 0.71 |
| 17 | 15-1243.00 | Database Architects | 0.70 |
| 18 | 15-1251.00 | Computer Programmers | 0.69 |
| 19 | 43-9021.00 | Data Entry Keyers | 0.68 |
| 20 | 15-1241.01 | Telecommunications Engineering Specialists | 0.68 |
| 21 | 17-2061.00 | Computer Hardware Engineers | 0.68 |
| 22 | 17-2112.01 | Human Factors Engineers and Ergonomists | 0.68 |
| 23 | 51-1011.00 | First-Line Supervisors of Production and Operating Workers | 0.67 |
| 24 | 11-9111.00 | Medical and Health Services Managers | 0.67 |
| 25 | 17-1022.01 | Geodetic Surveyors | 0.66 |
| 26 | 19-3022.00 | Survey Researchers | 0.65 |
| 27 | 17-2041.00 | Chemical Engineers | 0.64 |
| 28 | 15-2099.01 | Bioinformatics Technicians | 0.63 |
| 29 | 15-2031.00 | Operations Research Analysts | 0.63 |
| 30 | 17-2112.00 | Industrial Engineers | 0.62 |

Table 12: Business support activities: top 30 full digit occupations by (rescaled) cosine similarity.

## Working Papers
## Dipartimento di Politica Economica

1. *Innovation, jobs, skills and tasks: a multifaceted relationship.* M. Piva, M. Vivarelli. Vita e Pensiero, maggio 2018 (ISBN 978-88-343-3654-0)
2. *A bridge over troubled water: Interdisciplinarity, Novelty, and Impact.* M. Fontana, M. Iori, F. Montobbio, R. Sinatra. Vita e Pensiero, settembre 2018 (ISBN 978-88-343-3793-6)
3. *Concordance and complementarity in IP instruments*. M. Grazzi, C. Piccardo, C. Vergari. Vita e Pensiero, gennaio 2019 (ISBN 978-88-343-3879-7)
4. *Sustainable finance, the good, the bad and the ugly: a critical assessment of the EU institutional framework for the green transition*. L. Esposito, E.G. Gatti, G. Mastromatteo. Vita e Pensiero, febbraio 2019 (ISBN 978-88-343-3892-6)
5. *Technology and employment in a vertically connected economy: a model and an empirical test.* G. Dosi, M. Piva, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, giugno 2019 (ISBN digital edition [PDF]: 978-88-343-4008-0)
6. *Testing the employment impact of automation, robots and AI: A survey and some methodological issues.* L. Barbieri, C. Mussida, M. Piva, M. Vivarelli. Vita e Pensiero, settembre 2019 (ISBN digital edition [PDF]: 978-88-343-4052-3)
7. *A new proposal for the construction of a multi-period/multilateral price index*. C.R. Nava, A. Pesce, M.G. Zoia. Vita e Pensiero, ottobre 2019 (ISBN digital edition [PDF]: 978-88-343-4114-8)
8. *Lo Stato Sociale: da "lusso" a necessità*. L. Campiglio. Vita e Pensiero, febbraio 2020 (ISBN digital edition [PDF]: 978-88-343-4184-1)
9. *Robots and the origin of their labour-saving impact*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, marzo 2020 (ISBN digital edition [PDF]: 978-88-343-4196-4)
10. *Business visits, technology transfer and productivity growth*. M. Piva, M. Tani, M. Vivarelli. Vita e Pensiero, marzo 2020 (ISBN digital edition [PDF]: 978-88-343-4210-7)
11. *Technology, industrial dynamics and productivity: a critical survey*. M. Ugur, M. Vivarelli. Vita e Pensiero, settembre 2020 (ISBN digital edition [PDF]: 978-88-343-4406-4)
12. *Back to the past: the historical roots of labour-saving automation*. J. Staccioli, M.E. Virgillito. Vita e Pensiero, novembre 2020 (ISBN digital edition [PDF]: 978-88-343-4473-6)
13. *The present, past, and future of labor-saving technologies.* J. Staccioli, M.E. Virgillito. Vita e Pensiero, dicembre 2020 (ISBN digital edition [PDF]: 978-88-343-4479-8)
14. *Why Do Populists Neglect Climate Change? A Behavioural Approach*. L.A. Lorenzetti. Vita e Pensiero, dicembre 2020 (ISBN digital edition [PDF]: 978-88-343-4483-5)
15. *Relative wages, payroll structure and performance in soccer. Evidence from Italian Serie A (2007-2019)*. C. Bellavite Pellegrini, R. Caruso, M. Di Domizio. Vita e Pensiero, gennaio 2021 (ISBN digital edition [PDF]: 978-88-343-4490-3)
16. *Robots, AI, and Related Technologies: A Mapping of the New Knowledge Base*. E. Santarelli, J. Staccioli, M. Vivarelli. Vita e Pensiero, gennaio 2021 (ISBN digital edition [PDF]: 978-88-343-4499-6)
17. *Detecting the labour-friendly nature of AI product innovation*. G. Damioli, V. Van Roy, D. Vertesy, M. Vivarelli. Vita e Pensiero, aprile 2021 (ISBN digital edition [PDF]: 978-88-343-4600-6)
18. *Circular Economy Approach: The benefits of a new business model for European Firms*. C. Bellavite Pellegrini, L. Pellegrini, C. Cannas. Vita e Pensiero, luglio 2021 (ISBN digital edition [PDF]: 978-88-343-4817-8)
19. *The impact of cognitive skills on investment decisions. An empirical assessment and policy suggestions.* L. Esposito, L. Marrese. Vita e Pensiero, luglio 2021 (ISBN digital edition [PDF]: 978-88-343-4822-2)
20. *"Thinking of the end of the world and of the end of the month": the Impact of Regenerative Agriculture on Economic and Environmental Profitability*. L.A. Lorenzetti, A. Fiorini. Vita e Pensiero, ottobre 2021 (ISBN digital edition [PDF]: 978-88-343-4898-7)

**21**. *Labour-saving automation and occupational exposure: a text-similarity measure*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5089-8)
**22**. *Climate reputation risk and abnormal returns in the stock markets: a focus on large emitters*. G. Guastella, M. Mazzarano, S. Pareglio, A. Xepapadeas. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5092-8)
**23**. *Carbon Boards and Transition Risk: Explicit and Implicit exposure implications for Total Stock Returns and Dividend Payouts*. M. Mazzarano, G. Guastella, S. Pareglio, A. Xepapadeas. Vita e Pensiero, novembre 2021 (ISBN digital edition [PDF]: 978-88-343-5093-5)
**24**. *Innovation and employment: a short update*. M. Vivarelli. Vita e Pensiero, gennaio 2022 (ISBN digital edition [PDF]: 978-88-343-5113-0)
**25**. *AI technologies and employment. Micro evidence from the supply side*. G. Damioli, V. Van Roy, D. Vertesy, M. Vivarelli. Vita e Pensiero, gennaio 2022 (ISBN digital edition [PDF]: 978-88-343-5119-2)
**26**. *The Effect of External Innovation on Firm Employment*. G. Arenas Díaz, A. Barge-Gil, J. Heijs, A. Marzucchi. Vita e Pensiero, febbraio 2022 (ISBN digital edition [PDF]: 978-88-343-5146-8)
**27**. *The North-South divide: sources of divergence, policies for convergence*. L. Fanti, M.C. Pereira, M.E. Virgillito. Vita e Pensiero, maggio 2022 (ISBN digital edition [PDF]: 978-88-343-3524-4)
**28**. *The empirics of technology, employment and occupations: lessons learned and challenges ahead*. F. Montobbio, J. Staccioli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, novembre 2022 (ISBN digital edition [PDF]: 978-88-343-5383-7)
**29**. *Cognitive biases and historical turns. An empirical assessment of the intersections between minds and events in the investors' decisions*. L. Esposito, L. Malara. Vita e Pensiero, gennaio 2023 (ISBN digital edition [PDF]: 978-88-343-5420-9)
**30**. *Interaction between Ownership Structure and Systemic Risk in the European financial sector*. C. Bellavite Pellegrini, R. Camacci, L. Pellegrini, A. Roncella. Vita e Pensiero, febbraio 2023 (ISBN digital edition [PDF]: 978-88-343-5446-9)
**31**. *Was Robert Gibrat right? A test based on the graphical model methodology*. M. Guerzoni, L. Riso, M. Vivarelli. Vita e Pensiero, marzo 2023 (ISBN digital edition [PDF]: 978-88-343-5457-5)
**32.** *A North-South Agent Based Model of Segmented Labour Markets. The Role of Education and Trade Asymmetries*. L. Fanti, M.C. Pereira, M.E. Virgillito. Vita e Pensiero, maggio 2023 (ISBN digital edition [PDF]: 978-88-343-5529-9)
**33**. *Innovation and the Labor Market: Theory, Evidence and Challenges*. N. Corrocher, D. Moschella, J. Staccioli, M. Vivarelli. Vita e Pensiero, giugno 2023 (ISBN digital edition [PDF]: 978-88-343-5580-0)
**34**. *The Effect of Economic Sanctions on World Trade of Mineral Commodities. A Gravity Model Approach from 2009 to 2020*. R. Caruso, M. Cipollina. Vita e Pensiero, dicembre 2023 (ISBN digital edition [PDF]: 978-88-343-5686-9)
**35**. *Education and Military Expenditures: Countervailing Forces in Designing Economic Policy. A Contribution to the Empirics of Peace*. A. Balestra, R. Caruso. Vita e Pensiero, gennaio 2024 (ISBN digital edition [PDF]: 978-88-343-5757-6)
**36**. *Vulnerability to Climate Change and Communal Conflicts: Evidence from Sub-Saharan Africa and South/South-East Asia*. S. Balestri, R. Caruso. Vita e Pensiero, maggio 2024 (ISBN digital edition [PDF]: 978-88-343-5829-0)
**37**. *Assessing changes in EU innovation policy programs: from SME instrument to EIC accelerator for start-up funding*. M. del Sorbo, C. Faber, M. Grazzi, F. Matteucci, M. Ruß. Vita e Pensiero, luglio 2024 (ISBN digital edition [PDF]: 978-88-343-5860-3)
**38**. *AI as a new emerging technological paradigm: evidence from global patenting.* G. Damioli, V. Van Roy, D. Vertesy, M. Vivarelli. Vita e Pensiero, settembre 2024 (ISBN digital edition [PDF]: 978-88-343-5873-3)
**39**. *The KSTE+I approach and the AI technologies*. F. D'Alessandro, E. Santarelli, M. Vivarelli. Vita e Pensiero, settembre 2024 (ISBN digital edition [PDF]: 978-88-343-5880-1)
**40**. *Quo Vadis Terra? The future of globalization between trade and war*. L. Esposito, E.G. Gatti, G. Mastromatteo. Vita e Pensiero, settembre 2024 (ISBN digital edition [PDF]: 978-88-343-5895-5)
**41**. *The Agents of Industrial Policy and the North-South Convergence: State-Owned Enterprises in an International-Trade Macroeconomic ABM.* L. Fanti, M.C. Pereira, M.E. Virgillito. Vita e Pensiero, ottobre 2024 (ISBN digital edition [PDF]: 978-88-343-5909-9)

**42.** *The impact of US elections on US defense industry: Firm-level evidence from 1996 to 2022*. A. Balestra, R. Caruso. Vita e Pensiero, January 2025 (ISBN digital edition [PDF]: 978-88-343-5937-2)

**43**. *Forecasting the Impact of Extreme Weather Events on Electricity Prices in Italy: A GARCH-MIDAS Approach with Enhanced Variable Selection*. M. Guerzoni, L. Riso, M.G. Zoia. Vita e Pensiero, January 2025 (ISBN digital edition [PDF]: 978-88-343-5938-9)

**44**. *The Theoretical Properties of Novel Risk-Based Asset Allocation Strategies using Portfolio Volatility and Kurtosis*. M.D. Braga, L. Riso, M.G. Zoia. Vita e Pensiero, January 2025 (ISBN digital edition [PDF]: 978-88-343-5939-6)

**45**. *Sustainable Finance in the New Geo-Political Era: A Difficult Balancing Act*. L. Esposito, M. Cocco. Vita e Pensiero, February 2025 (ISBN digital edition [PDF]: 978-88-343-5940-2)

**46**. *New technologies and employment: the state of the art*. M. Vivarelli, G. Arenas Díaz. Vita e Pensiero, March 2025 (ISBN digital edition [PDF]: 978-88-343-5941-9)

**47**. *Leveraging Knowledge Networks: Rethinking Technological Value Distribution in mRNA Vaccine Innovations*. R. Mastrandrea, F. Montobbio, G. Pellegrino, M. Riccaboni, V. Sterzi. Vita e Pensiero, March 2025 (ISBN digital edition [PDF]: 978-88-343-5991-4)

**48**. *A Twin Transition or a policy flagship? Emergent constellations and dominant blocks in green and digital technologies*. L. Nelli, M.E. Virgillito, M. Vivarelli. Vita e Pensiero, April 2025 (ISBN digital edition [PDF]: 978-88-343-5992-1)

**49**. *The role of business visits in fostering R&D investment*. M. Vivarelli, M. Piva, M. Tani. Vita e Pensiero, June 2025 (ISBN digital edition [PDF]: 978-88-343-5993-8)

**50**. *A Deep Learning procedure for the identification of Artificial Intelligence technologies in patent data*. F. D'Alessandro. Vita e Pensiero, June 2025 (ISBN digital edition [PDF]: 978-88-343-5994-5)

**51**. *ESGs Scoring and Its Divergencies: An empirical Investigation in the Food and Beverage Industry*. C. Bellavite Pellegrini, R. Camacci, P. Cincinelli. Vita e Pensiero, September 2025 (ISBN digital edition [PDF]: 978-88-343-5995-2)

**52**. *Artificial intelligence as a method of invention*. G. Arenas Díaz, M. Piva, M. Vivarelli. Vita e Pensiero, November 2025 (ISBN digital edition [PDF]: 978-88-343-5996-9)

**53**. *Does corruption trigger political violence? Evidence from Sub-Saharan Africa (1970-2020)*. R. Caruso, E. Galli, G. Tringali. Vita e Pensiero, December 2025 (ISBN digital edition [PDF]: 978-88-343-6190-0)

**54**. *The determinants of defense burden sharing in the European Union from 1980 to 2024*. A. Balestra, R. Caruso, S. Mombelli. Vita e Pensiero, December 2025 (ISBN digital edition [PDF]: 978-88-343-6193-1)

**55**. *Arms Import and Civil Conflict Onset: Risk-Set Evidence from Sub-Saharan Africa, 1960–2022*. A. Balestra, R. Caruso. Vita e Pensiero, January 2026 (ISBN digital edition [PDF]: 978-88-343-6198-6)

**56**. *AI Worker Management technologies in traditional industries*. C. Collodoro, L. Fanti, J. Staccioli, M.E. Virgillito. Vita e Pensiero, January 2026 (ISBN digital edition [PDF]: 978-88-343-6217-4)