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AI-Enabled Automation, Labor Market Vulnerabilities, and Structural Transformation within an Applied Informatics Framework for Economic Analysis

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A R T I C L E I N F O

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A B S T R A C T

The accelerated expansion of machine learning and intelligent automation is profoundly reshaping the future of work and the structure of global labor markets, transforming production processes, skill requirements, and employment patterns. This paper provides a critical analysis, based on the specialized literature, of the main vulnerabilities generated by AI-based automation, with a focus on the automation of repetitive tasks, the reconfiguration of occupations, and the intensification of gaps between existing and emerging skills. In a multidisciplinary framework, the study examines the mechanisms through which AI influences job polarization, productivity dynamics, and the redistribution of economic opportunities, highlighting differential effects across sectors and categories of workers. A distinct focus is placed on the risks associated with algorithmic management and the digitalization of performance evaluation, including the impact on work quality, occupational health, autonomy, and the contestability of decisions. The paper also discusses the ethical and public policy challenges regarding the transparency of algorithmic systems, data governance and worker protection in automated work environments. The conclusions support the need for adaptive public policies that combine investments in education and continuous training with governance standards and occupational security, to strengthen the resilience, inclusion and competitiveness of the workforce in the era of smart technologies.

1. Introduction

Given that the accelerated development of machine learning and intelligent automation are important transformational forces of the 21st century (Liu et al., 2024), the rapid integration of artificial intelligence and data-driven automation into various economic activities is somehow required. These activities can be in the industry, healthcare, finance, logistics and public administration sectors. All these new technologies of this century modify production processes, organizational models and the structure of occupations (Damioli et al., 2021; Dixon et al., 2023; Shen & Zhang, 2024). Consequently, we can observe that the boundary between the work done by people and that done by intelligent systems is becoming increasingly permeable. This in the context of opening up a series of substantial opportunities for productivity and efficiency, on the one hand, but also amplifying the risks regarding employment stability, job quality and social equity.

Thus, looking at things from an economic perspective, we see that intelligent automation acts simultaneously as a driver of productivity growth but also as a factor of disruption of traditional labor market mechanisms. We can see that routine tasks and repetitive activities are increasingly taken over by a series of algorithms capable of learning quickly, but also of optimizing many decisions in real time. All of this can reduce operational costs and accelerate innovation in a very short time. At the same time, the specialized literature highlights a series of structural tensions generated by this process, such as the substitution of some tasks, the reconfiguration of occupations but also the accentuation of polarization between skill segments (Acemoglu et al., 2022; Acemoglu & Restrepo, 2019; Frank et al., 2019). Unlike previous waves of automation from past centuries, machine learning has the ability to extend the potential of automation to cognitive and analytical activities, including in knowledge-based occupations. This, experts say, amplifies both transitory uncertainty and the need for rapid institutional adjustments (Albaroudi, 2019; Damioli et al., 2021).

The digital transformation of work generates a dual dynamic. On the one hand, new roles associated with the development and implementation of AI systems, data analysis and human-machine collaboration appear; on the other hand, low- and medium-skilled occupations are exposed to pressure, especially where

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tasks are standardizable and easily automated. This tension is reflected in the increased risk of mismatches between the demand and supply of skills and in the deepening of the digital divide, both between and within economies, where access to infrastructure and digital skills becomes decisive for inclusion and competitiveness. In addition, recent literature shows that assessing the impact of AI on work cannot remain limited to the dimension of job substitution. A set of risks called "beyond substitution" associated with algorithmic management and the automation of coordination processes is increasingly emerging: work intensification, reduced autonomy, opacity of decisions and reduced contestability of performance evaluation. Thus, we can deduce that these mechanisms can affect both the quality of jobs and occupational health. In a number of sectors, where an accelerated adoption of algorithmic optimization is expected, such as logistics, and where real-time monitoring and dynamic KPIs are expected, an amplification of time pressure and ergonomic risks can be observed. Also, at the same time, in these sectors, it has been observed that ethical and governance challenges regarding confidentiality, algorithmic bias and the responsibility of automated decision-making in processes such as recruitment, evaluation or remuneration setting may arise (Babashahi et al., 2024; Mäkelä & Stephany, 2025; Salari et al., 2025).

The dimension of skills and education remains essential in this transition. This is because the demand for digital skills, or for a series of analytical capacities, or for problem-solving and interdisciplinary skills, has been growing, in recent times, at a pace that often exceeds the adaptation of curricula and training systems. Given these aspects, it can be said that this evolution underlines the importance of lifelong learning, but also of continuous training or cooperation between academia, industry and public authorities in the idea of developing viable reconversion trajectories. Specialists in the field have highlighted the fact that in the absence of investments in human capital or policies supporting transitions, then the risk of structural unemployment and deepening inequalities becomes more pronounced (Choi & Marinescu, 2024; Eurostat, 2024; Huang, 2024; OECD, 2023).

Considering these aspects, this paper carries out, on the one hand, a critical synthesis of recent specialized literature on the impact of machine learning and intelligent automation on the future of work, pursuing three main analytical directions, namely: O1. Mapping AI-induced vulnerabilities at the level of tasks, occupations and skills; O2. Highlighting emerging risks to the quality of work but also to occupational health, associated with algorithmic management; and O3. Discussing the implications through the lens of adaptive public policies for organizational strategies, so that the transition to the digital economy supports resilience, inclusion but at the same time the competitiveness of the workforce.

2. Literature review

Recent literature highlights the idea that artificial intelligence (AI), machine learning (ML) and intelligent automation are simultaneously reconfiguring productivity, occupational structures and work governance models. From an economic perspective, the effects are dualistic: on the one hand, efficiency gains and innovation; on the other hand, structural tensions – occupational polarization, displacement of routine work and increased need for digital skills. Empirical studies (from 2024 to 2025) that track these trends show that exposure to AI differs across occupations and regions, and that new tasks created by technology co-exist with processes of substitution in repetitive or standardizable tasks (Huang, 2024). In terms of measuring the impact on the labor market, recent work advances methodologies based on occupational exposure to AI, using data from job advertisements, patents or occupational projections. A recent study finds decreases in the employment-to-population ratio in areas with higher AI adoption, indicating a substitution effect in the aggregate, although heterogeneous across occupations (FMI,2024). In parallel, another study explicitly integrates AI into the 2023–2033 occupational projections, illustrating how some occupational families are being reconfigured by AI, not only in volume but also in the content of tasks (Machovec, 2025). At the skills level, recent work highlights the increasing demand for complementary AI skills (analytical, collaborative, ethical) and digital literacy (Portocarrero, 2025).

A second theoretical thread discusses the mechanisms of job creation vs. substitution recent work shows that the potential impact depends closely on the skill structure required by occupations, and studies in other economic journals show that AI creates demand for workers with AI skills, while there is a marginal decline in the demand for non-AI work in sectors with high adoption. In this sense, the "future of work" does not mean the disappearance of employment, but reconfiguration: the expansion of AI-augmented roles and the compression of strictly routine roles (Septiandri et al., 2024).

At the intersection of computer science and human resources, a growing literature examines recruitment algorithms and algorithmic management. A synthesis (2024) and studies from 2024 to 2025 show that while AI can improve selection efficiency, risks of algorithmic bias, transparency requirements, and the need for human oversight arise. Convergent, another study summarizes the emergence of algorithmic management in platform work and traditional organizations, with implications for autonomy, control, and well-being (Fabris et al., 2025).

The ethical and legal dimensions of AI in the workplace are taking shape, as a series of papers (2024) show how the promise of "non-discrimination" through AI in recruitment is often undermined by opaque decisions and unbalanced datasets, and other reviews (2024) inventory technical techniques for mitigating bias in hiring. At the same time, research from several years ago highlights the psychosocial costs of algorithmic management and the effects on workers' rights in platform contexts – an agenda that calls for updated regulatory frameworks and mandatory impact assessments (Seppälä & Małecka, 2024). At the skills level, several studies (2024–2025) document the growing demand for AI literacy and human-centered skills (problem-solving, critical thinking, collaboration), in both STEM and non-STEM occupations. Recent research highlights direct links between AI skills and graduate employability, while future-of-work perspectives outline a research agenda for companies and public policies: augmented job design, continuous training and ethical governance of AI (Bankins et al., 2024).

Finally, evidence based on job postings and comparative analyses confirms the hybrid picture composed of: AI replacing repetitive tasks, complementing complex cognitive tasks and stimulating new roles (prompting, algorithmic supervision, process design). In addition, a number of researchers indicate the need for occupational anticipation tools (projections, scenarios) and active policies for fair professional transitions (Engberg et al., 2025)

Overall, studies in recent years show that research on ML and intelligent automation is current and crucial. Moreover, it explains why productivity gains coexist with social risks (polarization, bias, precariousness) and why employment policies must be combined with technical solutions (bias mitigation, algorithmic audit) and educational interventions (upskilling/reskilling). It is precisely this framework that justifies the approach of our analysis, in the sense of carrying out an integrated, economic-informatics analysis of the emerging risks and structural challenges of the AI-augmented "future of work".

3. Sectoral Exposure to AI-Enabled Automation and the Polarization of Skill Demand

Related to sectoral exposure to AI enabled automation and the polarization of skill demand, we observe that the development of machine learning technologies and intelligent automation is redefining, at a global level, the structure of the labor market.

Table 1. Estimated Impact of Intelligent Automation by Economic Sector (2020–2025)

Economic Sector	Automation Potential (%)	Main Tasks Affected	Dominant Type of AI Integration	Expected Employment Effect (2025)	Trend Direction	Data Source
Manufacturing Industry	68	Assembly, quality control, machinery operation	Robotics, predictive maintenance, ML-based inspection	Moderate decline (−5%)	Decreasing manual labor, increasing supervision tasks	OECD (2024), McKinsey (2025)
Financial Services	47	Data processing, compliance monitoring, fraud detection	NLP, automation of decision-making	Role redefinition, no net job loss	Shift to analytical and advisory roles	WEF (2025), IMF (2024)
Education	22	Administrative, grading, student assessment	AI tutoring, adaptive learning systems	Increased demand for AI-assisted teaching (+4%)	Upward trend in hybrid teaching roles	UNESCO (2024), Eurostat (2023)
Healthcare	35	Diagnostics, patient data management, scheduling	Image recognition, decision-support AI	Moderate job growth in AI-assisted diagnostics	Upward (augmentation effect)	WHO (2024), OECD (2023)
Logistics and Transport	72	Routing, warehousing, autonomous delivery	Robotics, reinforcement learning systems	Job relocation, automation of procedural roles	Declining routine jobs, rising maintenance roles	WEF (2025), DHL AI Report (2024)

Source: authors, compiled from OECD (2024), WEF (2025), Eurostat (2023), IMF (2024), and McKinsey (2025) datasets. Automation potential based on share of automatable tasks and sectoral AI integration levels.

While these new technologies increase efficiency and productivity, they also seem to determine a profound reconfiguration of professional roles, the demand for skills and the distribution of jobs. It is thus observed that the transformation of the labor market through ML and intelligent automation is not uniform, but the impact differs depending on the sector, qualification level and the degree of technological adoption.

Intelligent automation extends the technological capacity for processing, analysis and decision-making, going beyond the phase of classical automation based on fixed rules. In the literature, two forms of automation are distinguished: "substitutive", in which AI systems completely replace certain repetitive human tasks, and "augmentative", in which AI complements human work, increasing the accuracy and speed of the decision-making process. The task-based model developed in recent years provides a useful framework for understanding these dynamics. Recent data also show that the degree of automation differs significantly across sectors. In industry and logistics, automation has more pronounced substitution effects, while in services and education, the effects are predominantly augmentative (OECD, 2024; Eurostat, 2023)

Table 1 demonstrates a sector-level risk mapping of AI-enabled automation, distinguishing displacement-intensive sectors from augmentation-dominant ones and indicating the expected direction of adoption dynamics through 2025.

The literature highlights the rapid growth in demand for digital, data analysis, and interaction skills with AI-based systems. On the other hand, it is emphasized that the LM has the role of transforming the structure of required skills, shifting the emphasis from execution to interpretation and monitoring (WEF, 2025; McKinsey, 2024). At the same time, a number of non-technical skills, such as critical thinking, empathy, and collaboration, seem to become essential in a number of roles augmented by AI.

Table 2. Dynamics of Digital and Cognitive Skill Demand under Intelligent Automation (2020–2025)

Skill Category	Examples of Competencies	Primary Industry Demand	Automation Sensitivity	Change in Demand (2020–2025)	Skill Function in AI Ecosystem	Data Source
Advanced Digital & Technical Skills	Python, TensorFlow, Data Science, Cloud Infrastructure	IT, finance, manufacturing	Low (complementary to AI)	+48%	Design and supervision of AI systems	WEF (2025), OECD (2024)
Data Literacy & Analytical Reasoning	SQL, PowerBI, Data Interpretation	All industries	Medium	+38%	Decision support and performance optimization	Eurostat (2024), McKinsey (2024)
Soft & Adaptive Skills	Communication, critical thinking, problem-solving	Services, education, management	Very low	+27%	Human-AI collaboration and coordination	WEF (2025), UNESCO (2024)
Ethical & Governance Skills	AI auditing, algorithmic transparency, fairness metrics	Public administration, legal, HR	Low	+21%	Ensuring accountability in automated decisions	IEEE (2024), EU AI Act (2025)
Operational & Procedural Skills	Manual process handling, task repetition	Logistics, manufacturing	Very high (substitution risk)	–31%	Declining relevance due to automation	OECD (2023), IMF (2024)

Source: authors, compiled from OECD (2024), WEF (2025), Eurostat (2023), IMF (2024), and McKinsey (2025) datasets. Skill-demand dynamics are inferred from reported skill taxonomies, occupational profiles, and sectoral digitalization indicators, harmonized for the 2020–2025 horizon.

Table 2 highlights the polarization of skill demand, strong growth in digital, analytical, and ethical competencies, and decline in routine operational skills. This supports the argument that machine learning systems favor adaptive and interdisciplinary skill sets, driving labor market transformation.

Figure 1 highlights the heterogeneous impact of intelligent automation across economic sectors. It is observed that industries with a high proportion of routine, procedural and manual tasks, such as manufacturing and logistics, have the highest potential for automation (over 65%). As a result, this faces a negative effect on employment. In contrast, sectors such as education and healthcare have a lower potential for automation. In these sectors, machine learning and intelligent systems function as augmentative tools that enhance, rather than replace, human work. All this supports the "task reconfiguration hypothesis", the hypothesis that emphasizes a shift from routine substitution to hybrid human-AI collaboration.

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Figure 1. AI adoption vs employment impact by sector

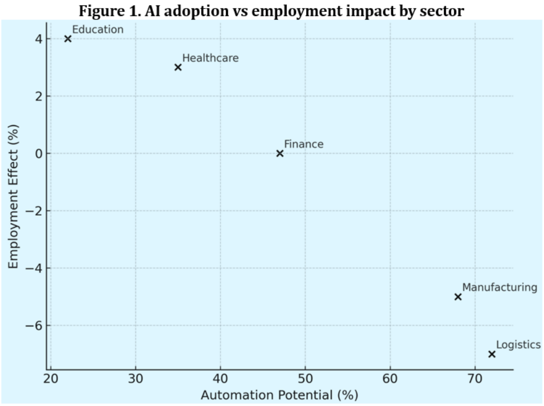
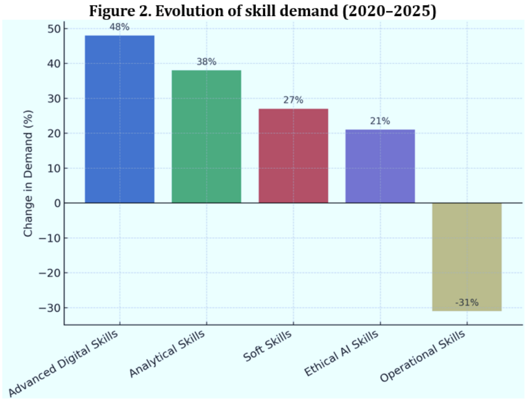


Figure 2. Evolution of skill demand (2020–2025)



Source: Authors, compiled from OECD (2024), WEF (2025), Eurostat (2023), IMF (2024), and McKinsey Global Institute (2025) datasets. Automation potential is based on the share of automatable tasks and the degree of AI integration across economic sectors.

Figure 2 complements the findings in Figure 1, highlighting on the one hand the rapid growth in demand for advanced digital skills, analytical and ethical competences in the field of artificial intelligence, especially between 2020 and 2025. While a number of technical and analytical skills (such as Python, data analysis, cloud computing) are experiencing strong growth, the sustained relevance of non-technical skills and AI governance knowledge underlines this multidimensional side of employability in this digital age. Together, the two figures demonstrate that machine learning and intelligent automation are not only reshaping occupational structures, but also redefining the skills ecosystem needed for sustainable participation in the future labor market.

We can say that intelligent automation and machine learning are two very powerful forces that have been shaping the labor market simultaneously in recent times. They can increase productivity, on the one hand, and even accelerate innovation, but on the other hand, they can also bring a series of negative effects. Thus, some jobs become highly demanded, while others risk disappearing or becoming less valuable, thus increasing the differences between categories and accentuating inequalities between occupational categories. Considering these aspects, we will analyze what follows this digital transition that needs proactive measures. Retraining and upskilling programs, sustained investments in digital skills, but also a clear ethical governance framework for the use of AI should be considered. In conclusion, it is obvious that the balance between automation and the development of human capital (at the same time flexible but also adaptable) would be decisive for a sustainable transformation towards an economy based on artificial intelligence.

3.1. Labor market vulnerabilities and risks associated with AI-based automation

With reference to the vulnerabilities existing in the labor market and the risks associated with AI-based automation, recent literature highlights a series of aspects that lead to the idea that AI does not inevitably lead to the disappearance of occupations, but rather to the reconfiguration of the content of work, by redistributing tasks between people and between certain digital systems (Acemoglu & Restrepo, 2019; OECD, 2023).

Consequently, vulnerability is not characterized as a binary attribute ("automatizable/non-automatizable"), but rather as a result of the interaction between: (i) the exposure of tasks to automation/assistance, (ii) the pace of technological diffusion at organizational and sectoral levels and last but not least (iii) the adjustment capacity of workers and institutions (training, mobility, protections) (Dixon, 2023; OECD, 2023).

In analytical terms, this approach aligns with the "task-based" approaches, which highlight the fact that technology modifies labor demand through simultaneous effects of dislocation (task substitution) and resettlement (creation/redefinition of tasks in which the comparative advantage remains human) (Acemoglu & Restrepo, 2019). In this framework of literary analysis, a useful operational distinction is that between substitution, in the sense that AI takes over standardizable, repetitive, easily verifiable tasks, and that between complementarity, that is, AI amplifies human productivity in tasks that involve judgment, communication, contextual integration. (OECD, 2023). A series of literary analyses emphasize a series of aspects such as the fact that the effects of AI are increasingly visible at the task level (including cognitive), but no simple pattern of automatic reduction in total labor demand emerges; rather, restructurings and redistributions of demand across occupations and skills are observed, depending on the implementation mode and the institutional architecture of the transition (OECD, 2023).

Thus, an empirical reference example for this logic is the study on the introduction of an AI-based conversational assistant in a call center: the results indicate an increase in average productivity, but also a robust heterogeneity of effects, with greater benefits for less experienced workers (Brynjolfsson et al., 2025). It is observed that the implications for labor market vulnerabilities are twofold: on the one hand, some roles become more accessible (lower entry barrier, greater procedural support), and on the other hand, pressure increases on segments where added value came from standardized intermediate tasks—feeding the premises of polarization of skills demand (Acemoglu & Restrepo, 2019; OECD, 2023). AI-assisted programs, called "co-pilots", are not only making us more efficient at work, but are also changing the way we learn and share our knowledge. Recent studies show that while AI provides support, there is a high risk of employees becoming vulnerable. This is especially if these tools take over important tasks and if the organization fails to provide clear rules for use and adequate training. Therefore, the success of AI integration depends crucially on an organizational culture that establishes clear and transparent procedures to protect the role and meaningful work of people (Callari & Puppione, 2025).

At the same time, contemporary literature insists that vulnerability analysis cannot remain limited to substitution and productivity, as the implementation of AI introduces emerging risks to work quality and occupational health (algorithmic management, real-time monitoring, automated assessment). Recent specialized literature highlights the fact that algorithmic management is already widespread and that it is associated with concerns about accountability, opacity and worker health protection (Milanez et al., 2025; OECD, 2024). Recent studies indicate that algorithmic management fundamentally transforms the quality of work, with direct implications for public health. This influence manifests itself in the reshaping of critical dimensions, interconnected with employee well-being, including workload, income security and stability, schedule predictability, quality of social relationships, decision-making autonomy and organizational trust. Thus, the way in which algorithms govern work becomes a determining factor in the management of psychosocial risks, and the freedom felt by employees is essential for an effective occupational health policy (Vignola et al., 2023). The relevance of these risks "beyond substitution" is also supported by empirical evidence: a study on logistics workers shows that higher exposure to algorithmic management is associated with higher prevalences of psychological stress, musculoskeletal pain and work-related accidents (Fana, 2024; Nilsson et al., 2025).

Overall, we note that the literature review synthesized here allows for some integrated operationalization of labor market vulnerabilities, which underlines the objectives of the paper.

3.2. Emerging risks beyond substitution: work quality, occupational health and algorithmic management

A major contribution of the literature in the last three years is the extension of the framework of analysis beyond "how many jobs are exposed" to what happens to the work: autonomy, intensity, performance evaluation, schedule stability and occupational health. In this context, we can see that AI-based automation intersects with algorithmic management, that is, with task allocation, monitoring, evaluation, operational optimization. In this way, risks are created that can arise even when the number of jobs remains relatively stable. A reference point is the analysis of the health of workers under algorithmic management, which shows that algorithms can influence dimensions of work quality with known links to health: workload, income security, schedule stability, decision-making authority and organizational trust (Choi, 2024; Vignola et al., 2023).

In addition, a paper in the area of occupational health explicitly discusses the "hazards" and risks associated with implementing AI in the workplace (including through robotics and algorithmic management), arguing that "trustworthy AI" approaches need to be translated into concrete prevention and governance practices in organizations (Howard & Schulte, 2024). Recent empirical evidence suggests that the effects may also be observable in health and safety indicators. For example, a study in logistics reports associations between exposure to algorithmic management and adverse outcomes such as psychological distress, musculoskeletal pain and occupational accidents (in a cross-sectional design), which reinforces the idea that AI risks in the labor market include an occupational health dimension and not just an employment/wage one (Nilsson et al., 2025).

Table 3 summarizes, for the logistics sector, a set of risks of AI-based automation and algorithmic management that go beyond the classic discussion of "job replacement". The central message is that AI-induced transformation frequently manifests itself through process reconfiguration and increased organizational control, with direct effects on work quality, occupational health, and workplace equity.

Table 3. AI-Related Workplace Risks in Logistics Beyond Job Substitution

Emerging risk	Typical manifestations in logistics	Recommended mitigation (organizational and policy)	Key recent sources
Work intensification and time pressure	Dynamic KPIs, real-time task/route allocation and optimization → faster pace, compressed breaks	Cap workload/pace metrics; enforce minimum break standards; worker participation in KPI design; periodic workload reviews	(Bowdler et al., 2025; Milanez et al., 2025; Noponen et al., 2024)
Reduced autonomy and algorithmic control	Automated scheduling/routing; micro-management of picking/loading; performance scoring → lower discretion over work methods	Human-in-the-loop for critical decisions; transparency on allocation rules; appeals process; internal governance and audits	(Cameron, 2024; Milanez et al., 2025; Mirbabaie et al., 2025)
Psychosocial risks (distress, burnout, anxiety)	Continuous monitoring (GPS/scans/time-on-task); automated feedback → distress, fatigue, burnout symptoms	Mandatory psychosocial risk assessments; limits on intrusive surveillance; non-punitive use of data; anti-burnout interventions	(Cefaliello et al., 2023; Hennum Nilsson et al., 2025; Zayid et al., 2024)
Physical health and injury risk	Accelerated pace + operational constraints → musculoskeletal pain; higher accident risk in warehouses and transport	Integrate ergonomics into algorithm design; safety constraints that override "optimization"; incident monitoring by task/shift; OSH audits	(Hennum Nilsson et al., 2025; Howard & Schulte, 2024; Jetha et al., 2025)
Decision opacity and low contestability	Hard-to-explain performance scores and task assignments → perceived unfairness, reduced trust	Minimum explainability requirements; right to access/correct data; formal appeal procedures; decision logging and auditing	(Cefaliello et al., 2023; Lane, 2023; Milanez et al., 2025)

Emerging risk	Typical manifestations in logistics	Recommended mitigation (organizational and policy)	Key recent sources
Job quality deterioration	Over-standardization; reduced decision authority; unpredictable shifts/workload volatility	Job-quality standards (autonomy, predictability, support); include health and equity criteria in AM rollouts	(Cefaliello et al., 2023; Hauer et al., 2023; Mirbabaie et al., 2025; Vignola et al., 2023)

Source: Authors' compilation based on the studies cited in the "Recent sources" column

The table, structured as it is, highlights a simple and easy-to-follow causal logic: (1) the mechanism (real-time monitoring, dynamic KPIs, automated task allocation, scoring), (2) the concrete manifestation in logistics (warehouses, transportation, sorting, last-mile), and (3) mitigation directions (organizational and public policy measures). Thus, the table shows that vulnerabilities are not just "technological," but arise at the intersection of system design, management practices, and institutional capacity to enforce standards (e.g. OSH/SSM, transparency, right to appeal).

An important result that the table makes visible is the cumulative nature of risks: work intensification and reduced autonomy tend to correlate with psychosocial risks (distress, burnout) and physical/ergonomic risks (musculoskeletal pain, injuries), especially in contexts with high volume, tight deadlines and granular monitoring. In logistics, these channels are particularly relevant because processes are often standardized, and algorithmic optimization aims to minimize "unproductive" times, which can reduce the space for recovery and ergonomic adjustment. At the same time, the table emphasizes that risks are not only related to how much is monitored, but also to how decisions are made: opacity and reduced contestability (scores difficult to explain, proprietary rules) can erode trust and amplify perceptions of injustice, even when aggregate performance increases. This is where the relevance of the measures proposed in the table comes from: human-in-the-loop, minimal explainability, appeal procedures, decision logging and auditing.

Overall, Table 3 functions as an applied "map" of recent literature, useful for anchoring the argument that the AI transition in logistics must be assessed through a broader framework than net employment: job quality, health and governance. For the article, it can be used as a bridge to the public policy chapter, justifying interventions that combine OSH/SSM standards, transparency and data protection rules, with training and work redesign measures, so that productivity is not achieved with hidden social costs.

At the organizational level, these risks are amplified by decisional opacity, in the sense of difficulty in challenging automated decisions, excessive standardization and the intensification of work through monitoring. In the same vein, a study on algorithmic management practices discusses mediating mechanisms such as burnout and threat perception, indicating that workforce well-being can be affected through psychosocial channels, not just through changes in occupational structure (Sarala, 2025; Soleimani, 2025). In fact, an important work highlights through a survey of employers the degree of spread of algorithmic management and its implications. The authors conclude that vulnerability is also becoming a problem of labor governance (rights, transparency, accountability) and not just exclusively of productivity (Milanez et al., 2025; Peterlongo, 2025; Wang, 2024).

In summary, the latest generation of literature outlines a picture in which vulnerabilities are multi-layered. First, we have a differential exposure of tasks to automation/AI assistance, then we have a polarization of skills demands through task recomposition, and in the last layer we talk about risks to work quality and occupational health through algorithmic management and intensification. This framework justifies the focus on adapting public policies and on sets of interventions that combine training (reskilling/upskilling) with governance and protection standards in the implementation of AI.

4. Conclusions

The paper clarified, through a critical synthesis of recent literature and an applied integration of the results in tables and figures, that AI-based automation does not produce a uniform effect on employment, but mainly generates a reconfiguration of work. Vulnerability in the labor market cannot be treated as a binary attribute, but as a multi-level phenomenon, determined by the interaction between the exposure of tasks to automation, assistance, the pace of technological adoption and the adjustment capacity of workers and institutions (training, mobility, protection). In this sense, the proposed analysis shifts the focus from "job replacement" to the redistribution of tasks and the transformation of the skills' ecosystem.

In relation to O1, the mapping of vulnerabilities at the task–occupation–skills level highlighted a pronounced sectoral heterogeneity. The results summarized in Table 1 and Figure 1 indicate that sectors with a high share of routine, procedural and standardizable tasks (e.g. industry and logistics) tend to have a higher potential for automation and, implicitly, higher pressures on employment and role reorganization. In contrast, sectors such as education and health are more frequently associated with augmentative effects, where intelligent systems function as supporting tools, not as full substitutions. This differentiation confirms that the structural transformation induced by AI is asymmetric and can amplify differences between sectors and occupational categories.

In relation to O1 and O3, the analysis showed that intelligent automation changes not only the distribution of jobs, but also the structure of skill demand. Table 2 and Figure 2 indicate a polarizing trend: robust growth for digital, analytical and AI governance skills, while the relevance of routine operational skills diminishes. The main result is that employability is becoming increasingly dependent on interdisciplinary combinations: technical skills + higher cognitive abilities + socio-cognitive skills (collaboration, communication, adaptability). In the absence of rapid adaptation of education and training systems, the risk of skills mismatch becomes a major channel of vulnerability.

In relation to O2, the paper explicitly highlighted the risks "beyond substitution" associated with algorithmic management and the digitalization of performance evaluation. Even in scenarios where aggregate employment remains relatively stable, degradations in work quality can occur: increased pace, reduced autonomy, decisional opacity and limited contestability. Table 3, applied to the logistics sector, synthesized these mechanisms and highlighted their cumulative nature: time pressure and algorithmic control correlate with psychosocial and ergonomic risks, especially in contexts with granular monitoring, high standardization and optimization focused exclusively on efficiency.

Overall, the paper argues that the transition to the digital economy is sustainable only through integrated public policies and organizational strategies: accelerated investments in skills (upskilling/reskilling, AI literacy, lifelong learning), coupled with AI governance in the workplace (transparency, audit, right to object, data protection and minimum standards of job quality and occupational security). Ultimately, the discussion about AI and work must move from the question of "how many jobs disappear?" to the question of "how is work redesigned and who bears the costs of the transition?", because the effective direction of change depends on institutional and organizational choices made today.

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