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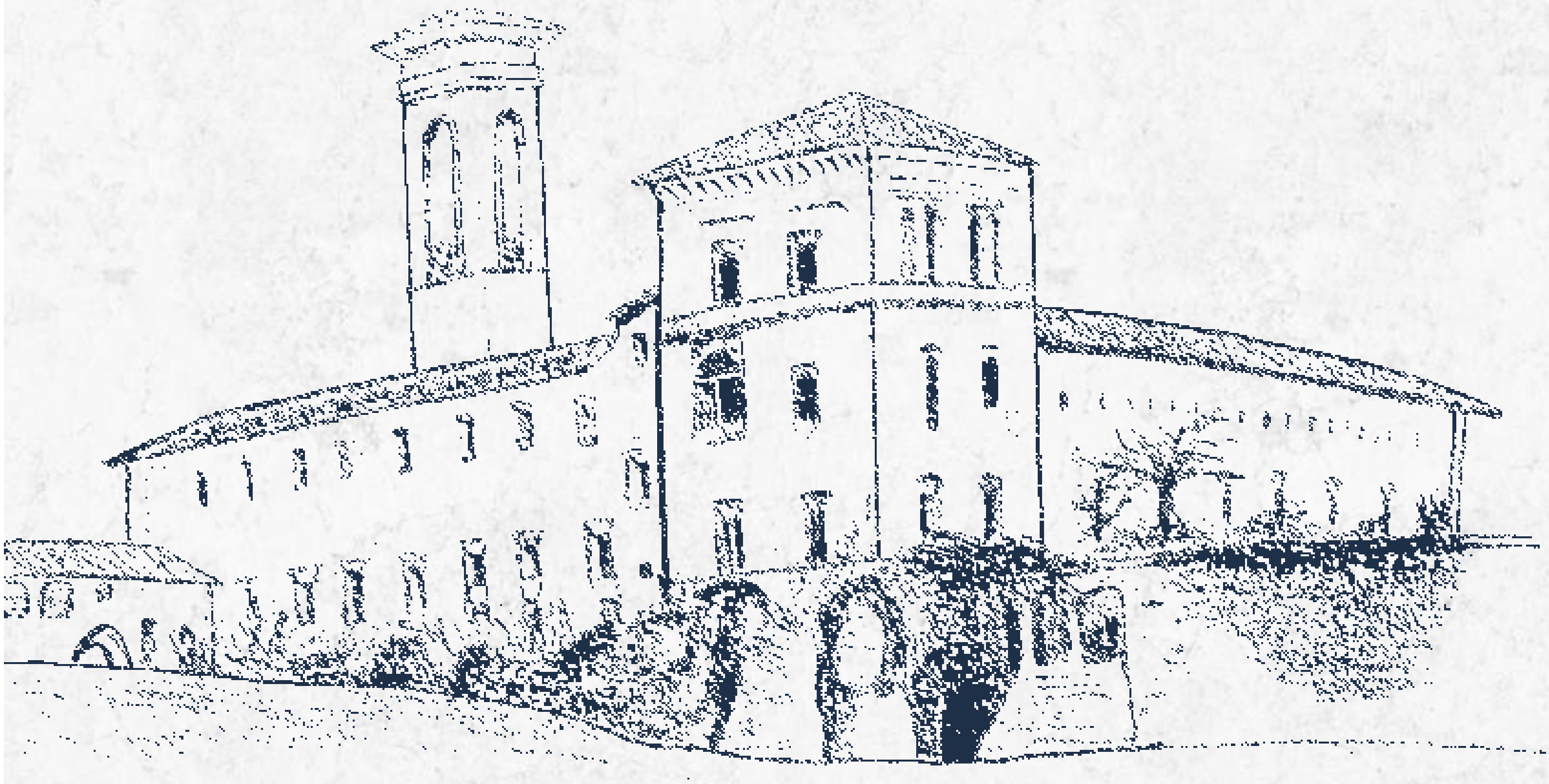

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Artificial Intelligence at Work: A Driver of Inequality or a Catalyst for Better Job Quality?

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Abstract. The paper examines artificial intelligence (AI) in the context of labour law and broader legal frameworks, highlighting its ambivalent role as both a potential source of inequality and as a catalyst for improved job quality. The aim is to identify the main risks and benefits associated with AI deployment in societal processes, the former including algorithmic discrimination, social selection and privacy concerns, monopolisation of technologies, and labour market disruption; the latter enhancing job quality by optimising tasks, supporting occupational health and safety and overall workers' wellbeing. Methodologically, the analysis draws on a comparative review of selected case studies and court decisions in Europe and the United States, complemented by an examination of current regulatory framework, strategic documents and reports of international organisations. The findings indicate that, although AI entails significant risks of reproducing historical biases and deepening inequalities, it can also serve as an instrument to promote personalised education, enable inclusivity and improving work-life balance. Crucially, the realisation of these benefits depends on the presence of a strong and comprehensive regulatory framework that guides AI deployment towards fair, safe, and high quality work, ensuring that technological innovation serves the collective good rather than reinforcing existing disparities.

Keywords: *Artificial Intelligence; Algorithmic discrimination; Job quality*

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1. Introduction

Today, amidst a multitude of scientific, professional, popular, or lifestyle contributions, no one doubts that the development of artificial intelligence (hereinafter "AI") is among the most significant technological and societal changes of the 21st century. This new phenomenon can confidently be regarded as a source of a new technological revolution, comparable to Gutenberg's printing press, Watt's steam engine, or, more recently, the rise of the internet.

Similarly, speaking from historical experience – like in every industrial revolution – the potential of new technological changes associated with AI is ambivalent: on one hand, there is fear and anxiety about the unknown, awareness of the risks of losing control over decision-making, and fundamental changes in social relations; on the other hand, it enables more efficient service delivery, accessibility for a wide range of people, and unexpected opportunities at a relatively low cost.

The aim of this contribution is to analyse the legal (*rectius*: labour law-related) risks of the advent of AI in relation to the principle of non-discrimination. We examine the risk of reproducing societal biases, deepening the digital divide, and weakening individual rights.

At the same time the contribution reflects on AI's potential to enhance job quality: whether by creating safer working conditions, boosting career prospect and wages, automating tedious and boring tasks or fostering more inclusive working environment. It poses the fundamental question: is AI a tool of inequality, or can it, on the contrary, serve as a catalyst for improving the quality of work?

2. AI as a Tool of Inequality

AI can be defined as systems that exhibit intelligent behaviour by analysing their environment and taking actions with a certain degree of autonomy to achieve specific goals[1]. These can include software solutions

[1] OECD, *Recommendation of the Council on Artificial Intelligence*, 2019, OECD Legal Instruments, OECD/LEGAL/0449, available at: https://legalinstruments.oecd.org/en/instruments/oecd-legal-0449. See the analysis of K, Yeung, *Introductory Note to Recommendation of the Council on Artificial Inteligence*, in *International Legal Materials*, 2020, Vol. 59 , Iss. 1, 27-34. Legally binding definition in the EU is provided in Reg. 2024/1689 (AI Act); according to Art. 3, par. 1, n. 1, AI is «a machine-based system that is designed to operate with varying levels of autonomy and

(voice assistants, voice and image recognition systems, search engines, large language models) as well as hardware devices (autonomous vehicles, robots, drones, Internet of Things devices). Thanks to deep learning, performance in tasks such as image or speech recognition has improved to the point that, in some cases, it exceeds human capabilities[2]. AI systems, however, are fundamentally dependent on data. Machine learning relies on large amounts of labelled data to identify patterns and apply them to new cases. These technical foundations have significant implications for labour law, data protection, and issues of equality. AI introduces a new model of human-machine collaboration, which can be emancipatory on one hand, yet reproduce or deepen inequalities on the other[3].

The types and definitions of risks associated with AI's integration into work and daily life vary. From the authors' perspective – and for the purpose of this streamlined discussion – they can be grouped into four main categories:

- algorithmic discrimination – the risk of transferring historical biases hidden in data into decision-making processes;
- social selection, excessive monitoring, and intrusion into privacy – the risk of discrimination arises from the evaluation of personal and private information, which may also carry biases;
- technology monopolization – the risk of advantage by large multinational corporations controlling access to data and infrastructure, potentially creating a digital divide;
- labour market distortion – the risk of precarisation and the disadvantage of less-skilled workers.

2.1 Algorithmic discrimination

According to available statistics, following the COVID-19 pandemic, up to 88% of companies worldwide utilise AI in the field of human resources, with 67% of HR professionals believing that its application

that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments».

[2] Y. LeCun, Y. Bengio, G. Hinton, *Deep learning*, in *Nature*, 2015, Vol. 521, 436–444.

[3] See V. De Stefano, *"Negotiating the algorithm":Automation, artificial intelligence, and labor protection*, in *Comparative Labor Law & Policy Journal*, 2019, Vol. 41, Iss. 1.

positively impacts the recruitment process[4]. The main advantages are generally considered to be the acceleration of the selection process and the reduction of employer costs. The use of AI in recruitment is therefore often referred to as a "new era of human resources": the technology assumes routine tasks, allowing HR professionals to devote more time to strategic planning and transforming the traditional recruitment model. A key benefit, in most cases, is the improvement of the quality of the selection process and, frequently, the mitigation of unconscious biases, which can significantly contribute to promoting workplace diversity. Many authors, however, rightly highlight the opposite phenomenon, known as algorithmic discrimination[5].

The essence of algorithmic discrimination can be illustrated by several prominent cases. One of the most widely discussed is the Amazon case. Amazon developed an internal recruitment algorithm designed to automate resume screening and candidate selection. However, the system demonstrated bias against women: the algorithm downgraded female candidates or favoured them less for technical positions because it had been trained on historical data predominantly featuring male applicants. Specifically, the algorithm was trained on resumes reflecting the fact that the majority of technical roles at Amazon had historically been filled by men. The system penalised terms such as "women's" (e.g., "women's chess club captain") and resumes from schools with higher female enrolment. The testing team observed that the AI assigned lower scores to female candidates and reinforced gender stereotypes. When Amazon identified these biases, the project was ultimately suspended and the algorithm withdrawn[6].

Algorithmic discrimination has also gained attention in the United States outside the context of labour law. A notable example is *State v. Loomis* (2016)[7], in which a court's sentencing decision was influenced by the COMPAS algorithm[8]. This system relied on historical data containing

[4] A. Pantelakis, *Top AI in Hiring statistics in 2024*, in *Resource for employers*, 2024, cited from D. Rudžiková, *Vplyv AI na pracovné právo*, in *Inovatívne právo a inovácie v práve*, University of P.J.Šafárik, Košice, 2024., 30-38.

[5] D. Rudžiková, *op.cit.*

[6] M. Langekamp, A. Costa, Ch. Cheung, *Hiring Fairly in the Age of Algorithms,* 2021, available online https://ssrn.com/abstract=3723046 or http://dx.doi.org/10.2139/ssrn.3723046.

[7] Available at: https://harvardlawreview.org/print/vol-130/state-v-loomis/.

[8] COMPAS is an abbreviation for Correctional Offender Management Profiling for Alternative Sanctions. See F. Lagioia, R. Rovatti, G. Sartor, *Algorithmic fairness through group*

elements of racial and gender bias, producing a tangible risk of discriminatory outcomes. The case involved Eric Loomis, who faced charges relating to a shooting and subsequent flight from the police. During sentencing, the court used the risk-of-recidivism score generated by COMPAS, which prompted significant objections from the defence. Loomis argued that this procedure violated his right to due process on several grounds: the algorithm was proprietary, and its internal workings were inaccessible to the defence ("black box"); there was potential discrimination based on race and gender; and the judge explicitly referenced the algorithmic output when justifying the sentence. The Wisconsin Supreme Court ultimately ruled that the use of COMPAS was not unconstitutional but established limits on its application: algorithmic assessments could not serve as the decisive factor in sentencing and were to be considered only as supplementary informational tools. This case is now frequently cited as an illustration of the risks associated with algorithmic decision-making in criminal law, particularly concerning transparency, discrimination, and the protection of defence rights.

Another example is the Chicago Police Department's predictive policing tool, which in 2013 identified hundreds of young Black men as likely perpetrators or victims of gun violence – even though many had no prior criminal record. Known as the Strategic Subject List, or informally the "Chicago Heat List," this system was designed to flag individuals deemed at high risk of involvement in violent incidents. Its assessments were based on aggregated data, including a person's proximity to gun-related crime and their social connections to individuals involved in shootings, whether as perpetrators or victims. In practice, inclusion on the list had tangible consequences, as some individuals were subjected to police visits or increased surveillance solely because they had been flagged by the algorithm[9].

These cases illustrate how prediction – long a cornerstone of legal practice – is now being significantly enhanced by recent advances in AI, which enable more accurate forecasting of legal outcomes through the analysis of vast datasets and complex patterns[10].

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parities? The case of COMPAS-SAPMOC, in *AI & SOCIETY*, 2023, 38, 2, 459-478; J. Larson *et al.*, *How we analysed the COMPAS recidivism algorithm*, in *ProPublica*, 2016.

[9] B.E. Harcourt, *Exposed: Desire and Disobedience in the Digital Age*, in *Harvard University Press*, 2015.

[10] For the rich debate on predictive justice see, for all: F. Pasquale, G. Cashwell, *Prediction, persuasion, and the jurisprudence of behaviourism*, in *University of Toronto Law Journal*, 68, 1, 2018, 63-81; F. Bex, H. Prakken, *Can predictive justice improve the predictability and consistency of*

Similar debates are ongoing in the European legal context regarding the use of so-called risk assessment systems in criminal justice[11]. However, despite growing research, real-world applications in European context remain limited, especially within judicial systems, most uses being still experimental or private-sector oriented. In Italy, predictive justice initiatives are relatively advanced but remain mostly in experimental or pilot phases. Several projects – often led by courts, universities, or research centers – focus on tasks such as case classification, estimating the duration of proceedings, annotating judgments, and extracting summaries using AI techniques[12]. While these initiatives show strong development and institutional interest, fully operational AI systems are not yet integrated into judicial decision-making.
A comparable phenomenon occurred in the United Kingdom during the COVID-19 pandemic (A-level scandal, 2020). In 2020, traditional written A-level and GCSE examinations were cancelled in the UK. In their place, a system of so-called calculated grades was introduced, in which teachers proposed expected grades (centre-assessed grades, CAGs) and ranked students within each subject. These proposals were not directly approved but were adjusted through an algorithm developed by the regulatory body Ofqual[13]. The algorithm aimed to ensure that the final grade distribution aligned with historical trends and to prevent grade inflation. It took into account the historical performance of schools in each subject, students' previous results (particularly GCSEs), and the teacher-assigned rankings. In practice, this meant that teachers' proposed grades were frequently significantly reduced. Up to 40% of students received lower than expected grades, with major implications for university admissions and further educational trajectories. Students from schools with poorer historical performance or less prestigious backgrounds were particularly disadvantaged, as their proposed grades were systematically reduced more

judicial decision-making?, in *Proceeding of The Thirty-fourth Annual Conference* (JURIX2021), Vilnius, Lithuania, 2021, 207-214. For Italian scholarship on the matter: M. Ferrari, *Predizione algoritmica, intelligenza artificiale generativa e rischi di cristallizzazione dell'ermeneutica giurisprudenziale*, in *Il Foro italiano*, 2023, 3, 5, 117-122.

[11] See, for instance G. Cascone, *The use of artificial intelligence in EU criminal justice systems: first insights and emerging trends in an evolving landscape*, in *Open Research Europe*, 2025, 5, 361, available online: https://open-research-europe.ec.europa.eu/articles/5-361.

[12] For a comprehensive analysis of Italian (and not only) predictive justice applications, see F. Galli, G. Sartor, *AI approaches to predictive justice: a critical assessment, in Humanities and rights global network journal*, 5, 2, 191-194, available online: https://www.humanitiesandrights.com/journal/index.php/har/article/view/118.

[13] Office of Qualifications and Examinations Regulation.

often. Conversely, students from prestigious, often private schools were more likely to retain or even improve their grades. This approach was widely perceived as unfair and discriminatory. Following extensive public criticism, student protests, and pressure from professional and political stakeholders, the government and Ofqual abandoned the algorithmically adjusted grades, and students ultimately received the grades originally proposed by their teachers (CAGs)[14]. This case is now frequently cited as a textbook example of "bias in AI": the algorithm was not a neutral technical tool but reproduced existing structural inequalities in the educational system.
These cases demonstrate that algorithmic discrimination constitutes a qualitatively new form of discriminatory conduct. It is not merely the result of technical flaws or programming errors; rather, it must be recognised that AI systems learn autonomously and assess historical data according to broad, predefined guidelines. Discrimination is latent, emerging from the complex interplay of model parameters, historical data, and statistical patterns. Consequently, it operates subtly, is difficult to detect, and is systematically reproduced. A significant consequence is its invisibility: affected individuals are often unaware that they have been evaluated automatically and lack access to information regarding which factors influenced the outcome, thereby undermining their ability to mount an effective challenge. The situation is further exacerbated by the societal legitimisation of AI: its outputs are perceived as objective and neutral, even though they may, in reality, conceal and perpetuate deeply embedded structural biases.

2.2 Social Selection, Excessive Monitoring, and Intrusion into Privacy

The risks of social selection and disproportionate intrusion into privacy by AI can be illustrated through two case studies. The *SyRI v. Netherlands* (2020) case represents a key moment in the debate on the limits of algorithmic systems in public administration. The SyRI system (System Risk Indication) was designed by the Dutch government to detect social fraud, such as unlawful claims for social benefits, illegal employment, or tax evasion. It operated by linking and analysing extensive data from various public databases, including social security, tax records, housing,

[14] A. Kelly, *A tale of two algorithms: The appeal and repeal of calculated grades systems in England and Ireland in 2020*, in *British Educational Research Journal*, 2021, Vol. 47, Iss. 3, 725-741.

and healthcare information. Based on this data, the system flagged individuals or groups as "high risk".
The national court in the Netherlands (*Rechtbank Den Haag*) ruled that the operation of SyRI violated Article 8 of the European Convention on Human Rights, which guarantees the right to respect for private life[15]. The court's reasoning rested on several key grounds. Firstly, the court highlighted the principle of proportionality: the extensive collection and linking of sensitive data were not sufficiently justified by the needs of a democratic society. Secondly, the court emphasised the lack of transparency, as citizens had no means of understanding how the system operated or the criteria it applied, effectively preventing any meaningful oversight of its legality. Thirdly, the court noted the high risk of discrimination: although direct discriminatory effects were not proven, there was a genuine concern that the system would lead to systematic profiling of the poor and vulnerable groups. The SyRI ruling thus established a clear framework for assessing proportionality, transparency, and potential discriminatory effects when implementing algorithmic tools in the public sector[16].
In C-203/22 *CK v. Magistrat der Stadt Wien*[17], the Court of Justice of the European Union (CJEU) addressed the scope of a data subject's right to access "meaningful information about the logic" used in automated decision-making under Article 15(1)(h) of the GDPR. The dispute arose after the Austrian company Dun & Bradstreet refused to provide CK with a full explanation of the algorithm used to assess her creditworthiness in contract negotiations, citing protection of trade secrets. The district and federal administrative courts in Austria found that the right of access to information had been violated, and the matter was referred to the CJEU to balance the right to transparency against trade secret protection. In its judgment of 27 February 2025 (ECLI:EU:C:2025:117), the CJEU emphasised that controllers must provide sufficiently understandable information enabling individuals to comprehend the essence of an automated decision, even where algorithmic details are protected as trade secret.

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[15] File reference number: C-09-550982-HA / ZA 18-388.
[16] See N. Appelman, R. Ó Fathaigh, J. Van Hoboken, *Social Welfare, Risk Profiling and Fundamental Rights: The Case of SyRI in the Netherlands*, in Journal of Intellectual Property, Information Technology and E-Commerce Law, 2021, Vol. 12, 257 para 1, available online: https://www.jipitec.eu/jipitec/article/download/324/317/1610.
[17] Court of Justice of the European Union. (2025, February 27). *Case C-203/22, CK v. Magistrat der Stadt Wien*, ECLI:EU:C:2025:117.

What conclusions can be drawn? Both cases share a common emphasis on the need for transparency and proportionality in the use of algorithmic systems by public or private institutions. In *SyRI*, the Dutch court stressed that the extensive linking of data by the state, without adequate oversight or citizen access to information about the system's operation, was disproportionate and violated the right to privacy under Article 8 ECHR. In *CK v. Magistrat der Stadt Wien*, the CJEU confirmed that, even in private law contexts, individuals must have access to comprehensible information about the logic of algorithmic decision-making under Article 15 GDPR, even when controllers rely on trade secret protection. The common denominator of both cases is the tension between the efficiency of algorithmic tools and individuals' fundamental rights. Both courts highlighted that technological complexity, economic interests, or administrative convenience cannot justify complete opacity. The overarching lesson from these cases is that algorithmic systems must be designed and implemented in a manner that is not only legally predictable and controllable but also fair and accessible to affected individuals. These rulings advance the standard of fundamental rights protection in the digital environment and reinforce the requirement that AI and automated decision-making serve the public interest without discriminatory or non-transparent effects.

2.3. Technology Monopolisation

In the field of AI and data technologies, concepts such as the digital divide and data colonialism are increasingly emerging, highlighting the imbalance in access to resources, power, and profit. The digital divide is not limited to access to hardware or the internet: while large technology companies possess enormous computational power, extensive datasets, and specialised expertise, many smaller actors, poorer regions, or individuals are excluded from this ecosystem. Those who control data and computing capacity can dominate technological processes, decision-making, and innovation, further deepening the gap between "major players" and peripheral actors.

The concept of data colonialism criticises the fact that technology giants "extract" data from the public – acquiring raw data from social networks, applications, sensors, and infrastructure – while the value, analysis, and decision-making processes remain concentrated in their hands. According to parts of the academic and professional literature, this relationship resembles colonial patterns, in which colonised territories were stripped of natural resources while control, processing, and profit remained with the

colonial power. In the digital realm, this means that countries or communities provide data but have only very limited access to how it is processed, used in decision-making, or leveraged, thereby restricting their ability to benefit from its potential[18].
Finally, some economic scholars have even argued that new technologies have fundamentally transformed entire current capitalistic system into a modern feudalism. According to Durand[19] and Varoufakis[20], techno-feudalism would explain a new economic order in which a few technology giants control digital "lands"– data, platforms, and digital infrastructures – forcing users and workers to comply with their rules to participate in economic life. In this system, value and power derive not only from traditional waged labour but also from unpaid digital work and platform rents, turning platform workers into "digital serfs" subject to pervasive algorithmic control and surveillance. For example, online merchants on Amazon must pay commissions and follow the platform's unilateral rules to reach customers, while riders on delivery apps have no control over customers, schedules, or algorithmic evaluations, and cannot leave the platform without losing their livelihood. Similarly, streaming services such as Spotify or Netflix extract value from both content creators' unpaid contributions and users' engagement, concentrating control and profit in the hands of the platform operators.

2.4. Labour Market Distortion

Labour market distortions will be addressed here only briefly, although the change is indisputable. In its January 2024 report, the International Monetary Fund (IMF) warned that the development of AI could affect up to 40% of jobs worldwide, with this proportion reaching as much as 60% in advanced economies[21]. These figures suggest that the impact will not be evenly distributed, but will depend heavily on the structure of individual economies and the share of jobs susceptible to automation. Similar

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[18] N. Couldry, U.A. Mejias, *The costs of connection: How data is colonizing human life and appropriating it for capitalism.* Stanford University Press, Stanford, CA, 2019, https://doi.org/10.1515/9781503609754.
[19] C. Durand, *How Silicon Valley Unleashed Techno-Feudalism: The Making of the Digital Economy*, Verso, 2024.
[20] Y. Varoufakis, *Technofeudalism: what killed capitalism*, Bodley Head, 2023.
[21] M. Cazzaniga, F. Jaumotte, L. Li, G. Melina, A. J. Panton, C. Pizzinelli, E. J. Rockall, M. M. Tavares, *Gen-AI: Artificial Intelligence and the Future of Work* (IMF Staff Discussion Note No. 24/001), 2024, International Monetary Fund. https://doi.org/10.5089/9798400262548.006.

conclusions were drawn in a May 2024 analysis by McKinsey & Company, which predicted that up to 12 million job transitions in Europe will be required by 2030 due to automation and the implementation of AI. This projection also indicates that the pace of change is approximately twice as fast compared with the pre-COVID-19 period, illustrating the rapid acceleration of labour market transformation.

The risks associated with technological change are also highlighted by the Organisation for Economic Co-operation and Development (OECD). Its July 2023 report states that, on average, up to 27% of jobs in member countries are highly susceptible to automation. Eastern European countries are particularly vulnerable, given that their economic structures contain a higher proportion of routine and manual tasks.

Taken together, these findings suggest that automation and AI not only fundamentally alter the nature of work but also exacerbate regional and structural inequalities. Addressing these challenges will require proactive state policies focused on reskilling, supporting labour mobility, and ensuring a fair and equitable transformation of the labour market.

3. Job Quality as a Lens for Assessing AI's Potential

In the first part of our analysis we have tried to illustrate how the AI's transformative potential adversely affects multiple dimensions of work, including equal treatment, privacy, labour market and overall societal dynamics. In order to provide a more comprehensive assessment, it is now essential to identify and analyse the positive contributions that AI can make in these areas. This requires drawing on real-world examples, policy and normative approaches that highlight AI potential to be used for good[22].

The academic, institutional, and public discourse has so far been dominated by risk-centred narratives. While precautionary approaches remain indispensable, they should be complemented by a balanced assessment of AI capacity to generate improvements.

Lately some noteworthy scholars have started to explore also the AI's beneficial potential. Some of the experts argue that current AI regulation focuses too narrowly on preventing harms and should instead adopt a more balanced, cost-benefit approach that also recognizes the value of automation in advancing public goals like fairness, welfare, and justice,

[22] See European Commission's pursuit of "AI for public good" AI for Public Good | Shaping Europe's digital future, as well as ILO's mission to use AI in line with UN Sustainable Development Goals, see: ILO Live - AI for Good.

even proposing a set of "AI-for-good rights", such as a right to automated decision making and a right to data collection[23]. Others rather explore how to achieve the beneficial potential of AI through a coherent accountability framework that integrates data protection, equality and employment law, collective bargaining, and regulatory oversight to ensure transparent and fair algorithmic management in the workplace[24]. Similarly, robust and effective regulatory framework – already partly outlined at both the European and national levels – appears in the literature as a key mechanism capable of transforming algorithms from drivers of discrimination into powerful tools for its prevention[25].
Against this backdrop, assessing the impact of AI through a comprehensive analytical framework – namely job quality indicators – appears particularly useful. Job quality, however, is not a *strictu sensu* legal category, while it occupies a central place in economic analysis[26] and has long been a key concept for the sociology of work[27] and occupational psychology[28]. For the purposes of this contribution, an attempt is therefore made to translate job quality into a concept that is ontologically meaningful for labour law.
The notion of job quality attracted systematic scholarly attention in the United States during the 1960s as a part of "social indicators movement"[29], linked to the broader efforts to conceptualise and measure quality of life. Early definitory approaches were predominantly subjective,

[23] See O. Lobel, *The Law of AI for Good*, in *Florida Law Review*, 75, 2023. For Italian labour law scholarship attempting more balanced approach in assessing AI see M. Biasi, *The bright side of the AI for work: from (unbrindled) risks to (regulated) opportunity*, in M. Biasi (ed.), *Artificial Intelligence and Labour Law: a Global Overview*, Routledge-Giappichelli, forthcoming
[24] A. Blackham, *Setting the framework for accountability for algorithmic discrimination at work*, in *Melbourne University Law Review*, 47, 2023, 63-113.
[25] G. Gaudio, *Le discriminazioni algoritmiche*, in *Lavoro Diritti Europa*, 2024, 1.
[26] B. Burchell, K. Sehnbruch, A. Piasna *et al., The quality of employment and decent work: definitions, methodologies, and ongoing debates*, in *Cambridge Journal of Economics*, 2013, 38, 2, 459-477.
[27] See, for instance, M. Adamson, I. Roper, *'Good' Jobs and 'Bad' Jobs: Contemplating Job Quality in Different Contexts*, in *Work, employment and society*, 2019, vol. 33, n. 4, 551-559.
[28] Their approach typically concentrates on the determinants of subjective well-being and productivity at the level of task characteristics, including variety, challenge, meaningfulness of work, autonomy, and teamwork. See J.R. Hackman, G.R. Oldham, *Development of the job diagnostic survey*, in *Journal of Applied Psychology*, 1975, vol. 60, no. 2, 159-170.
[29] H.H. Noll, *Social indicators and quality of life research: background, achievements and current trends*, in N. Genov (ed.), *Advances in Sociological Knowledge*, VS Verlag für Sozialwissenschaften, Wiesbaden 2004, pp. 151-182.

relying on workers' self-evaluations of job satisfaction and on the aspects of work perceived as contributing to well-being, but were criticised for their lack of objective benchmarks and methodological robustness[30]. This strand of research emphasised the impact of job characteristics on the well-being of workers: instead of measuring the inputs (the quality of numerous work characteristics) they prioritised looking at one single indicator in the form of desired output: the level of job satisfaction[31].

Nowadays, job quality is predominantly conceptualised as a complex, multidimensional construct encompassing a range of relevant job characteristics[32].

Despite decades of research, however, the absence of a shared set of indicators for job quality continues to constrain effective policy and regulatory responses[33]. Moreover, as workplaces have been reshaped by both internal and external forces – for instance introducing new health risks, shifting tasks from predominantly physical to increasingly cognitive and psychosocial demands – the criteria for measuring job quality has also been necessarily evolving[34]. More recent developments, including algorithmic management and AI, add further variables to job quality assessments, which this analysis seeks to explore.

From the policy standpoint, what clearly emerges as urgent priority is ensuring that all AI-enabled working arrangements are of good quality, and that AI is deployed to enhance working conditions and the overall functioning of the labour market. Looking at the job quality is consistent with the long-standing EU policy going beyond quantitative indicators of the healthy labour market. Since the launch of the Lisbon Strategy in 2000, the EU has consistently framed labour market success in terms of

[30] J.C. Taylor, *Job satisfaction and quality of working life*, in *Journal of Occupational Psychology*, 1977, 50, 4, 243-252.

[31] R. Muñoz de Bustillo, E. Fernández-Macías, J. I. Antón, F. Esteve, *Indicators of job quality in the European Union*, 2009, Policy Department Economic and Scientific Policy, Brussels, 34 ff. https://www.europarl.europa.eu/document/activities/cont/201107/20110718ATT24284/20110718ATT24284EN.pdf,

[32] Other methods consider different weight of the indicators, their interaction and so on. See S. Vandekerckhove, *Norm-based job quality indicators: an application to European survey data*, 2021, Deliverable 13.3, Leuven, InGRID-2 project 730998 – H2020, 4 ff, available online: https://www.inclusivegrowth.eu/files/Output/D13.4-Quality-indicators.pdf.

[33] A. Piasna, B. Burchell, K. Sehnbruch, *Job Quality in European Employment Policy: One Step Forward, Two Steps Back?*, in *Transfer: European Review of Labour and Research,* 2019, 25, 2, 165–180.

[34] See B. Burchell, K. Sehnbruch, A. Piasna *et al., The quality of employment and decent work*, cit., p. 3-4.

both quantity and quality of employment, embedding the objective of "more and better jobs"[35] at the core of its socio-economic model and ushering in what is often characterised as a "golden age" of job quality in EU policymaking[36]. Job quality was framed as a transversal objective, encompassing working conditions as well as broader dimensions of social policy, education and training, and industrial relations. This approach was institutionalised in 2001 through the recognition of the qualitative dimension of employment as a horizontal objective of the European Employment Strategy, the adoption of a set of job quality indicators at the Laeken European Council, and the European Commission's first Communication on job quality[37]. Together, these initiatives placed job quality at the centre of EU employment and social policy.

The interest in job quality is not only visible in the EU context through its policies, but its measurement through harmonised EU-wide surveys. There is good access to comparative data on working conditions and the political will to explore such data through surveys.

Early attempts to operationalise job quality at EU level, such as the aforementioned Laeken indicators, were limited by their inability to capture key aspects of the working environment, including wages,

[35] "The Union has today set itself a new strategic goal for the next decade: to become the most competitive and dynamic knowledge-based economy in the world capable of sustainable economic growth with more and better jobs and greater social cohesion". Par. 5, Title I of Lisbon Strategy, 2000*, https://www.europarl.europa.eu/summits/lis1_en.htm*.

[36] P. Caillaud, D. Ghailani, R. Peña-Casas, *Conceptual and Legal Framework for Quality of Work and Employment in International Institutions – The European Union and the International Labour Organisation*, in S. Borelli, P. Vielle, (eds.), *Quality of Employment in Europe Legal and Normative Perspectives*, Peter Lang, 2012, 33-68, Collection: Travail et Société/Work and Society, 35.

[37] European Commission, *Communication From The Commission To The Council, The European Parliament,The Economic And Social Committee And The Committee Of The Regions Employment And Social Policies: A Framework For Investing In Quality*, Brussels, 20.6.2001 COM (2001) 313 Final https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2001:0313:FIN:EN:PDF. The so called Laeken job quality dimensions are: intrinsic job quality, lifelong learning and career development, gender equality, health and safety at work, flexibility and security, inclusion and access to the labour market, work organisation and work–life balance, social dialogue and worker involvement, diversity and non-discrimination, and overall economic performance and productivity.

working time arrangements and the nature of work tasks[38]. Furthermore, they represented more conceptual framework, not necessarily adequate for monitoring purposes. Subsequent policy frameworks have addressed these shortcomings. Eurofound, for example, identifies seven key dimensions of job quality – physical environment, work intensity, working time quality, social environment, skills and discretion, prospects, and earnings – which are systematically analysed through the European Working Conditions Survey, conducted since 1990[39].

Within evolving work landscape, social partners played a crucial role in steering EU initiatives towards better-quality jobs. Recent developments, such as the European Commission's Quality Jobs Roadmap of December 2025 and the EMCO Opinion of June 2025, underline the centrality of social dialogue and collective bargaining, opening of first phase of consultation leading to Quality Jobs Act[40]. The EMCO Opinion seeks to foster a shared understanding of job quality at EU level by identifying thirteen policy dimensions[41].

Beyond the EU context, parallel frameworks have been developed, both contingent and diverging from the European approach to job quality. Most notably, the International Labour Organization's concept of decent work[42], introduced in 1999, has been widely used alongside – and at times

[38] See OECD, *OECD Guidelines on Measuring the Quality of the Working Environment*, 2017, Chapter 2, available online: https://www.oecd.org/content/dam/oecd/en/publications/reports/2017/11/oecd-guidelines-on-measuring-the-quality-of-the-working-environment_g1g7ca23/9789264278240-en.pdf.

[39] https://www.eurofound.europa.eu/en/topics/job-quality#eurofound-research.

[40] European Commission, *First-phase consultation of social partners under Article 154 TFEU on possible direction of EU action to improve working conditions, health and safety at work and implementation of workers' rights – Quality Jobs Act*, Brussels, 4.12.2025 C(2025) 9944 final. https://employment-social-affairs.ec.europa.eu/document/download/059a1e18-2508-4520-9b15-5831c50e0f91_en?filename=Consultation_Quality-Jobs-Act_2025.pdf.

[41] Including earnings, working conditions (with particular attention to stress and psychosocial risks), job security, work–life balance, access to training, social protection, collective bargaining coverage, and equal opportunities, see: Council of the European Union, *Opinion of the Employment Committee on the dimensions of job quality*, Brussels, 6 June 2025,(OR. en), 9417/25, https://data.consilium.europa.eu/doc/document/ST-9417-2025-INIT/en/pdf.

[42] The concept of decent work was first introduced in the report of ILO Director-General Juan Somavia to the 1999 International Labour Conference, which proposed a new integrated approach to the Organisation's activities. Its aim was to bring coherence to the ILO's work by framing it around a shared purpose and a common interest between the ILO and its Member States in improving the conditions of people across the world of work. At the time, the ILO presented decent work - promoted as a global

as a substitute for – the notion of job quality. From its inception, decent work combined a strong normative orientation grounded in fundamental rights, rather than the analytical framework[43]. While its broad scope has facilitated global uptake and policy relevance, this normative breadth has also posed challenges in terms of operationalisation, measurement, and cross-country comparability[44]. A parallel effort is reflected in the OECD framework, which conceptualises job quality through three core dimensions: earnings quality, labour market security, and the quality of the working environment[45].
In contrast, the EU concept of job quality has evolved as a more operational and policy-oriented framework, explicitly designed to support monitoring, benchmarking, and regulatory intervention within specific labour market contexts.
Despite these advances, the conceptualisation of job quality indicators is not straightforward and lacks necessary neutrality. This has reprecussions on the legal understanding and use of the concept.

4. Legal References for Quality AI-enhanced Work

In primis, the notion of job quality must be disaggregated into legally intelligible components.
Job quality is understood through a core distinction between the characteristics of the job itself and the wider employment context, following the interpretation of the concept as coined in afforementioned European Commission's first Communication on job quality from 2001. This separation differentiates quality of work (covering intrinsic job features such as pay, working time, job content, skills, career prospects, and job satisfaction) from quality of employment (which refers to the broader policy and institutional conditions of the labour market, including

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objective shaped by regional challenges - as the pursuit of productive work carried out in conditions of freedom, equality, security and human dignity, in full accordance with the ILO's mandate as set out in the Declaration of Philadelphia. Report of the Director-General Juan Somavia: *Decent work*, 87th Session of International Labour Conference, Geneva, June 1999, available online: https://www.ilo.org/public/english/standards/relm/ilc/ilc87/rep-i.htm.

[43] For the list of indicators see P. Caillaud, D. Ghailani, R. Peña-Casas, *op. cit.*

[44] B. Burchell, K. Sehnbruch, A. Piasna *et al., The quality of employment and decent work*, cit., 459-477.

[45] OECD, *OECD Employment Outlook 2014*, OECD Publishing, Paris, 2014, https://www.oecd.org/en/publications/oecd-employment-outlook-2014_empl_outlook-2014-en.html.

health and safety, gender equality, flexibility and security, work–life balance, social dialogue, and non-discrimination). While closely interrelated, the distinction is legally relevant, as it links job quality both to individual working conditions and to labour market governance[46].

Various soft and hard law initiatives at the EU level make explicit reference to the job quality.

The European Pillar of Social Rights aims to foster convergence across the EU towards fairer working and living conditions[47]. While the majority of the Pillar's 20 principles do not explicitly address job quality, the pillar on fair working conditions substantially overlaps with its core dimensions, including contractual arrangements, wages, social dialogue, work-life balance, and occupational health and safety. The only explicit reference to quality of working conditions appears in Principle 5(c), in connection with the promotion of innovative forms of work, entrepreneurship, and self-employment, providing a normative foundation for regulatory intervention against the most severe manifestations of poor-quality work.

European Pillar of Social Rights constitutes a non-binding soft law instrument and does not entail direct implementation obligations for Member States; nevertheless, it functions as an important reference framework for the European Commission in the development of social policy and related regulatory initiatives. This guiding function is clearly reflected in recent legislative efforts addressing AI and algorithmic management at work. The Recital 3 of Directive (EU) 2024/2831 of the European Parliament and of the Council of 23 October 2024 on improving working conditions in platform work (hereinafter Platform Work Directive) expressly recalls the aforementioned Principle 5(c), according to which innovative forms of work – such as platform work –

[46] P. Caillaud, D. Ghailani, R. Peña-Casas, *op. cit.,* 36.

[47] Monitoring is ensured through the Social Scoreboard, which tracks convergence using indicators on employment and social trends, https://ec.europa.eu/eurostat/cache/dashboard/social-scoreboard/. However, these indicators predominantly emphasise quantitative aspects of work – for example, the employment rate measures the volume of jobs without accounting for the nature of employment contracts or working time arrangements – and therefore capture only to a limited extent the qualitative dimensions of jobs. For the overall critical assessment see: A. Piasna, B. Burchell, K. Sehnbruch, *Job Quality in European Employment Policy*, cit. 8 ff, https://researchonline.lse.ac.uk/id/eprint/102888/1/2018_11_30_Transfer_Job_quality_in_the_European_employment_policy.pdf; for the employment rate indicator see ETUI, *The social scoreboard revisited*, 2017, 20-23, https://www.inclusivegrowth.eu/files/Call-42/4-2017.03-Background-analysis-Social-Scoreboard-Web-version.pdf.

should be promoted only where they guarantee quality working conditions. This quality-centred orientation is further strengthened in Recital 4, which acknowledges that new forms of digital interaction and technological innovation in the labour market may enhance access to decent and high-quality employment – particularly for groups traditionally excluded from the labour market – provided that such developments are subject to appropriate regulation and effective enforcement.
More recently, in its resolution on a need to regulate algorithmic management and use of AI at work[48], European Parliament has called for a regulatory approach that goes beyond both the narrow application scope of Platform Work Directive and the non-work specific content of AI Act, advocating for rules that „enhance job quality“[49]; in parallel, the European Commission is considering addressing these issues in another forthcoming legislative initiative, the aforementioned Quality Jobs Act.
Labour law has traditionally been characterised by a strong reliance on qualitative notions – such as reasonableness, standard, and fairness – through which its executes its regulatory function[50]**.** Similarly, many labour law categories possess an intrinsic normative quality that aligns closely with measurable indicators of work and employment quality, creating a conceptual coherence between legal principles and empirical assessment. Some of the most salient of these indicators, which help translate these qualitative notions into observable dimensions of job quality, will be examined in the following sections.

[48] European Parliament, *Digitalisation, artificial intelligence and algorithmic management in the workplace – shaping the future of work*, 2025/2080(INL), 17/12/2025, https://oeil.europarl.europa.eu/oeil/en/document-summary?id=1881354.
[49] Proposal reiterated in recent years also by ETUC, see for instance: ETUC, The *EU needs a Dedicated Directive on Algorithmic Management and AI at work*, 18 October 2025, https://www.etuc.org/en/circular/eu-needs-dedicated-directive-algorithmic-management-and-ai-work.
[50] See A. Perulli, *I concetti qualitativi nel diritto del lavoro: standard, ragionevolezza, equità*, in *Diritti, lavori, mercati*, 2011, 3, who sustains that labour law uses qualitative notions to guide behaviour and to assess whether economic and organisational practices align with social values and norms, but simultaneously create legal uncertainty, because it moves away from purely calculable and predictable rules.

4.1 The Impact of AI on Earnings Quality

Earnings quality refers both to the material well-being of individual workers, as reflected in wage levels, and to the broader distributional patterns of income within society[51].

Existing empirical evidence on the AI's wage effects is, however, heterogeneous and at times contradictory. A growing strand of literature points to the emergence of an "AI penalisation effect", whereby workers who rely on AI tools may experience reduced compensation because their individual contribution is perceived as diminished[52]. This dynamic appears to affect not only wage-setting practices but also workers' behaviour, as employees often report reluctance to disclose the use of AI in routine work tasks for fear of devaluation[53]. Such negative wage effects are most clearly documented in non-standard forms of work, particularly freelancing, crowdwork, and platform-based labour, where weaker legal safeguards and limited collective bargaining leave workers more exposed to unilateral wage adjustments[54].

By contrast, studies focusing on standard employment relationships tend to identify neutral or even positive wage effects associated with AI exposure. Evidence from Germany between 2010 and 2017 shows that occupational exposure to AI technologies was associated with wage growth among certain segments of the workforce, especially non-professional workers such as technicians, clerical staff, service and sales workers, suggesting that AI adoption may have supported task upgrading and productivity gains[55]. Similarly, research based on Italian data from 2011 to 2019 indicates positive wage effects concentrated among highly

[51] OECD, *OECD Employment Outlook 2014*, cit., 80.

[52] J. Kim, S. Schweitzer, C. Riedl, D. De Cremer, *The AI Penalization Effect: People Reduce Compensation for Workers Who Use AI*, in *arXiv.org*, 2025.

[53] M. Morrone, *Secret chatbot use causes workplace rifts*, 29 May 2025, https://www.axios.com/2025/05/29/secret-chatgpt-workplace.

[54] Research indicates that crowdworkers in areas affected by generative AI experienced significant income losses, with earnings on platforms like Upwork declining by about 5%, and freelance translators facing drops of up to 30% after the introduction of tools such as ChatGPT. Upwork: X. Hui, O. Reshef, L. Zhou, *The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market*, CESifo Working Papers, 2023, available online: https://www.ifo.de/DocDL/cesifo1_wp10601.pdf; Freelance translators: D. Qiao, H. Rui, Q. Xiong, *AI and Jobs: Has the Inflection Point Arrived? Evidence from an Online Labor Platform*, in *ArXiv*, ArXiv231204180, 2023.

[55] E. Engberg, M. Koch, M. Lodefalk, S.Schroeder, *Artificial intelligence, tasks, skills, and wages: Worker-level evidence from Germany*, in *Research Policy,* 2025. Vol. 54, Iss. 8, 9-11, https://www.sciencedirect.com/science/article/pii/S0048733325001143.

qualified employees and top occupational positions, pointing to a skill-biased dimension of AI-related wage dynamics[56].
At the same time, these results must be interpreted with caution. Most available studies rely on data from the pre-generative AI era, preceding the rapid diffusion of tools such as ChatGPT and other large language models. As a result, the wage effects of generative AI specifically cannot yet be directly observed, and systematic empirical evidence on its distributional consequences remains scarce[57]. What can nonetheless be inferred is a differentiated pattern: workers possessing AI-specific or complementary skills are more likely to benefit in terms of wages, whereas general exposure to AI tools does not automatically translate into higher earnings[58].
Moreover, AI may have ambivalent effects on lower-skilled workers, potentially enhancing their productivity and skill sets, but also exposing them to intensified monitoring and downward pressure on pay in less regulated labour market segments[59].
Taken together, the emerging evidence suggests that labour law plays a crucial mediating role in shaping AI-driven wage outcomes. Employment status, contractual stability, and collective protections appear to transform AI exposure into a positive factor by limiting arbitrary wage reductions, fostering reskilling and upskilling, and enabling workers to capture productivity gains. Conversely, in contexts characterised by weak legal safeguards, AI adoption risks reinforcing existing structural vulnerabilities and exacerbating earnings inequality, raising important questions for future research and policy intervention.

[56] I. Brunetti, C. Mussida, *AI occupational exposure and wage distribution:the case of Italy*, Inapp Working paper n. 135, Inapp, Roma, 2025, https://oa.inapp.gov.it/server/api/core/bitstreams/12e6e437-c122-4766-afe8-457c02a43469/content.
[57] What is possible to measure as for the effects of generative AI on work are the productivity gains of individual workers and improving subjective working experience. See: E. Brynjolfsson, D. Li, L. Raymond, *Generative AI at Work*, in *The Quarterly Journal of Economics*, Vol. 140, Iss. 2, 2025, 889-942.
[58] OECD, *OECD Employment Outlook 2023*. Artificial intelligence and the labour market, OECD Publishing, Paris, 2023, 131, available online: https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/07/oecd-employment-outlook-2023_904bcef3/08785bba-en.pdf.
[59] OECD, *OECD Employment Outlook 2023*, cit., 144-145.

4.2 Task Approach in Evaluating Job Quality. The Specific Impact of GenAI

Attention to task content and execution is considered central for understanding how new technologies may affect job quality[60].

Task characteristics – ranging from routine and monotonous to complex and creative – interact with task execution factors such as pace, intensity, and overall workload.

Work intensity is a widely recognised indicator of the quality of the working environment, signalling situations in which excessive workload or accelerated work pace can undermine job quality and increase psychosocial risks[61]. The introduction of labour-intensifying technologies, including algorithmic management and AI, has frequently been associated with heightened work intensity, as routine tasks are automated and more cognitively demanding or complex activities are concentrated on workers, potentially reducing opportunities for mental recovery and increasing stress[62].

Generative AI (herinafter GenAI), with ChatGPT as a prominent example, exemplifies a new wave of technologies affecting task execution. OpenAI's own analysis reports substantial global adoption in professional roles, particularly in knowledge-intensive work, with U.S. usage rates ranging from 28% to 43% among workers using ChatGPT on a daily basis[63].

While ChatGPT's use in paid work is increasing in absolute terms, work-related queries constitute a declining share of overall activity, suggesting that ChatGPT is becoming more embedded in everyday, non-work practices rather than being driven mainly by employment-related tasks. Legal and compliance concerns – such as copyright, confidentiality, and privacy – have prompted some organisations to develop internal AI models or host LLMs on approved infrastructure to safeguard data and ensure regulatory compliance.

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[60] D.H. Autor, *The "task approach" to labour markets: an overview*, in *Journal for Labour Market Research*, Vol. 46, 2013.

[61] EMCO, *Quality in Work – Thematic Review 2010*, Publications Office of the European Union Brussels, 2010.

[62] OECD, *OECD Employment Outlook 2023*, cit., p. 142.

[63] OpenAI, *ChatGPT usage and adoption patterns at work*, 22 January 2026, https://openai.com/business/guides-and-resources/chatgpt-usage-and-adoption-patterns-at-work/.

In Europe, GenAI adoption remains lower – between 5% and 20% of the workforce – with significant cross-country variation (e.g., approximately 5% in Italy, 8% in Slovakia, and 20% in Belgium)[64]. Despite overall lower adoption rates in Europe, existing evidence consistently identifies specific professions as more exposed to GenAI. These include clerical occupations (such as data entry clerks, typists, accounting and bookkeeping staff and administrative secretaries), as well as professional and technical roles characterised by a high cognitive content of work, including financial analysts, software and multimedia developers, translators, and investment advisers. This pattern confirms that GenAI use is more prevalent in occupations where tasks are predominantly cognitive, analytical, or language-based[65].

Again, given the very recent and rapid diffusion of GenAI, empirical evidence on its actual workplace use and on its broader consequences – both positive and negative – remains partial and evolving[66]. Preliminary findings nevertheless suggest a generally positive perception among workers. According to the Apply AI Strategy survey, approximately 67% of European workers report that AI helps them perform tasks more efficiently[67].

The advent of GenAI introduces a qualitatively new element into the labour process, often described as computational agency: the capacity of AI systems to autonomously perceive, generate outputs, and act within work processes, frequently without a corresponding clarification of accountability or liability. This development raises concerns within the scholarly literature[68] about a potential erosion of human agency at work,

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[64] Eurofound, *European Working Conditions Survey 2024. First findings*, 21, available online: https://www.eurofound.europa.eu/en/surveys-and-data/surveys/european-working-conditions-survey/ewcs-2024. Complete data to be available in February 2026.

[65] Using Polish datapool, P. Gmyrek, J. Berg, K. Kamiński, F. Konopczyński, *et al.*, *Generative AI and Jobs: A Refined Global Index of Occupational Exposure*, ILO Working Paper 140, International Labour Office, Geneva, 2025.

[66] In November 2022, OpenAI introduced ChatGPT as a consumer-oriented application, marking a turning point in the diffusion of generative AI. The system achieved exceptionally rapid uptake, reaching approximately 30 million weekly users within two months of launch, and expanding to around 100 million users within its first year of deployment. By November 2025 it counts 810 million users. F. Duarte, *Number of ChatGPT users* (January 2026). Exploding Topics. Last updated December 14, 2025.

[67] European Commission, Communication from the Commission to the European Parliament and the Council. Apply AI Strategy, Brussels, 8.10.2025, COM(2025) 723 final.

[68] J. Adams-Prassl, *Platform workers' rights in the age of generative AI*, in P. Hacker et al. (eds), *The Oxford Handbook of the Foundations and Regulation of Generative AI*, online edn, Oxford

particularly where GenAI systems increasingly shape decision-making and task execution. From a task quality perspective, however, GenAI may also offer novel opportunities in positive sense. *In primis*, it can enhance job quality by supporting productivity, efficiency and overall enjoyment of the worktask[69]. Early evidence suggests that lower-skilled workers may see particular benefits, as GenAI can enhance engagement with cognitively demanding tasks and consequently reduce productivity inequality[70].

It can provide guidance and training resources that promote upskilling and reskilling. Some large companies already use AI to identify skills gaps, a method considered more effective than procedures based on assumptions or simple direct questions to employees. Employers can collect detailed information on employee performance and certifications and employ machine learning algorithms to pinpoint areas requiring further training[71]. GenAI (and, more broadly, other innovative AI-related techno-legal tools) can thus contribute to creating new infrastructures for skills development and recognition in today's labour market[72].

GenAI can automate repetitive or low-value tasks, freeing workers to focus on higher-order, creative, or strategic activities[73]. Finally, streamlined

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Academic, 2025; see also E. Walkowiak , *Generative AI at the Workplace and Protection of Workers' Rights*, in SSRN Electronic Journal, 2024, 3.

[69] S. Noy, W. Zhang, *Experimental evidence on the productivity effects of generative artificial intelligence*, in Science, 2023, 381, 187-192, https://www.science.org/doi/10.1126/science.adh2586.

[70] S. Noy, W. Zhang, *op. cit.*

[71] For example, IBM has been able to reskill its workforce in strategic areas such as cybersecurity through AI-based micro-credential systems (see Upskilling and Reskilling for Talent Transformation in the Era of AI, 15 October 2024, available at: AI Upskilling Strategy | IBM). The world's largest private employer, the US-based company Walmart, has launched a partnership with OpenAI to develop a customised AI certification programme for its employees (Walmart taps OpenAI for employee training | Retail Dive.)

[72] Such tools can support the recognition of skills actually acquired, the traceability and enhancement of professional trajectories, and the reliable certification of reputational profiles, thereby ensuring their transferability and applicability to new employment opportunities, including across diverse sectoral contexts. See: E. Lackova, *Riconoscimento e portabilità delle competenze nel mercato del lavoro europeo: norme, tecnologie e prospettive future*, Franco Angeli, curatela del progetto PRIN "Politiche attive attive del lavoro, divari Nord-Sud e aree di crisi. I nuovi programmi per lo sviluppo territoriale, le transizioni e il mercato del lavoro, ruolo degli attori pubblici e delle parti sociali", 2025, forthcoming.

[73] Even if there is still the potential of cycling back to routine tasks when controlling the GenAI outputs. See: M. Law, R.A. Varanasi, Generative AI & Changing Work: Systematic Review of Practitioner-led Work Transformations through the Lens of Job Crafting, in Arxiv, arXiv:2502.088542025, https://arxiv.org/pdf/2502.08854.

processes may improve schedule flexibility and facilitate better work–life balance. By increasing the proportion of time spent on core, meaningful work, these developments could even support structural innovations such as a four-day working week[74].

4.3 AI for Improvement of Occupational Health and Safety

Empirical research and institutional survey data provide relatively clear and immediate evidence regarding AI's positive impact on occupational health and safety, a field that constitutes a long-standing and highly regulated dimension of EU labour law[75]. The widespread development of technology notably impacts job quality in multiple ways. Through the reconfiguration of working time and place, changes in organisational and management practices, as well as the broader fragmentation of social classes and weakening of trade unions, it can either foster the conditions for the emergence of increasing work-related stress and new forms of labour vulnerability[76], or contribute to improved overall well-being and safety in the workplace.

EU-OSHA has conducted extensive studies concerning the impact of AI-based worker management on the workplace safety and health[77]. The findings suggest that such AI systems can improve job quality by optimising task allocation, monitoring workplace risks, supporting workers' health and well-being, and providing personalised assistance.

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[74] E. Bennet, AI could make the four-day workweek inevitabile, BBC, 26 February 2024, https://www.bbc.com/worklife/article/20240223-ai-could-make-the-four-day-workweek-inevitable.

[75] EU regulation on occupational health and safety has developed progressively since the adoption of the founding treaties, with early references already present in the ECSC Treaty of 1951 and the Treaty of Rome of 1957. A major step was taken with the 1974 Social Action Programme, which introduced a broad set of measures on health and safety at work. The cornerstone of EU OHS legislation is the 1989 Framework Directive on Safety and Health at Work (Council Directive 87/391/EEC of 12 June 1989), which establishes minimum requirements across Member States and emphasises prevention of workplace accidents and occupational diseases. This framework has been complemented by a series of individual directives addressing specific risks and working conditions, including the Working Time Directive (Dir. 2003/88/EC), which sets minimum health and safety standards for the organisation of working time, such as rest periods, maximum working hours, and protections related to night and shift work.

[76] See C. Di Carluccio, *Lavoro e salute mentale, dentro e fuori l'istituzione*, Editoriale Scientifica, Napoli, 2022, 313 ff.

[77] For the list of publications see: https://healthy-workplaces.osha.europa.eu/en/tools-and-publications/publications?f%5B0%5D=publications_priority_area%3A1707.

Moreover, the data generated can also be used to develop more effective occupational health and safety training and programmes, as well as support the targeted planning of health and safety inspections[78]. And this is without even considering the implementation of AI application embedded in hardware, such as the use of robots to perform heavy and hazardous tasks, exoskeletons that can help reduce the risk of musculoskeletal disorders, and other applications that improve the quality of human work.
Also findings from OECD surveys and selected case studies suggest that the introduction of AI is generally associated with improvements in both physical and mental well-being at work. In particular, a majority of AI users report increased job enjoyment and satisfaction, as well as a greater perceived attractiveness of their tasks. These positive effects, however, are not evenly distributed and vary according to workers' roles and modes of interaction with AI: the most favourable outcomes are reported by those involved in developing, maintaining, or supervising AI systems, whereas workers directly subject to AI use or algorithmic management tend to experience more limited benefits[79].
There is also some evidence[80] of GenAI being increasingly used to address concrete work-related challenges – such as stress, career transitions, and workplace conflicts – indicating its potential to support worker well-being and job quality in digital workplaces.

4.4 From non-discrimination to Inclusive AI

As already analysed (*supra*, par. 1.1), without adequate legal safeguards, AI and algorithms can reproduce historical biases and exacerbate structural inequalities; conversely, when embedded within an appropriate regulatory framework, they also hold the potential to mitigate such biases and contribute to more equitable outcomes[81].
Transparency laws can play a critical role in converting the inherent opacity of algorithmic decision-making into a mechanism for preventing

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[78] EU-OSHA, *The future role of big data and machine learning in health and safety inspection efficiency*, 2019.
[79] OECD, *OECD Employment Outlook 2023*, cit., 139 ff.
[80] Even if, based on an analysis of 4.5 million Claude conversations, emotional support constitutes only 2.9% of GenAI interactions, McCain, M. *et al.*, *How People Use Claude for Support, Advice, and Companionship*, 2025, available online: https://www.anthropic.com/news/howpeople-use-claude-for-support-advice-and-companionship.
[81] G. Gaudio, *op. cit.*

systemic discrimination. By mandating that companies disclose the functioning, logic, and consequences of automated decision-making processes, current regulatory framework allows workers to obtain prior knowledge of algorithmic reasoning and potential biases. Unlike human cognitive biases, which are well hidden and unobservable (the highest form of black box[82]), algorithmic rules and outputs are formally codified, making discrimination potentially detectable and auditable.

European regulations provide a layered and complementary system of rights that operationalise this principle. The GDPR (Articles 13(2)(f), 14(2)(g), and 15(h)) guarantees that all individuals whose personal data are processed have rights to information and access regarding automated decision-making, including profiling, when it affects employment, job access, or contract management. These rights apply equally to employees and self-employed workers, and impose obligations on both data controllers and processors – including employers and digital platforms – to disclose the logic, significance, and potential consequences of algorithmic processes. Building on the GDPR, the AI Act (Articles 14 and 86) codifies a more explicit framework for high-risk AI systems, establishing both a right to explanation and the obligation for human oversight to mitigate risks to health, safety, and fundamental rights. The Platform Work Directive (Articles 9-11) extends these principles specifically to platform-mediated work, requiring transparency obligations not only toward individual workers but also toward their representatives and, upon request, national authorities.

A crucial feature of this regulatory ecosystem is the interdependence of transparency, explainability, and human oversight. The GDPR rights to information and explanation are meaningful only if they enable effective human review of automated outputs; the AI Act similarly links the right to human supervision with obligations for traceability and comprehensible

[82] Human decision-making is inherently affected by systematic imperfections – "bugs" – that often operate silently and remain unnoticed. These imperfections may ultimately manifest as distorted judgement or random chance variability in decisions. The former is better known unconscious bias, understood as a lack of awareness of the cognitive shortcuts individuals rely on when processing information. The latter is commonly referred to as judgement noise, which affects decision-making not through consistent directional bias, but through the undue influence of irrelevant, contextual, or purely incidental factors, resulting in inconsistency across decisions. Both biased or otherwise distorted forms of human judgement constitute basis of discrimination. See: K. A. Houser, *Can AI solve the diversity problem in the tech industry? Mitigating noise and bias in employment decision-making*, in *Stanford Technology Law Review*, 2019, Vol. 290, No. 22, 318-323.

documentation. Under the Platform Work Directive, transparency rights are embedded alongside participatory and consultation rights, recognising that collective mechanisms are often better equipped to analyse complex aggregated data, identify systemic bias, and engage experts for technical assessment[83].

In this way, the combined effect of these regulations transforms the traditional opacity and unpredictability of algorithmic systems into structured mechanisms for accountability and discrimination prevention. By codifying algorithmic logic "in black and white" and pairing it with legally enforceable rights, the European legal framework enables both individual and collective actors to detect, challenge, and mitigate systemic biases.

Not only preventing discrimination and enforcing anti-discriminatory legal mechanisms, but – in the light of prescriptive (rather than descriptive) nature of the principle of equality[84] – it appears necessary also actively impose the obligation for inclusive AI in the workplace. Some scholars call for extending the principle of reasonable accommodation – duty for the employers towards employees with a disability, introduced in the Council Directive 2000/78/CE – beyond its traditional, reactive, and disability-specific scope. According to this interpretation employers would have a responsibility to develop and deploy AI and algorithmic systems in ways that proactively prevent discrimination. This would entail evaluating the potential and actual impacts of the AI system, and, wherever possible, implementing adaptive or flexible measures to minimise risks and ensure equitable outcomes[85], thereby securing fair access to work, balanced task allocation and equal opportunities for career progression. Ultimately, embedding this principle in AI governance could steer technological innovation to become a tool for inclusive and high quality employment.

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[83] Thus avoiding information overload for the workers, J. Adams-Prassl *et al.*, *Regulating algorithmic management: a blueprint* in *European Labour Law Journal*, 2023, 14, 3, 12 ss

[84] R. Voza, *Eguaglianza e discriminazioni nel diritto del lavoro. Un profilo teorico*, Aidlass – XXI Congresso nazionale Messina, 23-25 maggio 2024, 11 ff, https://aidlass.it/wp-content/uploads/2024/05/Relazione-VOZA.pdf.

[85] F. Palmirotta, *Disruptive, yet Inclusive AI: Solutions and Boundaries from a Labour Law Perspective*, in *Italian Labour Law e-Journal*, 2025, vol. 1, no. 18, 83-111, argues for a proactive reinterpretation of the principle of reasonable accommodation toward inclusive AI.

5. Final Remarks

The reflections presented in this contribution suggest that AI is a technology with multiple effects: it is not *a priori* a tool of inequality, but neither is it a guarantee of inclusion and job quality. The social impact of AI depends on its design, transparency, the possibilities for oversight, and above all on the legal framework that determines the limits of its deployment. The case law examined confirms that, in the absence of adequate safeguards, AI tends to reproduce historical biases, amplify inequalities, and interfere with rights to privacy and equal treatment.

Conversely, when systems are designed in accordance with principles of equality and accessibility, AI has the potential not only to transform work but to contribute to fairer, healthier, and more fulfilling employment. Assessing AI's impact on work through the lens of job quality provides a comprehensive framework in this sense.

AI has differentiated effects on job quality: workers with AI-complementary skills tend to benefit from wage growth, while those in non-standard or precarious work face greater risk of pay reduction and devaluation of their contribution. Generative AI directly affects task execution by automating repetitive tasks and supporting more complex activities, improving productivity, engagement, and opportunities for upskilling. These effects positively influence well-being and work–life balance, though benefits are unevenly distributed depending on the role and interaction with AI.

Overall, ensuring that AI-enhanced work is of high quality requires a multi-faceted approach. This involves embedding AI within robust legal frameworks, operationalising job quality indicators, and fostering inclusive, adaptive practices that anticipate risks while amplifying benefits across the workforce.

The above considerations show that the future of AI is not determined by the technology itself but by the value-based decisions made by society. Regulation grounded in the principles of equality, transparency, and human dignity can transform AI from a potential source of inequality into a tool for the common good. The task of legal scholarship is therefore not only to retrospectively analyse these developments but also to actively propose normative and policy solutions that enable AI to uphold the principles of equality, justice, and participation. Only in this way can technological progress be translated into an inclusive framework in which innovation serves society as a whole rather than a narrow group of actors.

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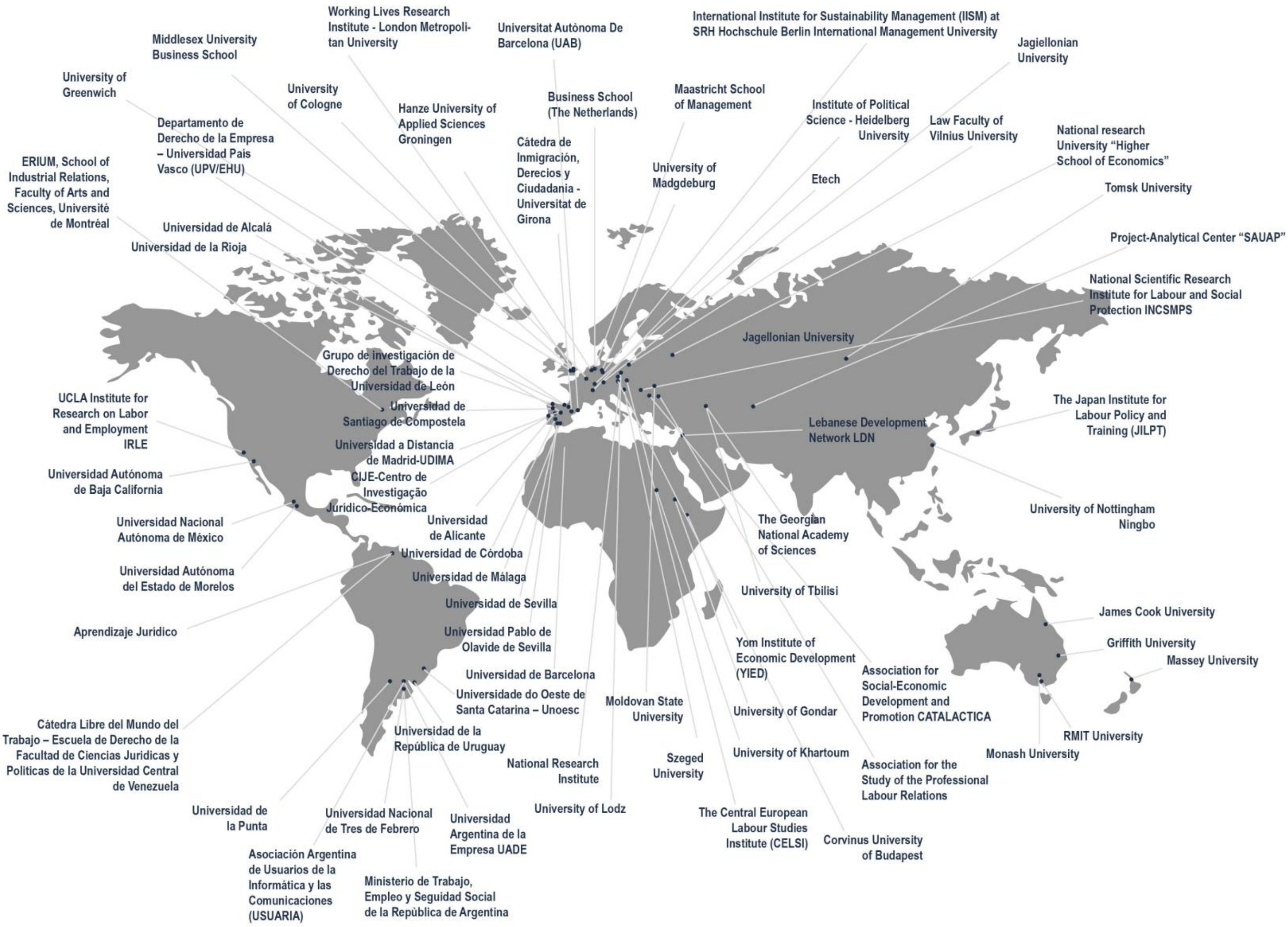

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