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Facultad de Ciencias Económicas y Empresariales

TRABAJO FIN DE GRADO

Programa Internacional del Doble Grado en Administración y Dirección de Empresas y
Economía

**ARTIFICIAL INTELLIGENCE. LEGAL FRAMEWORK AND EFFECTS ON THE
ECONOMY**

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Pamplona-Iruña 30/05/2024

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RESUMEN

La Inteligencia Artificial (IA) está transformando múltiples sectores, mejorando la eficiencia, impulsando la innovación y abriendo nuevas oportunidades. Esta investigación explora las amplias implicaciones de la IA, examinando las dimensiones jurídicas, económicas y sociales de su desarrollo y despliegue. Analiza el marco normativo, centrándose en la legislación de la UE, y destaca que una gobernanza eficaz es crucial para aprovechar los beneficios de la IA y minimizar los riesgos.

El análisis económico revela que la IA impulsa significativamente la productividad y la innovación, aunque también presenta retos como el desplazamiento de puestos de trabajo y la necesidad de recualificar la mano de obra. Se examina el potencial de la IA para impulsar el crecimiento económico o agravar la desigualdad, lo que refleja la naturaleza del doble filo de su impacto. La investigación aborda también los principales retos de la integración de la IA, tales como la privacidad de los datos, la concentración de poder en sólo algunas empresas grandes, los problemas de transparencia, la desinformación y la discriminación.

Palabras clave: Inteligencia Artificial, Regulación, Impacto Económico, Privacidad de Datos, Transparencia.

ABSTRACT

Artificial Intelligence (AI) is transforming diverse sectors, improving efficiency, driving innovation, and opening up new opportunities. This research explores the broad implications of AI by examining the legal, economic and social dimensions of its development and deployment. It analyses the regulatory framework, focusing on EU legislation, and highlights that effective governance is crucial to harnessing the benefits of AI and minimising the risks.

The economic analysis reveals that AI significantly boosts productivity and innovation, although it also presents challenges such as job displacement and the need to reskill the workforce. The potential for AI to boost economic growth or aggravate inequality is examined, reflecting the double-edged nature of its impact. The research also addresses the main challenges of AI integration, such as data privacy, concentration of power in a few large companies, transparency issues, misinformation and discrimination.

Keywords: Artificial Intelligence, Regulation, Economic Impact, Data Privacy, Transparency.

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1.INTRODUCTION

Artificial Intelligence (AI) is revolutionising the way we live and work, bringing unprecedented changes to a wide array of fields. As AI technologies continue to advance, they promise to enhance efficiency, foster innovation, and unlock new possibilities.

This research investigates the multifaceted implications of AI, focusing on three critical areas: the legal frameworks shaping its development and deployment, the economic impacts driving and resulting from its integration, and the various challenges that accompany its rapid advancement. By exploring the evolving regulations, the economic opportunities and disruptions, and the ethical and practical challenges posed by AI, this study aims to provide a holistic view of AI's role in contemporary society and its future trajectory.

In light of its rapid development and the challenges involved in its governance, AI regulation is essential as it ensures that its deployment is conducted responsibly and ethically. Effective regulation helps protect against potential harms such as privacy breaches, biased decision-making, and misuse of AI systems. It also promotes transparency, accountability, and fairness, fostering public trust in AI technologies. Most of the legislation reviewed and analysed is EU legislation, although there is also a mention of US laws and a brief comparison of their similarities and differences in some key aspects.

In this line, the work refers firstly to the proposals and legislative developments of the European Union, which is one of the first comprehensive regulatory frameworks for artificial intelligence globally. The legislation categorises AI tools according to whether they are unacceptable, high, limited or low risk and aims to encourage the use of AI while protecting rights and freedoms. Current regulations, including that of the United States, reflect an attempt to balance between promoting AI innovation and protecting citizens on the one hand, while not hindering competition in the race to develop AI on the other.

The paper also analyses the impacts that this technology will have on the economy, considering that it has the potential to transform it by driving innovation, enhancing productivity, and creating new market opportunities. By automating routine tasks and optimizing complex processes, AI enables businesses to operate more efficiently and effectively. This technological advancement leads to cost savings, improved performance, and the development of new products and services. However, the economic transformation driven by AI also poses significant challenges, particularly in the areas of job displacement

and workforce reskilling. As AI systems and automation technologies take over routine and repetitive tasks, many traditional jobs are at risk of becoming obsolete and this shift can lead to unemployment and economic inequality.

Due to its complexity, rapid evolution and profound impact on society, AI raises certain concerns and for this reason the last part of the paper discusses the main challenges of its integration. First, it examines the emergence of so-called superstars, the concentration of AI's potential in a few large companies and the risks that this may bring. Additionally the deployment of AI technologies involves the collection and processing of large volumes of data, which can lead to significant privacy concerns. This data can include personal information about individuals, raising questions about how it is used, stored, and protected. Moreover, the lack of transparency in AI decision-making processes makes it difficult to ensure accountability and fairness. Finally, the paper explores how AI can exacerbate discrimination due to biased training data, which can perpetuate existing social inequalities and the potential risk that as more jobs are taken over by AI and automation, human workers may lose part of its bargaining power.

2.CURRENT REGULATION OF ARTIFICIAL INTELLIGENCE IN THE EU - THE “AI ACT”

The European Union's digital strategy aims to implement regulations for Artificial Intelligence to ensure better conditions for its development and use. The Horizon Europe and Digital Europe programs will jointly allocate €1 billion per year towards AI. Additionally, the Commission intends to get investment from the private sector reaching a target of €20 billion throughout the digital decade (European Commission, 2023). Moreover, the Recovery and Resilience Facility allocates €134 billion for digital initiatives, which can entail an opportunity for Europe to position itself as a global leader in the development of cutting-edge AI.

With the aim of ensuring that the AI systems used in the EU are safe, trustworthy and overseen by people, in April 2021, the European Commission presented its AI package which included the Coordinated Plan on Artificial Intelligence and the AI ACT. The Coordinated Plan on Artificial Intelligence was first published in 2018 and updated last in 2021 and seeks to accelerate investment and implement strategies that harmonise AI policy within Europe (European Commission, 2023). On the other hand, the Artificial Intelligence ACT is the Commission's regulatory framework proposal on artificial intelligence.

2.1 Introductory remarks - the four risk levels.

The regulatory proposal provides AI developers, deployers and users with clear requirements and obligations regarding specific uses. Simultaneously, it pursues to reduce the burden, both administrative and financial, for businesses, specially that small and medium sized ones (European Commission, 2023).

The proposed rules aim to mitigate risks associated with AI applications by identifying and regulating high-risk scenarios. Additionally, the proposal suggests establishing a governance structure at both European and national levels to oversee its regulation. The majority of obligations fall on providers (developers) of high-risk systems and these obligations extend to those seeking to introduce systems within the EU regardless of their country of origin. In contrast users, defined as natural or legal persons that deploy an AI system in a professional capacity(not affected end-users), have some obligations, but fewer than providers.

The regulatory framework defines 4 levels of risk in AI systems; unacceptable, high, limited and minimal risk according to which the legal framework is enforced.

A. Unacceptable risk (Chapter II, Art.5)

Title II, Article 5 stipulates the prohibition of AI systems that present intolerable risks, identified as hazards to individuals. These include systems utilising subliminal or manipulative tactics to alter behaviour, as well as systems exploiting vulnerabilities associated with age, disability, or socio-economic status.

Additionally, the ban includes biometric categorization systems that can infer sensitive attributes and social scoring, which evaluates individuals or groups based on social behaviour or personal traits, leading to unfair treatment. Moreover, assessing an individual's risk of committing criminal offences only based on profiling or personality traits is prohibited as well as the compilation of facial recognition databases from the internet or CCTV footage.

“Real time “ remote biometric identification (RBI) is accessible for law enforcement only when searching for missing persons, abduction or human traffic victims, when there is a substantial and imminent threat to life, or a foreseeable terrorist attack or for the purpose of identifying suspects in serious crimes, such as murder, rape, armed robbery, narcotic and illegal weapons trafficking.

Prior to deployment, law enforcement agencies are required to conduct a fundamental rights impact assessment and register the system in the EU database. Additionally, authorization from a judicial authority is mandatory before deployment.

B. High risk (Chapter III)

High risk AI systems are defined in Article 6 in 8 different categories that represent areas of application with potential societal impact, requiring higher regulatory oversight. These include biometric systems for remote identification, emotion recognition, and sensitive attribute categorization. The second category, critical infrastructure, encompasses systems used in management of digital infrastructure, road traffic, and utilities. In the educational area, considered as high risk are all those systems used for admission, evaluation, and monitoring in institutions. Similarly in the employment area AI used for recruitment, decision-making, and performance evaluation in workplaces are high risk. Regarding access to essential services, this category includes systems for public assistance, creditworthiness evaluation and insurance risk assessment. The law enforcement category includes all those AI systems intended to be used by authorities for risk assessment, evidence evaluation, and profiling in criminal investigations. Regarding migration and border control, systems that assess risks or process visas or asylum applications fall into the high-risk category. Finally, AI applications in justice and democracy for law application, dispute resolution or election influence are considered as high risk.

AI systems are always classified as high risk when engaging in profiling individuals or when processing personal data to evaluate aspects like work performance, economic situation, health, preferences or interests. Providers can prove their system is not high risk by providing the necessary documentation before being placed in the market.

a. Requirements for providers of high-risk AI systems (Art. 8-15)

Articles 8 to 15 of the EU AI ACT establish the key requirements high risk AI providers must meet. These include setting up a solid plan to manage risks, ensuring data is handled properly, and creating documents to prove compliance. They must also record any issues automatically and give clear instructions to users. Additionally, high-risk AI systems must be designed to facilitate human oversight by deployers, while also prioritising accuracy, robustness, and cybersecurity measures. Furthermore, establishing a quality management system is deemed crucial to ensure continual compliance with regulatory standards.

C. Limited risk

AI systems with limited risk are required to meet basic transparency standards, enabling users to make informed decisions. Following interactions with the applications, users have the discretion to decide whether to continue using them. It is essential to inform users when they are engaging with AI, particularly in the case of systems generating or manipulating image, audio, or video content, such as deepfakes and chatbots.

D. Minimal risk

Minimal risk systems are unregulated. This includes the majority of AI applications currently available on the EU single market, such as AI enabled video games and spam filters. However, this might change with generative AI¹.

2.2 General purpose AI (GPAI) (Chapter V)

The term GPAI refers to an AI model that presents remarkable generality and is capable of performing a wide range of tasks regardless of the way the model is marketed and that can be integrated into a variety of downstream systems or applications. It's important to note that this definition excludes AI models used exclusively for research, development, and prototyping activities before their release on the market.

Similarly, a GPAI system refers to an artificial intelligence system built upon a versatile AI model, possessing the capacity to fulfil diverse purposes, including direct utilisation and integration into other AI systems. Given that GPAI systems may be used as high-risk AI systems or integrated into them, its providers should cooperate to comply with the high risks requirements established in the AI ACT.

All providers of GPAI models need to create technical documents that cover how the model was trained and tested, including the results. They also need to provide information for other providers who want to use the GPAI in their systems, explaining what it can do, what it can't do, and how to follow the rules. Additionally, there needs to be a policy in place to respect copyright laws. Lastly, they have to share a detailed summary of the data used to train the GPAI model to be transparent about how it was made.

Free and open licence GPAI models (defined as those whose parameters, model architecture and use are publicly accessible) only have to comply with the latter two obligations above, unless the GPAI model is considered systemic.

¹ Deep-learning models that can generate high-quality text, images, and other content based on the data they were trained on

GPAI models reach systemic status when the total computing power used during their training surpasses 10^{25} floating point operations per second (FLOPS)². Providers are required to inform the Commission within a two-week period if their model hits this level although the provider can argue that despite meeting the criteria, their model does not present systemic risks. The Commission has the authority, either independently or advised by a qualified panel of independent experts, to determine if a model possesses high-impact capabilities, thereby classifying it as systemic.

In addition to the obligations mentioned before, providers of GPAI models categorised with systemic risk have further responsibilities. This includes conducting thorough model evaluations, testing it against potential risks and understanding their sources. Providers must diligently track, document, and report any serious incidents and potential corrective measures to both the AI Office and relevant national authorities. Additionally, ensuring an appropriate level of cybersecurity protection is crucial in fulfilling these obligations.

Regarding the code of practice, the GPAI framework will consider international perspectives and cover a broad range of obligations, including those related to technical documentation for authorities and downstream providers. It emphasises identifying systemic risks and their sources and addressing challenges in risk management throughout the value chain. The AI Office may invite providers, national authorities, and other stakeholders to contribute to the development of codes, fostering collaboration among society, industry and downstream providers.

2.3 Governance (Chapter VII)

Regarding governance at the Union level, the Commission will develop expertise and capabilities in the field through the AI Office, which was established in February 2024. Additionally, the European Artificial Intelligence Board shall be composed of one representative from each Member State and will advise and assist the Commission and the Member States to ensure the consistent and effective application of the regulation. To that end, the Board may collect and share technical and regulatory expertise and best practices, provide advice on the implementation, particularly regarding the rules on general-purpose AI models, and issue recommendations including the development and application of codes of conduct and practice.

² It's a measure of a computer's performance based on the number of floating-point arithmetic calculations that the processor can perform within a second.

At the nation level, each Member State must designate at least one notifying and one market surveillance authority that shall operate independently and impartially. Member States must inform the Commission of the identities and tasks of these authorities and make contact information publicly available within 12 months of the regulation's entry into force. Moreover, they shall take appropriate measures to ensure an adequate level of cybersecurity.

2.4 Sanctions

Companies not complying with the rules will be fined. Fines would range from €35 million or 7% of global annual turnover (whichever is higher) for violations of banned AI applications, €15 million or 3% for violations of other obligations and €7.5 million or 1.5% for supplying incorrect information. More proportionate caps are foreseen for SMEs and start-ups in case of infringements of the AI ACT (European Commission, 2023)

2.5 Next steps

Given the rapid evolution of AI technology, the proposal adopts a future-proof approach, enabling rules to adapt to technological changes.. This requires ongoing quality and risk management by providers.

On December 9th, 2023, the European Parliament reached a provisional agreement with the Council on the AI ACT. On March 13th, 2024, the Parliament approved the AI ACT, and while the regulation is still subject to a final lawyer-linguist check, it is expected to be finally adopted before the end of the legislature.

The AI ACT will enter into force twenty days after its publication in the Official Journal, and will be fully applicable 24 months thereafter, except for the following provisions: bans on prohibited practises, which will apply six months after the entry into force date; codes of practise (nine months after entry into force); general-purpose AI rules including governance (12 months after entry into force); and obligations for high-risk systems (36 months).

2.5 Artificial intelligence regulation in Spain

On April 15, 2024, the Council of Ministers in Spain approved the Artificial Intelligence Strategy. This strategy builds upon previous initiatives undertaken by the Spanish Government in the field of Artificial Intelligence. It is an ambitious plan aimed at enhancing and expanding the use of AI across the economy and public administration. The implementation is scheduled for 2024 and 2025, with a budget allocation of 1.5 billion euros. The Artificial Intelligence Strategy 2024 is organised around three key pillars (Gobierno de España, 2024). The first pillar reinforces the capabilities for the development of AI. Firstly,

the focus is on the reinforcement of supercomputing, a fundamental pillar for the advancement of AI. 90 million euros will be invested in the implementation of new highly specialised clusters to improve the performance of the MareNostrum 5, a supercomputer at the Barcelona Supercomputing Center. These actions aim to significantly increase the available data processing capabilities, which, as mentioned throughout the work, are essential for the development of this technology. This pillar also focuses on boosting specialised talent in AI, addressing the significantly increased demand for these professionals in recent years. The Strategy will allocate 6 billion euros to establish networks and an additional 160 million euros in scholarships for worker training (Fernández Rozas, 2024).

The second pillar seeks to facilitate the adoption of AI in both the public and private sectors, with a particular focus on SME, who, as discussed later in this work, face disadvantages compared to larger entities with greater access to AI development resources. To support this effort, 400 million euros will be allocated through the NextTech Fund to finance companies developing AI solutions. This initiative will be complemented by the forthcoming Cybersecurity Law, which will establish a clear and comprehensive framework to develop national cybersecurity and improve the protection of information systems, networks, and data.

The third pillar focuses on promoting transparent, ethical, and humanistic AI. The Spanish Agency for the Supervision of Artificial Intelligence (AESIA) will play a central role in achieving the objectives and will function as a centre for AI analysis, identifying best practices and emerging risks, and as a supervisory body ensuring that deployment complies with European regulations.

Lastly, in terms of governance, the Artificial Intelligence Strategy and its initiatives will be coordinated by the Secretary of State for Digitalization and Artificial Intelligence. Given its extensive scope and impact, the strategy will also receive support from the Interministerial Commission for the Coordination of Measures for Connectivity and Digitalization of the Economy and Society (Fernández Rozas, 2024).

2.6 Artificial intelligence regulation in the US

On October 30th, 2023, President Biden signed the Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. It mandates that major artificial intelligence developers share their safety tests and other critical information with the U.S.

government, and it directs agencies to establish safety and testing standards on cybersecurity, civil rights, and labour market impacts among others.

Similarly, it issued an AI Bill of Rights that sets the following 5 principles; safe and effective systems, algorithmic discrimination protection, data privacy, notice and explanation and human alternatives, consideration and fallback. These principles are aimed at helping the design, use and deployment of automated systems to protect the rights of the American public (The White House, 2023). Finally, the Equal Employment Opportunity Commission (EEOC) has also been adamant that it will continue to enforce Title VII of the Civil Rights Act, which focuses on preventing discrimination against job applicants and workers, whether the threat comes from a human or a robot.

Section 1 of the Executive Order, similar to the European regulation, emphasises the immense potential of artificial intelligence to tackle challenges and enhance prosperity and security while recognising the risks such as fraud, bias and misinformation (Biden, 2023).

The second section details the Biden administration's policy for governing AI development and use. The Executive Order emphasises a collaborative approach to AI development, involving stakeholders from diverse fields. It aims to protect individuals from foreseeable negative impacts of unsafe AI systems, safeguard against abusive data practices, and ensure user agency over data collection and use. Transparency is prioritised, requiring users to be informed about AI usage and providing an option to opt for human alternatives (Biden, 2023). The Order also seeks to prevent discrimination by ensuring AI systems are designed equitably. Additionally, it mandates compliance with AI regulations and accountability for those who fail to meet established standards.

Furthermore, sections 4 and 5 focus on ensuring safety and security and promoting innovation and competition. Section 6 highlights the importance of supporting workers, a point that is not mentioned as much in the European regulation. The Order requires the Secretary of Labour to assess and strengthen the government's capacity to support workers who may be displaced by AI (Biden, 2023). Moreover, sections 8 and 9, similar to the European regulation, focus on protecting consumers, patients and students from the potential risks of AI and on data protection.

Finally, section 11 expresses the United States' commitment to global leadership in artificial intelligence. It calls for a multifaceted strategy to strengthen collaboration with international partners and to develop consistent AI standards worldwide. Section 12, regarding

implementation, establishes the White House Artificial Intelligence Council within the Executive Office of the President. This council will coordinate federal agency activities to ensure the effective development and implementation of AI-related policies as outlined in the order (Biden, 2023).

Comparing the approach taken by the US and the EU, both share a concern and focus on AI risks and agree on the key principles of trustworthy AI. The EU's approach to AI risk management, however, is characterised by a broader range of legislation tailored to specific digital environments. The US legislation emphasises support for workers who may be replaced by AI, a point that is not mentioned as much in the EU legislation. In addition, they also underline their commitment to lead the race in AI.

Regarding this last point, it is important to mention that major powers such as the US and China are competing for a head start in the AI revolution in all areas of human activity. While some European-based tech startups are concerned that more heavy-handed EU legislation will hinder innovation, it seems clear that for the other players, the absence of legislation or more lax legislation will be an advantage over the nearest competitor. It is therefore a difficult balance between promoting innovation in a competitive way and protecting citizens.

3. AI EFFECTS ON THE ECONOMY

The past decades have witnessed major developments in artificial intelligence technology. The deployment and progress of AI applications in the production of goods and services, transportation and logistics, or service provision have led to significant social and economic changes, which have sparked a debate on the present and future impact of AI on society . As in the case of past general-purpose technologies, such as the steam engine, electricity or the internet, AI has the potential to disrupt almost all industries and businesses on a worldwide scale.

The magnitude of these disruptions will depend on two important factors: the speed and the factor bias of progress in AI . Regarding the first factor, productivity has increased at a rather slow pace, which suggests that transition may be slower than, for example, the wave of mechanisation in the 1950–1970s. However, this could be due to productivity being under measured, because quality improvements are not accurately captured or due to the aggregate

implications of AI adoption taking longer to realise, similar to what happened with computer introduction in the 80's.(Korinek et al., 2018)

Classical economic theories predict that, ultimately, economic growth depends on technological change and innovation (Solow 1957; Romer 1990). Newer theories, like the skill-biased technological change, predict that technological innovation can result in wage polarisation through relative increases in the demand of skilled workers with respect to unskilled ones (Autor et al. 2003; Barbieri et al. 2020), and to possible job losses due to task automation (Autor and Dorn 2013; Josten and Lordan 2020).

Regarding productivity, the potential displacement effects may be surpassed by a productivity effect if automation enhances labour demand by introducing efficiencies into the production process.(Acemoglu and Restrepo 2019, 2020). However, not all researchers share this optimistic view, some theoretical models forecast a persistent slowdown in productivity, attributed to increased inequalities (Gries and Naudé, 2018), learning costs (Jones 2009) and a lower rate of disruptiveness of AI compared to past general-purpose technologies (Gordon 2016, 2018).

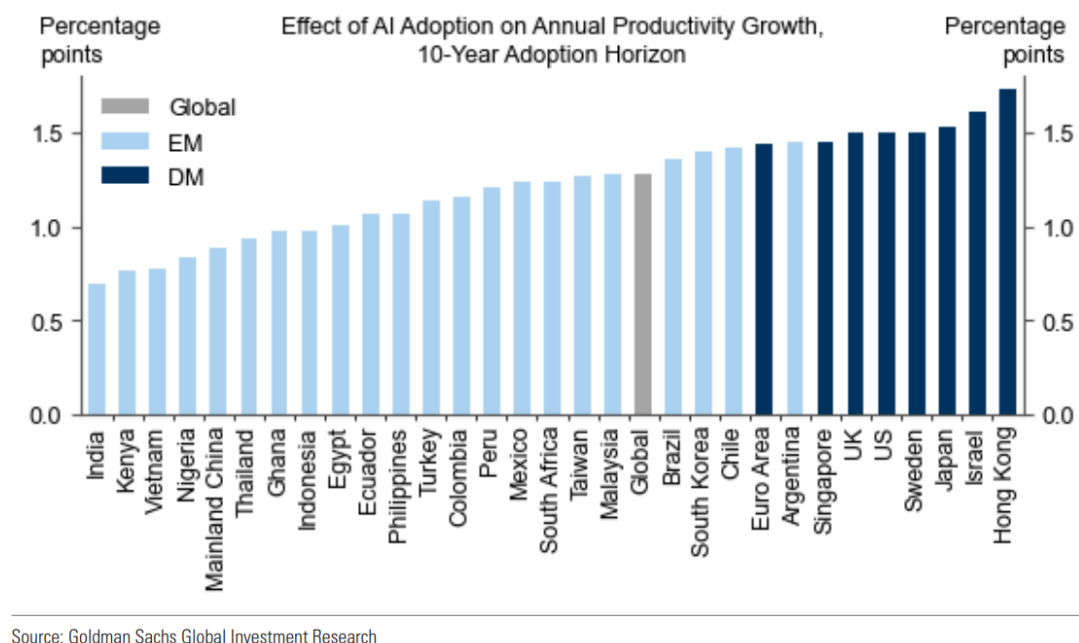
These contradictory predictions call out the need for qualitative studies to measure economic outcomes in both productivity and employment, yet the requirement and lack of accurate, high-quality data acts as an important barrier. (Raj and Seamans 2019). The increase of generative artificial intelligence raises the question on whether we are on the brink of a rapid acceleration in task automation that will drive labour cost savings and raise productivity or if, on the other hand, it will hinder economic growth.

3.1 Effects on productivity

AI enables companies to learn faster and more effectively from datasets, holding the potential to significantly improve decision-making in business. It functions as a general-purpose technology, fostering growth through heightened productivity and innovation across diverse sectors (Aghion et al., 2017; Agrawal et al., 2019). However, the question remains open as to whether AI can truly transform economies and drive economic growth, as economists are concerned on whether the benefits might be overestimated or take longer to materialise. (Mihet and Philippon, 2019; Brynjolfsson et al., 2019).

Despite the uncertain effects of automation on the workforce, economists are generally enthusiastic about the prospects of AI on productivity growth. Similar to earlier general-purpose technologies such as the electric motor and personal computer, automation holds the promise of boosting labour productivity through substantial cost savings, new job creation, and increased overall efficiency. Historical patterns suggest that the initiation of a labour productivity boom is challenging to predict, typically occurring around two decades after the technological breakthrough, when approximately half of the businesses have adopted the innovation.

The Goldman Sachs report, based on the assumption that the effects become evident over a 10-year span once half of businesses adopt generative AI, estimates that its widespread adoption could lead to an increase in overall labour productivity growth by approximately 1.5 percentage points per year. Despite the high level of uncertainty surrounding this estimation, it remains economically significant in most scenarios. Moreover, when the analysis was extrapolated to other countries, the estimation implied that AI adoption could boost productivity growth by 1.4pp over a 10-year period.



Graph 1: Productivity growth as a result of AI integration.

Source: Goldman Sachs Global Investment Research

In Babina et al. data from Cognism Inc., providing job histories for 535 million individuals worldwide, is used along with job postings data from Burning Glass, encompassing 180 million job vacancies, with the aim of analysing the patterns and benefits for the firms

investing in AI. Their main observation was that firms investing more in AI experienced higher growth through increased product innovation, which can be seen in increased trademarks, product patents, and firms' product portfolios. This finding indicates that, thus far, the primary impact of AI has been to facilitate growth through product innovation, aligning with the idea that AI effectively lowers the expenses associated with product development.

The study explores the mechanisms by which AI can drive firm growth, proposing a theoretical framework that encompasses two complementary channels: product innovation and process innovation. In the first channel, AI decreases the costs associated with product innovation, enhancing the quality of existing products and facilitating the creation of new ones (Hottman et al., 2016). Theoretically, AI holds the potential to achieve this by making the product development process faster through analysis of large datasets, thereby reducing uncertainty in experimentation and enhancing firms' understanding of customer preferences (Mihet and Philippon, 2019). The empirical findings reveal that firms with substantial AI investments witness increased product innovation, reflected in more patents and trademarks.

The second channel through which AI can stimulate growth is by increased process innovation, which lowers operating costs and improves productivity for existing products, for example, by replacing human labour for some tasks (Agrawal et al., 2019; Acemoglu and Restrepo, 2019) or by better forecasting of the inputs for the production process (Basu et al., 2001; Farboodi and Veldkamp, 2021). Empirically, they did not find support for this second channel. Instead, the relationship between AI investments and firm growth appears to be driven by product innovation.

The research documents a positive relationship between investment in AI and firm growth.. Specifically, a one-standard-deviation rise in AI investments over an 8-year span corresponds to a 19.5% increase in sales, an 18.1% rise in employment, and a 22.3% increase in market valuation. These outcomes are consistently evident across major industry sectors such as manufacturing, finance, and retail, reinforcing the notion that AI functions as a general-purpose technology. (Babina et al. 2024)

The relationship between firm AI investment and firm growth is increasing with firm size. This stronger positive connection between changes in AI investments and growth in larger firms aligns with the notion of big data and AI technologies exhibiting scale effects that favour larger enterprises. These larger firms tend to accumulate substantial amounts of data

as a natural by-product of their economic activities, as emphasised by Farboodi and Veldkamp (2022). Similarly, Akcigit and Kerr (2018) point out that larger firms encounter challenges in scaling due to elevated costs associated with product innovation so AI might serve as a mechanism through which they can overcome obstacles to innovation and scale by capitalising on their extensive data assets.

However, the research shows that although there's a subsequent increase in sales after AI investment, this boost is not immediate: it takes two to three years for firms to begin realising the benefits. The cumulative effect of a one-standard-deviation increase in annual AI investments on log annual sales is 1.5%–2% and this impact remains steady even five years after the initial investment.(Babina et al. 2024)

In summary, Babina et al. paper concludes that the benefits of AI technologies for firms primarily stem from product innovations rather than reductions in operating expenses or improvements in productivity. This contrasts what would have been expected of general-purpose technologies if we take past examples like electricity, which resulted in rapid productivity gains (Fizsbein et al., 2020). However, these findings align with Acemoglu et al. (2022a), who, using U.S. Census data, observed no correlation between artificial intelligence and labour productivity but identified positive productivity effects for other technologies such as robotics and specialised software. Finally, it's worth mentioning that the effect of product innovation on productivity is theoretically ambiguous since firms may have higher or lower productivity in the new product lines. Moreover, the research by Babina et al. shows that AI-investing firms are able to maintain the same level of productivity at a larger scale, which is consistent with other studies documenting that investments in technologies are associated with increased scale of the firm but no productivity gains (Aghion et al., 2019).

Another research conducted by Damioli et al. uses a data set covering 5257 worldwide firms, both in manufacturing and services, active in AI patenting from the years 2000–2016. While patents might have some limitations capturing innovation, for example because some firms may prefer to keep their inventions secret instead of patent them, it's a good proxy for measuring and analysing firms' innovative efforts.

Their analysis shows a positive impact of AI applications on labour productivity when measured by turnover per worker. “ If a firm increases its innovative effort in the field of AI and doubles its number of AI patent applications, the predicted increase in labour productivity amounts to 3%” (Damioli et al., 2021). For the aggregate model, the inventory

of patent applications in technologies other than AI is also significant but lower, of around 2%, confirming the potential of AI to increase overall productivity. This aligns with the result of Alderucci et al. (2020), that showed an average increase of 4.15% for US firms that made their first AI related investigation in the period between 1997 and 2016, as opposed to similar firms that didn't.

However, when examining the sample across industries, AI patent applications hold significance solely in the services sector and its effect on labour productivity is relatively strong, reaching 7.7%(Damoli et al., 2021). Interestingly, Alderucci et al. (2020) study on US companies also identifies a positive and significant impact of AI on sales per worker, but a negative one in manufacturing. This suggests that perhaps the impact of AI patenting in the manufacturing sectors may not be distinguishable from the non-AI patents or it might take longer to become apparent due to a time lag.

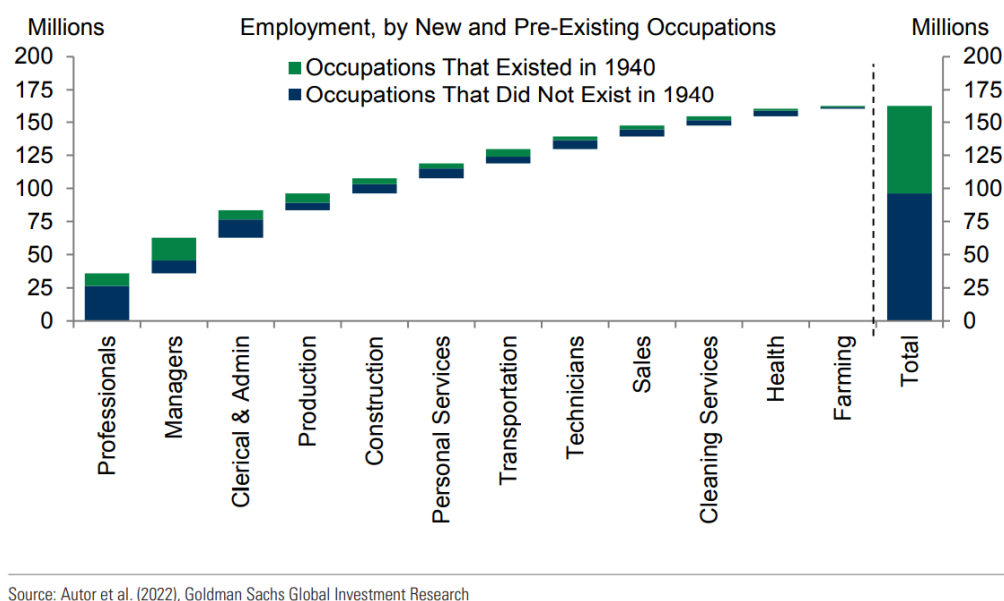
Finally, the effect is only shown in the latest years of the sample, which confirms the low economic maturity of the AI technology. More time will be required to extrapolate the results and evaluate whether AI technology will indeed result in productivity gains.

3.2 Effects on job substitution

The substantial portion of the workforce vulnerable to automation through generative AI suggests the possibility of a surge in labour productivity, leading to a significant rise in global output. Several research papers tried to isolate the extent to which AI will directly replace certain occupations or tasks. The question these researchers are asking is whether the impact from AI will be different than with past technologies. This could happen if in fact the pace of change is much quicker, simultaneously affecting employment throughout the entire economy or if it replaces a broader spectrum of skills, including those that were previously considered only human.

The report published by Goldman Sachs states that AI-driven automation holds the potential to impact global GDP through two primary avenues. Initially, a considerable number of workers are in roles partially susceptible to AI automation. After the integration of AI, these workers are expected to redirect a portion of their newly available capacity towards activities that enhance productivity, thereby contributing to increased output. Academic research appears to confirm this, revealing that employees in firms quick to adopt AI observe heightened growth in labour productivity, typically indicating a boost of 2-3 percentage points per year.

Additionally, workers that are displaced by AI automation will eventually become reemployed. This reemployment is expected to occur in new occupations that arise directly from AI adoption or in response to the heightened aggregate and labour demand resulting from the potential productivity boost AI might bring (Briggs and Kodnani, 2023). Historical examples support both of these channels. For instance, innovations in information technology gave rise to occupations such as web page designers, software developers, and digital marketing professionals. Simultaneously, these innovations increased overall income and indirectly stimulated demand for service sector workers in fields like healthcare, education, and food services.



Graph 2 : Creation of new occupations due to technological innovation.

Source: Goldman Sachs Global Investment research

In an alternative study conducted by economists Daren Acemoglu and Pascual Restrepo, it was demonstrated that technological change initially displaced and generated employment opportunities at a comparable rate during the first half of the post-war period. However, since the 1980s, technological advancements have led to a faster displacement of workers compared to the creation of new opportunities. These findings imply that if generative AI impacts the labour market similarly to earlier advances in information technology, the immediate consequences on labour demand could be negative in the short term. Different

occupations and industries may experience diverse outcomes, particularly in the short term, with some thriving and others facing disruption.

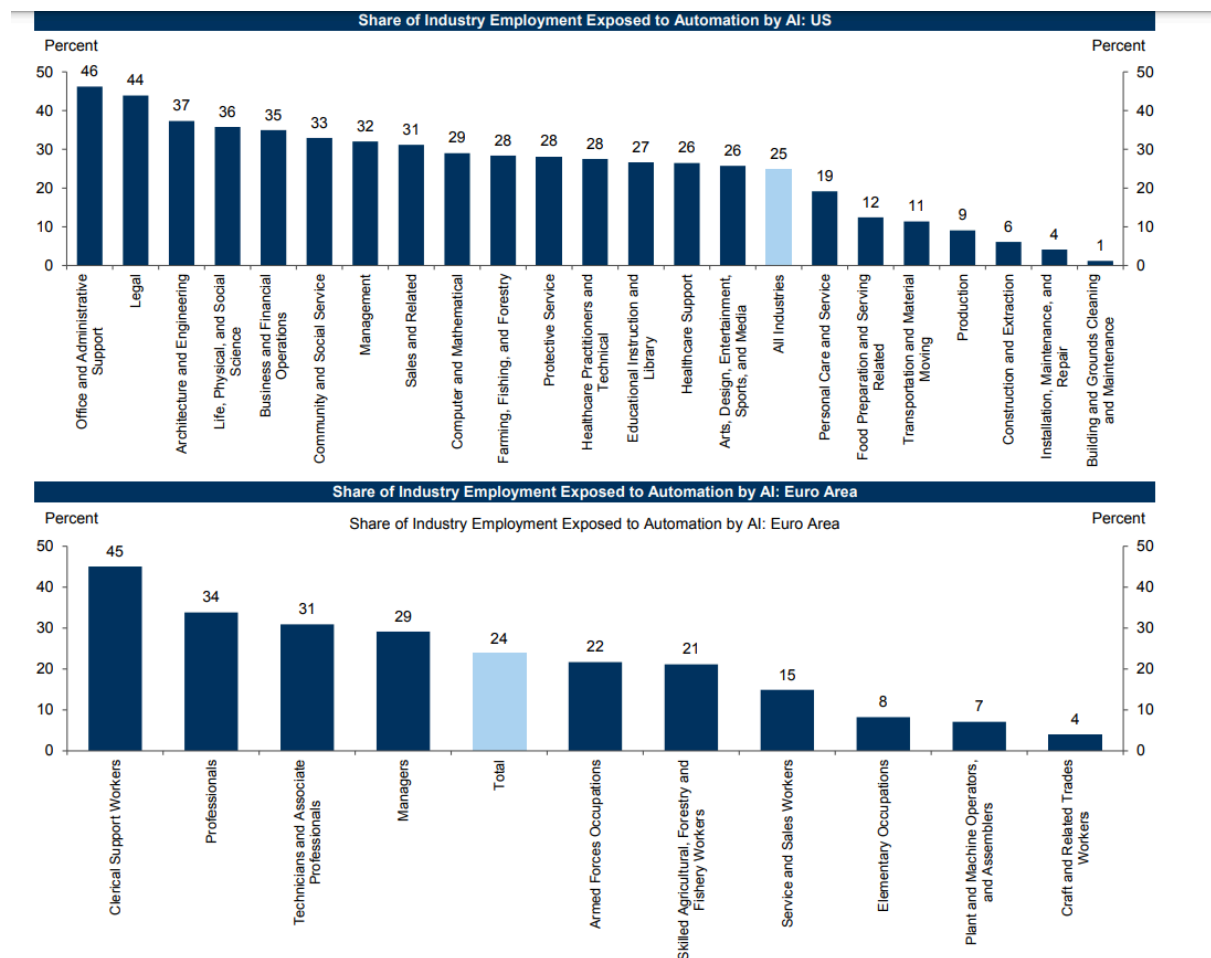
Similarly, the study by Korinek and Stiglitz identifies two primary reasons why innovation can result in technological unemployment. The first category stems from the inability of wages to adjust, even over the long term. According to the efficiency wage theory, employers may find it efficient to pay wages exceeding the market-clearing level to incentivize workers to exert optimal effort. If technological progress reduces the marginal productivity of workers, leading to a decline in their real wages below the cost of living, this would lead to unemployment, as workers, lacking government support, cannot sustain themselves on the market-clearing wage.

The second category of technological unemployment emerges as a transitional phenomenon, when technological advancements render workers obsolete at a faster rate than they can secure new employment or new job opportunities are created. This observation aligns with Keynes' insights from 1932. The transition period may be particularly prolonged if technology makes the existing skills of workers outdated, needing the acquisition of new skills (Restrepo, 2015).

With a more quantitative approach, the research by Briggs and Kodnani tries to estimate the proportion of positions vulnerable to automation using data from the O*NET, which details the task context of more than 9000 occupations in the US and from the European ESCO database, covering more than 2000 occupations. Their research finds that roughly two-thirds of current jobs are exposed to some degree of AI automation and a quarter of current jobs could be substituted by generative AI. This also aligns with the EU Parliament's Think Tank report from 2020, that states "14% of jobs in OECD countries are highly capable of automation and another 32% could face substantial changes" (European Parliament, 2020).

The study takes into account that jobs where a notable portion of the worker's time is spent in outdoor or physical activities are, generally, not susceptible to automation. Thus, it estimates using the US Occupational Employment and Wage Survey (OEWS) that administrative (46%) and legal (44%) professions exhibit high exposure, while physically demanding fields like construction (6%) and maintenance (4%) show lower susceptibility to automation. Similarly, using the ISCO occupation classification and the Eurostat Labor Force Survey (LFS) database, the results are of similar magnitude, in both aggregate and specific industries. This supports the idea that professions required to compile and analyse huge sets

of data are at particular risk of being automated by GAI technologies (Briggs and Kodnani, 2023).



Graph 3: Work tasks that could be automated.

Source: Goldman Sachs Global Investment Research

Similarly, in the Council of Economic Advisers (CEA, 2016) study, it was observed that occupations with wages below \$20 per hour had an 83% likelihood of automation. On the contrary, jobs with earnings exceeding \$40 per hour exhibited only a 4% probability of automation. While the results obtained in the OECD study differ, a consistent pattern emerges—the likelihood of automation is considerably higher for jobs requiring a high school degree or less, compared to those demanding a college or graduate degree. It’s important to note that a technology that replaces unskilled workers while complementing skilled workers could lead to a decline in relative wages for unskilled workers. This would preserve

employment in both sectors, but at a new equilibrium price, contributing to increased inequality.

According to Korinek and Stiglitz, innovation leads to inequality into two channels. First, inequality rises because innovators earn a surplus. Technology is categorised as an information good, indicating its non rivalrous nature, although it may possess excludability. Nonrivalry implies it can be utilised without being depleted, and therefore if widely used, it can provide welfare advantages for all users. However, the excludable aspect of information means that individuals can be restricted from acquiring or utilising a technology, for example through intellectual property rights like copyright or patents. The excludability characteristic may grant innovators market power, that enables them to charge a price and earn a surplus, referred as innovator surplus. A solution for this could be an open source technology, but given that in most cases private agents are superior in producing innovation, this seems unlikely. Korinek and Stiglitz state that in an ideally efficient economy, all individuals would collectively enjoy the advantages of technological progress. However, as the actual world diverges from this perfect scenario, redistribution becomes essential to guarantee that technological advancements don't move the Pareto frontier inwards, making individuals worse off. Similarly, alterations in intellectual property rights influence the distribution of innovation benefits, impacting the "incidence" of innovation.

The second mechanism involves innovations influencing market prices. Hicks (1932) noted that innovations typically alter the demand for factors, ultimately resulting in changes in factor prices, particularly in wages. If, as predicted by numerous technologists, artificial intelligence directly substitutes for human labour, the demand for human labour would decrease, and so will wages.

Korinek and Stiglitz propose various policies that can be implemented to address wage decreases faced by workers displaced by machines, even in low-skill jobs. These measures include wage subsidies and earned income tax credits. In cases where bargaining power in labour markets is biased in favour of employers, raising the minimum wage could contribute to safeguarding workers. Moreover, the imposition of a tax on capital would elevate the cost of capital, fostering a shift towards more capital-augmenting innovation rather than labour-saving innovation, this way balancing the impact of technological advancements on the workforce.

In instances where direct redistribution is not feasible or restricted, alternative institutional changes can be pursued to favour workers. As an example, a reduction in the duration of patent protection, effectively reallocates a portion of innovators' surplus to workers, to alleviate the wage-related externalities they face, and with the aim that benefits of innovations are more widely shared. When an innovation leads to a lower cost of production, the innovator harvests the rewards in the form of higher profits during the patent's lifespan and once it expires, society gains access to the benefits through lower prices. However, the inherent trade-off is that reducing the patent's duration may potentially reduce the pace of innovation (Korinek et al., 2018).

Currently, advancements in AI are concentrated in specific sectors of the economy, such as manufacturing. This is partly due to the reduction in manufacturing costs and partly influenced by preferences as the economy is shifting towards a service-sector orientation. The worth of these services is however, to a significant extent, socially determined, indicating reliance on public policies rather than purely market dynamics. If we assign high value to these services by offering competitive wages, ensuring favourable working conditions, and generating an adequate number of jobs, this approach can limit the increase in income inequality. Governments typically have a substantial influence in these sectors through employment policies, and thus play a significant role in navigating the AI transition.

Related to the service sector, a new business model may emerge characterised by lower margins but larger scale. Companies could use lower-tier services to expand their market reach and then upsell to more premium tiers. In many industries(legal, financial or medical advisory, media content creation, graphics design,) it's feasible to imagine the introduction of a lower tier of service that could be primarily or entirely based on GAI technology. This basic service would be offered free of charge (or generating revenue by featuring advertisements) while the elevation to human assisted services would trigger a payment.

In conclusion, it can be assumed that the adoption of AI technologies will drive a structural change in the global job market. Within several years some professions may be partially or completely replaced by automation. In principle the more the profession relies on “data to consolidated output” flow, the more likely it is to be replaced by AI.

On a brighter side, while the influence of AI on the labour market is anticipated to be significant, the majority of occupations are only partially susceptible to automation, and therefore there's a higher likelihood of AI complementing rather than replacing them.

Similarly, work displacement caused from automation has historically been counteracted by the creation of new jobs and the majority of long-term employment growth can be attributed to the emergence of fresh occupations following technological innovations.

4. ARTIFICIAL INTELLIGENCE IN ENTERPRISES

4.1 Demand of AI skills

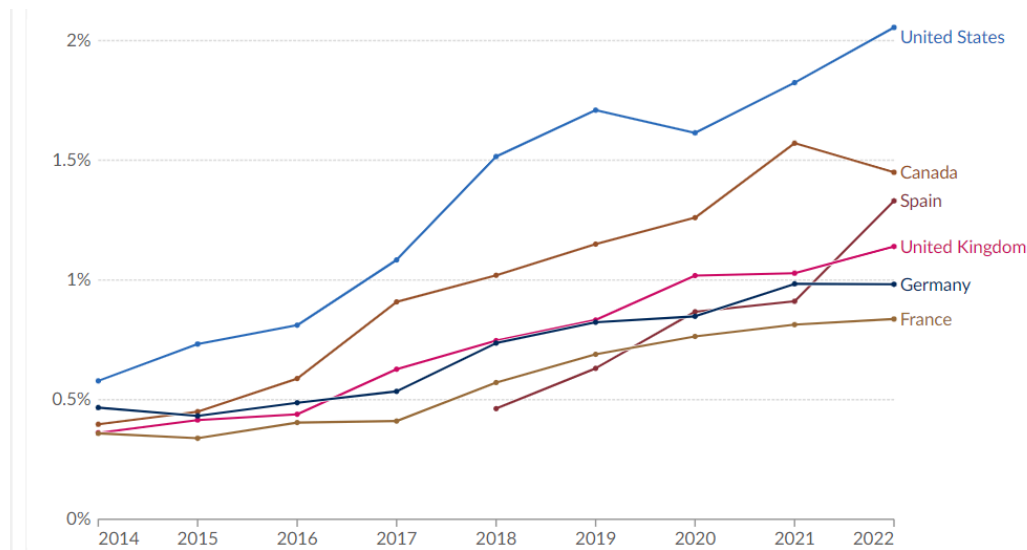
The extent to which firms use AI is difficult to measure as it requires information about the type of technology each company uses for its production. Since the use of these technologies requires highly specialised workers, the research by Alekseeva et al. tries to estimate the use of AI by using the demand for AI skills in different sectors and occupations.

To do so, they use data from the online job listings database by Burning Glass Technologies, a firm specialising in employment analytics. Covering the period from January 2010 to July 2019, this dataset comprises information on 192.3 million job vacancies. It includes data points such as job titles, standard occupation classification (SOC) codes, employer names and industries, as well as job locations. Additionally, the dataset includes details regarding the candidate profile, education background, work experience, and essential skills needed.

Furthermore, their investigation provides a framework to understand which companies are more prone to automate tasks using AI, consequently increasing the demand for AI-related skills in their job openings. Their research used the framework by Acemoglu and Restrepo (2018), which has been mentioned earlier in the paper, which illustrates how machines can exert a dual influence on labour markets. On one hand, machines can substitute human labour in certain tasks, leading to a reduction in labour share, employment, and wages. On the other hand, they can stimulate the emergence of new tasks where human labour holds a comparative advantage, potentially offsetting the substitution effect.

The results show that over the timeframe of 2010-2019, job postings requiring AI skills have experienced a significant surge, both in absolute terms and as a proportion of the total vacancies advertised. The count of AI-related job postings escalated from 20.6 thousand in 2010 to 180.9 thousand in 2019 and the ratio of job postings demanding AI skills relative to the overall number of vacancies quadrupled between 2010 and 2019. Moreover, the AI share of vacancies increased from 0.18% in 2010 to 0.72% in 2019. The results also show that "Machine Learning" stands out as the most frequently requested skill in AI-related job

postings. Following closely is the general skill of "Artificial Intelligence" and "Natural Language Processing" emerges as the third most sought-after skill, followed by "Deep Learning" and "Image Processing"(Alekseeva et al., 2021).



Graph 4: Share of AI jobs among all job postings.

Source: Our World in Data

As it could be anticipated, the results show that the Information industry emerges as the top sector in terms of AI skill demand, with an average of 2.2% of vacancies being AI-related . Following closely are the Professional, Scientific, and Technical Services sectors, with an AI share just below 2%. Subsequent industries, including Finance and Insurance, Administrative and Support Services, Agriculture, and Manufacturing, all exhibit AI shares around 1% (Alekseeva et al., 2021).

Overall, the need for AI skills spans across various industries, it's not limited to IT-related industries and even traditionally less tech-oriented sectors such as Mining, Educational Services, and Public Administration showing a growing demand for such skills.

According to the framework, companies with larger scales are expected to be more prone to automate tasks using AI, leading to a greater need for AI-skilled workers. By contrast, companies with higher fixed costs associated with automation are expected to employ AI less, reducing the demand for AI skills (Alekseeva et al., 2021) .

The findings indicate a positive correlation between several indicators of firm size—such as market capitalization, employment, and sales—and the demand for AI skills at the firm level. Additionally, cash reserves and research and development (R&D) intensity are also positively linked to the demand for AI skills.

The paper also explores whether discrepancies in the demand for AI skills at the firm level correlate with salary disparities among other job postings that do not require AI skills. On one hand, companies seeking AI skills tend to be larger, more oriented towards research and development, and cash rich, so demanding AI in job advertisements may indicate a certain quality of the firm that may be reflected in higher wages for positions that do not require AI skills. Moreover, demanding AI may enable the creation of new tasks that increase the demand for other high-skilled jobs that can complement this technology (Acemoglu and Restrepo, 2018). On the other hand, if AI algorithms are displacing workers within a company, lower salaries for non-AI jobs would be expected in companies with a higher share of AI.

The research by Alekseeva et al. indicates that firms with greater demand for AI, indicated by higher AI Shares, offer higher wages for non-AI roles, even after accounting for consistent firm characteristics. This aligns with the notion that AI technology can facilitate the creation of new tasks, thereby increasing the demand for highly skilled positions to complement its implementation. Their findings also reveal that positions requiring Software, Cognitive, Social, Project Management, and People Management skills are complementary to AI roles, whereas roles requiring Customer Service skills are being substituted by AI (Alekseeva et al., 2021).

4.2 AI integration in companies

Additionally, a research paper by Makarius et. al highlights how even if organisations are embracing AI at a growing rate, its implementation often overlooks the crucial factor of employee involvement. Their research explores how ai and employees can effectively collaborate to bring value to the organisation.

This holds particular significance as managers and employees frequently hold negative views regarding job displacement, training challenges, and uncertainties. Furthermore, there's often a lack of comprehension regarding the purpose and application of AI (Raisch & Krakowski,

2020), alongside trust issues with AI systems. By fostering a deeper understanding and integration of AI, employees can overcome these negative perceptions.

AI has been suggested as the “Fourth industrial revolution”, marked by a shift in decision-making from humans to machines, which sets it apart from its technological predecessors (Syam & Sharma, 2018). Unlike past technological advancements focused on automating manual tasks, AI will have the capability to collaborate, learn from, and adapt to employee interactions. Thus, the transformations brought about by AI integration differ significantly from those of earlier industrial revolutions and to successfully integrate it into the organisation, it’s important to consider its social aspect.

Despite the potential for AI to yield valuable outcomes for organisations, there is evidence suggesting that this potential often goes unrealized (Canhoto & Clear, 2020). As there is no established guidance or precedent for navigating human and AI collaboration, companies might not experience the benefits of AI despite investing significant time, effort, and resources into it (Kolbjørnsrud et al., 2017) .

The successful integration of AI technology and employees can lead to the development of sociotechnical capital, where both entities function as a closely interconnected system (Makarius et al., 2020). Similar to other types of capital, sociotechnical capital is an intangible asset that is valuable, rare, difficult to imitate, and organisation-specific that may be utilised to build a sustainable competitive advantage .

The challenge is therefore how to “bring AI into the organisation and successfully integrate such systems and employees to create a sustainable competitive advantage” (Makarius, 2020).

Many of the problems in terms of integration revolve around trust in artificial intelligence systems. Trust levels are influenced by various factors such as the embodiment of the AI (e.g., robot, virtual agent), its intelligence level or its perceived competence (Glikson & Woolley, 2020). However, some employees might be sceptical towards AI due to concerns about job displacement and increased competition and building trust with AI can be more challenging.

Prior to integrating AI into the organisation, managers must help employees make sense of AI systems. It's crucial for non-technical team members to comprehend the functioning of AI

systems, including the types of problems they excel at solving and those where their application is inappropriate, such as ethical dilemmas or interpersonal issues (Makarius, 2020). Employees should comprehend the purpose of AI, including its designated role within the team and the impact it has on altering employee roles. It's crucial to establish clear expectations regarding the roles of AI systems and how they differ from or intersect with tasks performed by employees. Additionally, because AI systems possess human-like attributes, it's crucial for employees to perceive an established social hierarchy where their social status is recognized as superior to that of the AI system (Makarius, 2020).

After successful integration into an organisation, AI can yield improve the psychological well-being and performance of employees. Research indicates that effective integration fosters greater productivity, increased commitment, and reduced turnover (Makarius, 2020). Specifically, AI is expected to enhance productivity through the automation of repetitive tasks, enabling employees to concentrate on tasks that contribute greater value to the organisation. The collaboration between employees and AI capitalises on their complementary skills, resulting in improved performance compared to either operating independently. For example, the research by Wilson & Daugherty published in the Harvard Business Magazine, involves 1500 firms from a wide range of industries and shows that the greater the collaboration between humans and AI, the more effectively AI initiatives perform across various operational metrics such as flexibility, speed, cost, revenues, and other key measures (Wilson & Daugherty, 2018).

While certain aspects of AI adoption can be replicated by competitors, understanding how trust is built and maintained in hybrid teams of humans and AI, as well as identifying effective coordination strategies, can become opportunities for companies to gain a competitive advantage. By focusing on these areas, companies can leverage AI more effectively and outperform competitors.

Nevertheless, the adoption and integration of AI within organisations can entail significant and transformative changes in their learning frameworks (Makarius, 2020). While numerous companies currently use big data sourced from platforms like social media, the incorporation of AI systems like deep learning models may need fundamental alterations in how organisations acquire and assimilate new knowledge. While certain AI systems possess autonomous decision-making capabilities, there remain concerns regarding the trustworthiness of their outputs. In scenarios where an AI system suggests a course of action

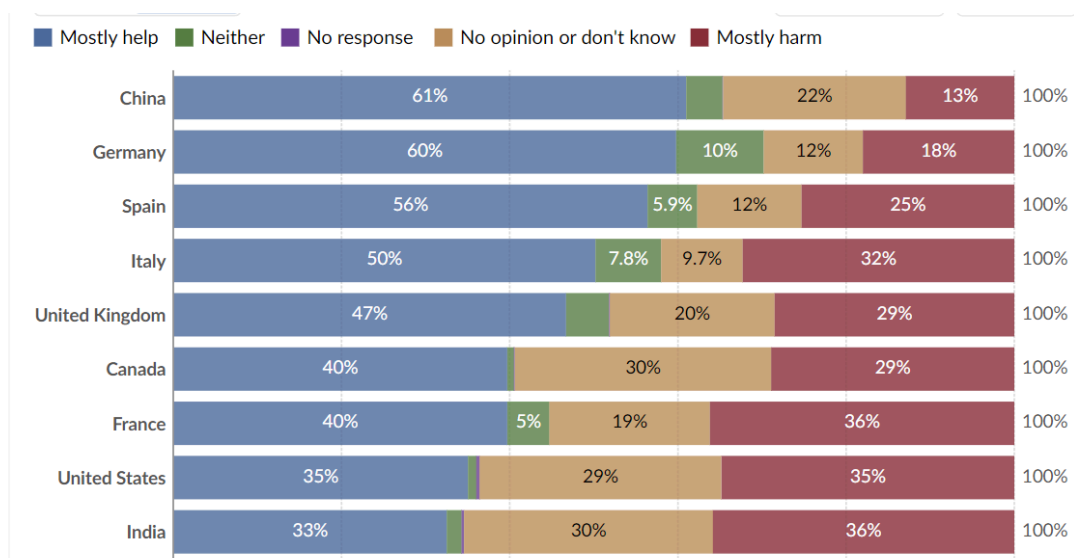
perceived as unwise by an employee, a dilemma arises: should preference be given to AI or the employee? (Makarius, 2020).

But that's not the only question that comes up: What weight should be given to these systems as they gain greater control over various processes? How can appropriate controls be applied in a decision-making process when an AI system encounters an anomaly that requires human interaction? (Makarius, 2020). Future research should explore how managers can shrink the gap between AI and employee skills, and how both can jointly reshape strategic decision-making processes.

5. CURRENT AND PROJECTED CHALLENGES FOR ARTIFICIAL INTELLIGENCE

The deployment of AI may result in a spectrum of social, economic, and political drawbacks. However, these drawbacks aren't necessarily intrinsic to AI technologies themselves, but rather originate from their current applications and development methodologies.

It's important to note that the potential harms discussed are largely theoretical. While some issues such as increased market power, job displacement and inequality might seem rooted in the development of AI, there's not enough evidence that AI is a significant driver of these trends. However, given AI's potential to revolutionise various sectors of the economy and social spheres, it's essential to examine its challenges and negative implications.



Graph 5: Views about AI's impact on society in the next 20 years, 2021

Source: Lloyd's register foundation (2022) via Our World in Data

5.1 The emergence of “Superstars”

Up to now, internet markets have tended to favour large digital platforms with significant market shares (Forman, 2005; Bessen, 2020). This concentration of digital assets among a few players can entail some risks for AI start-ups. Large datasets play a crucial role for firms engaging in the creation or utilisation of AI systems as they are essential for the initial training and fine-tuning of these algorithms. Currently, the LLM (Large Language Model) market is mostly controlled by OpenAI and Google (Alphabet). This could affect the industry dynamics by reinforcing a winner-takes-all situation. (Orchard and Tasiemski, 2023)

Although firms investing in AI seem to experience accelerated growth, the overall gains at the industry level might be zero-sum if the adoption of AI technologies generates a business-stealing impact on competitors, as indicated in studies like Bloom et al. (2013). Negative spillovers, demonstrated to outweigh positive firm-level effects, have been observed in the case of robotics, resulting in an overall adverse effect on aggregate employment (Acemoglu et al., 2020).

Babina et al. research links industry level growth in AI investment with changes in industry concentration in the time span of 2010-2018. Using the Herfindahl-Hirschman Index (HHI) to measure industry concentration, they show a positive relationship between industry level growth in AI and changes in industry concentration. This reinforces the theory that intangible assets drive the growth of major firms and contribute to heightened industry concentration, as observed in studies such as Crouzet and Eberly (2019). Notably, AI seems to mitigate the costs associated with product development, which are particularly substantial for large firms (Akcigit and Kerr, 2018), facilitating their ability to scale more efficiently, as mentioned earlier.

The rise of the so-called “superstar“ firms becomes a concern, especially considering the expectation that the advancement and commercialization of AI-related products and services will contribute to increased productivity growth. In the absence of competition from startups and other new entrants, the economy may experience a reduction in this potential growth.

5.2. Data control

Data constitutes the indispensable source for AI to operate effectively. However, as noted by numerous scholars, data and information can be misused and exploited in ways that benefit

digital platforms and tech companies at the expense of consumers and workers (Pasquale, 2015).

Concerns regarding control and misuse of information are also important when we consider the “social dimension” of data, which means that when an individual shares their data, they are also disclosing information about others. This social aspect is inherent in almost all AI applications because data use aims to learn from similar cases to generalise and apply insights to other contexts (Acemoglu, 2021). This means there could be negative data externalities when data revelations might affect other individuals’ privacy.

Acemoglu also argues that the social nature of data additionally generates a new type of interconnection that reduces each individual's willingness to safeguard their data when others are sharing theirs. This further contributes to negative externalities and suggests that costs will fail to reflect users' true value of data and privacy. If these data usage and privacy costs are significant, this proves the need for regulating data markets.

One of the benefits of AI is that firms can use data to forecast consumer preferences and behaviours, and it enables them to develop superior products tailored to customer needs. However, this can also reshape and create unfair competition, particularly when firms have a competitive advantage in collecting and using data. This can ease price competition within the market and consequently lead to price hikes.(Acemoglu, 2021)

Regarding data control and misuse of information, Chapter III, Article 15, “Accuracy, Robustness and Cybersecurity” states that high-risk systems shall be resilient against attempts by unauthorised third parties to alter their use or outputs by exploiting system vulnerabilities. The technical measures shall encompass strategies to prevent, detect and respond to attacks trying to manipulate the training data set and protect against attempts to extract confidential information (European Commission, 2023).

5.3 Transparency

As artificial intelligence (AI) becomes more capable of autonomous decision-making, there's a growing demand for insight into how these decisions are made. However, transparency encompasses various concepts, functions, and promises that are often difficult to implement effectively in real-world applications(Felzmann et al. 2020).

The advancement of machine learning and artificial intelligence (AI) has enabled the development of systems capable of making largely independent decisions, such as diagnostic tools in healthcare(Abràmoffet al. 2018), recommender systems like those used on YouTube

(Bishop 2018), or applications in criminal sentencing (Brayne and Christin 2020). Unlike traditional algorithms, which require manual programming of rules and weights, machine learning algorithms extract patterns from data and make predictions autonomously without human involvement (ICO 2020). Considering the legal implications and the potential negative effects of automated decision-making systems on society, it calls for the need for regulation. Systems that significantly impact individuals, such as loan denials, are either prohibited or, at the very least, individuals have a right to avoid them under European data protection laws (Felzmann et al. 2020). Scholars have extensively discussed the level of transparency required for such systems and whether individuals should have access to the decision-making process's underlying logic. (Casey et al. 2019)

There is widespread consensus that transparency plays a crucial role in promoting efficient resource allocation and increasing the accountability of those who hold information (Forssbaeck and Oxelheim, 2014). However, it's important to note that although transparency and accountability are closely related, they are not the same concept.

Transferring information from private to public domains, thereby making it open and accessible, helps diminish information asymmetries. Transparency doesn't mean total disclosure but rather indicates a state without problematic information asymmetries (Felzmann et al. 2020). Public disclosure can function as an equaliser, ensuring that everyone has access to the necessary information and that nobody holds an advantage.

However, information doesn't just require disclosure; it must also be tailored to the audience needs so that it can be interpreted and understood by the intended audience (Kemper and Kolkman, 2019). There's some criticism in the literature about the explainability of AI.

A significant challenge to transparency in AI lies in the complexity of its underlying technology. As modern AI systems adopt more sophisticated configurations and use greater amounts of training data, tracing their operations step-by-step becomes nearly impossible. Consequently, there's a trade-off between accuracy and explainability (Adadi and Berrada, 2018), where advanced systems achieving higher prediction accuracy tend to be less interpretable.

Privacy is another significant concern regarding transparency in AI. Full transparency can potentially expose sensitive and private data, especially if the underlying training data is disclosed (Ananny and Crawford, 2018). This issue becomes particularly critical when personal data, such as voice recordings, emails, social media posts, and images, is used to

train the algorithms. Releasing such data, even for the purpose of achieving less biased algorithms, could jeopardise the privacy and safety of vulnerable population groups. Additionally, transparency may pose challenges for companies from a competitive point of view. They may argue that revealing the inner workings of their AI systems could lead to imitation by competitors (Felzmann et al. 2020).



¹Asked only of respondents whose organizations have adopted AI in at least 1 function. For both risks considered relevant and risks mitigated, n = 913.
Source: McKinsey Global Survey on AI, 1,684 participants at all levels of the organization, April 11–21, 2023

Graph 6: Generative AI-related risks that organisations consider relevant and are working to mitigate.

Source: Mckinsey & Company

Given the potential constraints on the explainability of decision-making in complex AI systems, it is essential to provide detailed information on the data being used and how it's being used (Felzmann et al. 2020). Additionally, it should be clear which parts of the data processing can be checked and where humans are involved in making decisions or overseeing the system.

Overall, incorporating transparency into the design and deployment of an AI system is not an easy task. The rapid pace of technological advancement, the different dimensions of transparency, uncertainties about where transparency is needed and how to communicate with different parties involved pose problems on how to effectively integrate it.

Regarding transparency, Article 13 in Section 2 “Requirements for High-Risk AI Systems” of the EU AI Act, establishes that High-risk AI systems must prioritise transparency in their design and operation to enable deployers to understand and use system outputs appropriately.

These systems should be accompanied by instructions including details such as the provider's identity and contact information, the system's intended purpose, known limitations and risks, expected lifetime, technical capabilities and human oversight measures.

Moreover, Article 14 states that high-risk systems must facilitate effective oversight by natural persons throughout their operational lifespan, with appropriate tools to ensure supervision. This aims to mitigate risks to health, safety, or fundamental rights arising from its use, particularly in cases of foreseeable misuse. It also establishes that those responsible for deployment must be provided with the AI system in a way that allows individuals to understand its capabilities and limitations, monitor its operation, detect anomalies, and override or intervene in system decisions.

Finally, Article 50 on Chapter IV “Transparency Obligations for Providers and Deployers of Certain AI Systems and GPAI Models” establishes that providers must ensure that systems interacting directly with natural persons clearly disclose their artificial nature and providers of systems generating synthetic content must mark outputs as artificially generated. This excludes authorised uses related to criminal justice (European Commission, 2023).

5.4 Social media

Social media platforms are frequently viewed as catalysts for the formation of echo chambers, where individuals interact predominantly with others who share similar beliefs. This shields them from exposure to contrasting viewpoints and intensifies their biases (Acemoglu 2021). Scholars such as Sunstein stressed the dangers of echo chambers, arguing that engaging with individuals with different opinions is crucial to avoid extremism.

AI plays an important role in shaping social media. Platforms like Facebook and X, formerly Twitter, rely on algorithms driven by AI techniques to determine the types of news and messages individuals encounter (Mosleh et al., 2021). However, recent research highlights that these algorithms can worsen misinformation on social media because as users encounter news that align with their pre-existing views, they tend to share it without cross-checking it. Additionally social media platforms have incentives to foster echo chambers (or "filter bubbles") to gain engagement, as interrupting this circulation of unreliable messages would diminish user engagement (Levy, 2021).

5.5 Discrimination

AI can perpetuate and exacerbate biases, increasing discrimination towards certain demographic groups. This is because in many cases it's trained and relies on historical data which often reflects systemic biases and societal inequalities. If AI algorithms are trained on datasets that contain biased information or are derived from discriminatory practices, they may learn and reproduce these biases (Thompson, 2019). For instance, both the police and the legal system in the US are widely perceived to exhibit bias against certain demographic groups, such as Black Americans (Acemoglu 2021). In such scenarios, there's a risk that these biases will become ingrained within AI algorithms, perpetuating and potentially deepening societal biases. This process may not only sustain persistent bias and discrimination but also solidify these biases further within society (Acemoglu 2021). The same can happen if a hiring algorithm is trained on historical data that reflects gender bias in recruitment practices as it may continue to perpetuate gender inequality.

Related to discrimination, Article 10 in Section 2 “Requirements for High-Risk AI Systems” of the EU AI Act, establishes that management practices for training, validation, and testing data sets must align with the intended purpose of the system and that these practices must encompass bias assessment and measures to detect and mitigate biases. Additionally, the data sets must be relevant, representative and error-free (European Commission, 2023).

5.6 Labour market implications

One of the arguments in favour of those who argue that AI brings positive effects for the economy, is that it allows us to improve tasks that do not require human judgement and creativity and hence, workers can focus on those tasks. However, other scholars such as Acemoglu argue that the transfer of certain tasks from humans to AI can have some potential drawbacks. Workers accumulate experience from tackling different aspects of a problem, however when part of this shifts to AI, workers might lose their ability to understand the task, even in a field in which they specialize. Therefore if economies of scope are relevant for productivity, then AI might have a negative effect (Acemoglu, 2021). The author illustrates this with a simple yet effective example of mathematical reasoning. If students skipped learning arithmetic because they rely on calculators, their mathematical reasoning when solving more complex problems would be affected.

Moreover, AI-powered automation has the potential to exacerbate democratic erosion and weaken social cohesion. By potentially diminishing the indispensability of workers in workplaces, automation may reduce their political influence and potentially exacerbate

inequality. Furthermore, the mere threat of AI adoption can impact wages and inequality dynamics as employers may take advantage of it by boosting their bargaining power (Acemoglu 2021). Thus, the effects of AI extend beyond its direct labour market effects, influencing broader societal dynamics and power structures.

Lastly, AI technologies, through their capacity for improved information control, introduces more possibilities for monitoring of employees. While some degree of monitoring by employers can enhance worker incentives, it can also lead to inefficient levels, as it redirects profits from workers to employers. However, there's not enough evidence to confirm this argument.

Finally, as noted by Acemoglu, most of those drawbacks are not actually inherent to AI but rather come from corporate and social choices on how these technologies are deployed. Some costs could arise when they are developed in such a way that the use and control of data empowers governments and corporations against workers. However, Acemoglu suggests that regulation and other ways of distributing control rights could diminish these costs. Regulation in this case could entail either removing certain elements of an individual's data that could leak others information or implementing more systematic regulations on how platforms use the acquired information.

6. CONCLUSION AND LIMITATIONS

To conclude this research, reference will be made to the key issues that have arisen in relation to the development of AI and its impact on the economy.

1. Why is AI legislation necessary? AI carries risks, like any new technology, and the legal uncertainties created by the use of AI need to be addressed. A regulatory framework is needed to regulate the entire process from design, development, deployment and operation of AI. The ultimate goal according to governments and their institutions is to protect and guarantee the public interest, as well as to provide a legal framework that builds trust and safeguards the security of citizens. It is therefore necessary to devise a set of policies and legislative regulations that enable the use and vast potential of AI for the benefit of society.

2. But why is regulating AI so complex and demanding? It is highly likely that a determining factor in this complexity to regulate is its imprecise definition and the fact that by AI we can refer, not to a single technology, but to a complex set of technological methods and applications.

A second determining factor is that the two technological superpowers, China and the US, are competing for the lead in the AI revolution across all areas of human activity. The challenge they face is how to develop an ecosystem that is more competitive than the rival, so the absence of legislation or more lax legislation would be an advantage over the nearest competitor.

Ultimately, it can be argued that the benefits and harms of this technology depend on human decisions. This is why institutions are increasingly emphasising the need to establish a transparent legislative framework for artificial intelligence. This is the only way to avoid its risks and to take advantage of all the opportunities it offers.

3. The EU's Artificial Intelligence Act represents a comprehensive regulatory framework designed to ensure the safe and ethical development and deployment of AI technologies. By categorising them into four risk levels—unacceptable, high, limited, and minimal—the Act imposes strict requirements on high-risk providers while maintaining less demanding regulations for lower-risk ones. The Act also addresses governance by establishing the AI Office and the European Artificial Intelligence Board to ensure effective implementation across Member States. Financial penalties are foreseen for non-compliance, underlining EU's commitment to AI monitoring.

4. Based on the research carried out in this paper, it seems risky not to assert that the economic effects of artificial intelligence are still difficult to foresee. They can be both positive and negative. The digital revolution can either boost productivity and favour global and economic growth, or it can become a threat to employment and further widen the inequality gap.

Despite the uncertain effects of automation on the workforce, economists are generally enthusiastic about the prospects of AI on productivity growth and research seems to indicate that its widespread adoption could lead to an increase in overall labour productivity gains. Additionally, some of the work researched indicates that firms investing more in AI experienced higher growth through increased product innovation, aligning with the idea that AI effectively lowers the expenses associated with product development.

5. Regarding the effects on job substitution several research papers tried to isolate the extent to which AI will directly replace certain occupations or tasks. According to some research, workers that are displaced by AI automation will eventually become reemployed and this reemployment is expected to occur in new occupations that arise directly from AI

adoption. However, immediate consequences on labour demand could be negative in the short term if technological unemployment emerges as a transitional phenomenon, when technological advancements render workers obsolete at a faster rate than they can secure new employment or new job opportunities are created. The transition period may be particularly prolonged if technology makes the existing skills of workers outdated, needing the acquisition of new skills.

6. As mentioned throughout this research, the deployment of AI may result in a spectrum of social, economic, and political drawbacks. However, these drawbacks aren't necessarily intrinsic to AI technologies themselves, but rather originate from their current applications and development methodologies.

The first challenge considers that large datasets play a crucial role for firms engaging in the creation of AI systems, as they are essential for the initial training and fine-tuning of these algorithms. This can benefit larger players that can have greater access to these datasets and reinforce a winner-takes-all situation.

The second challenge has to do with data control as data and information can be misused and exploited in ways that benefit digital platforms and tech companies at the expense of consumers and workers. While one of the benefits of AI is that firms can use data to forecast consumer preferences and behaviours and develop superior products tailored to customer needs, this can also reshape and create unfair competition, particularly when firms have a competitive advantage in collecting and using data.

Transparency is another key challenge, not only because it encompasses various concepts, functions, and promises but also because the former are often difficult to implement effectively in real-world applications. The rapid pace of technological advancement, the different dimensions of transparency, uncertainties about where transparency is needed and how to communicate with different parties involved pose problems on how to effectively integrate it.

AI plays a key role in shaping social media as these platforms rely on algorithms to determine the types of news and messages individuals encounter. However, recent research highlights that these algorithms can worsen misinformation on social media because as users encounter news that align with their pre-existing views this shields them from exposure to contrasting viewpoints and intensifies their biases.

One of the most worrying social challenges is that of discrimination. In many cases AI is trained and relies on historical data which reflects systemic biases and societal inequalities and therefore it can perpetuate and exacerbate biases, increasing discrimination towards certain demographic groups. Finally, AI entails the potential risk that as more jobs are taken over by it, human workers may lose part of its bargaining power.

7. Overall, AI legislation will evolve and adapt in line with the rapid advances in technology, ensuring that regulatory frameworks remain relevant and effective. As its capabilities expand and new applications emerge, regulations will be regularly updated to address new risks and opportunities. In the same line, the effects of AI adoption on the economy will closely follow its technological evolution, as it advances and becomes more widely adopted, its ability to innovate and optimise processes will determine the scale and scope of its economic impact.

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