

The impact of Artificial Intelligence on the labour market: a thorough analysis of the Italian labour market

Giovanna Vallanti

SUPERVISOR

Rumen R. Georgiev (278131)

CANDIDATE

**For my mother, who taught
me the power of curiosity
and self-confidence.**

**For my father, who showed
me the power of
perseverance.**

**For my relatives, who
always believed in me.**

**For my friends, who turned
every challenge into an
adventure.**

**Thank you for making this
achievement, ours.**

Abstract

This thesis examines the impact of artificial intelligence (AI) on labour markets, with a particular focus on the Italian context. Building upon the methodological framework developed by Felten, Raj, and Seamans (2021), the study introduces novel metrics to assess AI exposure across different dimensions of the economy: these include the development of demographic-specific AI exposure metrics that analyse vulnerability patterns across educational attainment levels (AIDE-E), age groups (AIDE-A), and gender (AIDE-S). The findings reveal significant heterogeneity in AI exposure across different segments of the Italian economy, with certain occupations, industries, and regions demonstrating greater vulnerability to AI-driven transformation. By providing a granular assessment of AI exposure across multiple dimensions, this research contributes to our understanding of how technological change may reshape labour markets and informs policy approaches to managing the economic transition associated with AI advancement.

Table of Contents

ABSTRACT	2
INTRODUCTION	4
BACKGROUND AND MOTIVATION	4
RESEARCH QUESTIONS	4
ORGANISATION OF THE THESIS	5
1. ARTIFICIAL INTELLIGENCE: THE PAST AND PRESENT	7
THE ORIGINS OF ARTIFICIAL INTELLIGENCE	7
CURRENT STATE OF ARTIFICIAL INTELLIGENCE	10
2. ARTIFICIAL INTELLIGENCE AND THE LABOUR MARKET	13
INTRODUCTION OF ARTIFICIAL INTELLIGENCE IN THE LABOUR MARKET	13
SOCIOECONOMIC IMPLICATIONS OF AI'S IMPLEMENTATION	18
PUBLIC INSTITUTIONS' ROLE IN TACKLING THE EFFECTS OF ARTIFICIAL INTELLIGENCE	30
3. THE ITALIAN LABOUR MARKET AND AI	39
RESEARCH FOCUS AND OBJECTIVES	39
METHODOLOGICAL FRAMEWORK	40
DATA SOURCES AND ESTIMATION FORMULAS	43
EMPIRICAL OUTCOMES	46
DISCUSSION OF THE RESULTS OBTAINED	57
CONCLUSIONS	60
CONTRIBUTION TO ACADEMIC LITERATURE	60
POTENTIAL DRAWBACKS	60
POTENTIAL IMPLICATIONS	61
FINAL REMARKS	61
BIBLIOGRAPHY	63

Introduction

Background and motivation

In recent decades, artificial intelligence (AI) has emerged as a transformative force across economic sectors, reshaping labour markets and challenging traditional understanding of productivity dynamics. This thesis examines the multifaceted relationship between AI technology adoption and employment patterns across occupations, industries, and geographical regions, with a particular focus on the Italian economic landscape.

The accelerating pace of AI development has sparked vigorous academic and policy debates regarding its potential to either complement human labour through productivity enhancements or substitute workers through automation. While previous technological revolutions created more jobs than they displaced, the unique capabilities of modern AI systems—particularly their ability to perform cognitive tasks once thought to be exclusively human domains—raise important questions about whether historical patterns will continue.

This research builds upon the pioneering methodological framework developed by Felten et al. (2021), who created a novel dataset quantifying occupational exposure to artificial intelligence. By extending their approach to the Italian context and developing additional metrics including AI Regional Exposure (AIRE) and AI Demographic Exposure (AIDE), this thesis provides a comprehensive analysis of how AI technologies intersect with labour markets across multiple dimensions.

Research questions

This thesis contributes to this emerging literature by developing and applying a methodological framework to measure AI occupational exposure (AIOE) across the Italian labour market, by focusing on the most exposed occupations. By building on the work of Felten et al. (2021), who created exposure metrics for the U.S. context, this research will adapt and extend their approach to account for the specific structural characteristics of the Italian economy and labour market. By combining detailed occupational ability data with information on AI capabilities and regional employment patterns, this thesis provides one of the first comprehensive assessment of AI exposure across Italian occupations, industries, and regions, while also considering demographic impact.

The central research questions guiding this investigation are:

1. How does AI occupational exposure vary across the job categories in the Italian labour market?
2. To what extent do regional economic structures and specialization patterns create geographical disparities in AI exposure?
3. What are the implications of these exposure patterns for regional economic resilience and labour market policies?
4. Does AI exacerbate existing demographic disparities, or will it reduce the disparities across gender, age and education?

To address these questions, this research employs a multi-level methodological approach that progresses from occupational-level analysis to industry and regional assessments.

First, we will construct an AI Occupational Exposure (AIOE) index that quantifies the relatedness between AI applications and occupational abilities, weighted by the importance and prevalence of these abilities within specific jobs. This index is then aggregated to calculate industry-level exposure (AIIE) and subsequently mapped to geographical regions to measure regional exposure levels (AIRE). The previously cited exposure indexes will be obtained by following an approach similar to the one used by Felten et al. (2021).

In addition to the previous indexes, we will make use of the AIOE index in order to construct the demographic exposure of the employed individuals with respect to AI (AIDE), by considering the age classes (AIDE-A), gender (AIDE-S) and level of education attained (AIDE-E).

The analysis that we will perform draws data across multiple sources, including the ISTAT's Labor Force Survey and the O*NET occupational database, complemented by crosswalks to ensure compatibility across different occupational classification systems.

Organisation of the thesis

The thesis is organised as follows: the first chapter will discuss the advancements that artificial intelligence has undergone, from its inception to its latest iterations. The second chapter will explore the potential implications that the artificial intelligence may have on the labour market, while considering the public institutions' policies in response to the rapid advancements of artificial intelligence

by analysing its recent uses, the existing academic literature, and the policies introduced by the public institutions across the globe.

The third chapter will perform an empirical analysis of how AI may have impacted the high-skilled jobs in the Italian labour market for the years 2008 – 2018.

Finally, in the section talking about the conclusions of the thesis, there will be:

1. The discussion of the results obtained from the former chapter.
2. The addressment of the potential drawbacks that the methodology may have.
3. How the results achieved will contribute to the existing and future literature and what kind of challenges policymakers, business leaders and stakeholders in general may face in the future.

1. Artificial Intelligence: The past and present

The origins of Artificial Intelligence

The first concept of “mechanical reasoning” was developed in the 1950s by the English mathematician Alan Mathison Turing: in his paper he introduced a test which allowed to describe whether or not a machine has the capability to think, which will be later known as the Turing Test¹.

Thanks to Turing’s test and its approach, there was the start of the establishment of “mechanical reasoning” as a field of research: this field, during the Dartmouth Summer Research Project (1956), acquired the name of “Artificial Intelligence”.

Unfortunately, the period between the 1970s and the 1980s was characterised by the first “AI winter”. During such period, researchers were convinced that they would succeed in creating a machine having a “general intelligence”³.

However, AI experts focused their efforts elsewhere: with the dawn of electronic computers, miniaturisation of electrical circuits and the start of the information age, researchers started with experimenting on technology by making machines capable of emulating human decision-making. These kinds of machines were called “expert systems”: an expert system is a computer system that makes use of knowledge-based approaches to solve problems in a specialised domain which would require human expertise⁴. The first expert systems were introduced around 1965 with Stanford’s Heuristic Programming Project (HPP), which was initially known as the DENDRAL project: the HPP had the objective of performing research on AI and of developing community tools who can be used for building expert systems for multiple scientific domains, like the MYCIN program, a consultation system which identified – via prior medical knowledge and information from medics regarding symptoms– the bacteria behind many serious infections like meningitis and blood infections. However, even if the MYCIN system was not used in the clinical sector, it

¹This test is based on a game – he calls it “imitation game” – where there are 2 individuals and a machine: one of the individuals takes the role of interrogator and he must pose questions to the machine and to the other human individual, which are in separate rooms. The interrogator must understand which answer is provided by the machine and which is provided by the individual.

²The term “AI winter” is a reference to the phenomenon of nuclear winter. If you want to deepen the understanding of the concept of AI winter, here’s a webpage discussing the different AI winters that occurred: <https://www.ainewsletter.com/newsletters/ai-winter-phenomenon/#:~:text=The%20phrase%20was%20coined%20by%20an analogy%20with%20%22nuclear,a%20frozen%20Earth%2C%20and%20the%20extinction%20of%20humanity.>

³It is considered to be a type of AI that had the capability to match or surpass the cognitive abilities of humans across a wide spectrum of cognitive tasks.

⁴For those who want to know in detail the reasoning strategy behind expert systems: <https://www.geeksforgeeks.org/expert-systems/>

represented the first foundation for the development of more complex medical expert systems.

As expert systems became increasingly widespread and covered in multiple fields of knowledge, in the early 80s, there was a second wave of research on connectionism⁵, which led to the development of the neural network⁶: a neural network can be expressed as a non-linear function having some “artificial neurons”, which are smaller mathematical functions representing the unit of an artificial neural network⁷. One of the first forms of neural networks was the “Perceptron”: developed by Frank Rosenblatt, it takes inspiration from neuroscience due to how similar the “on-off units” (i.e., the binary digits) are with respect to how a neuron works. Thanks to this discovery, a lot of network models were developed in order to perform specific algorithm patterns.

In 1989, Yann LeCun published a research paper where he experimented with the ability of neural networks to learn by applying constraints to the domain of a specific task in order to demonstrate that it can be used to train algorithms: his experiment of making the neural network recognize handwritten ZIP code digits was successful and the neural network “learned” how to recognise these digits, starting from the normal image of the character (input) to its classification (output).

As we can observe, in the 80s there was a flourishing period for research on Artificial Intelligence, and in 1997, IBM’s Deep Blue has beaten the world chess champion Garry K. Kasparov. The technology that was behind Deep Blue was one which allowed supercomputers to perform complex operations like evaluation of patterns in databases, exploration of biological processes, or even assess financial risks. The “Deep Blue” also represented an important stepping stone for the development of deep learning neural networks.

Deep learning can be defined as a subset of machine learning which makes use of multilayered neural networks to simulate the decision-making power of the human brain. The major factor that allowed for the start of deep learning networks was

⁵Connectionism is an approach making use of mathematical models, known as connectionist networks or artificial neural networks, with the goal of studying the human mental processes.

⁶The neural network is a model that makes decisions in a pattern which replicates the process occurring in the human brain: hence, it makes use of mathematical processes that mimic the way biological neurons work to perform tasks like identifying phenomena and weighing options.

⁷If you want to deepen the knowledge about how a neural network works in general, here’s a link to a video explaining how it works from a mathematical point of view:

<https://youtu.be/aircAruvnKk?si=sdOEu4VgETcah--8>

linked to hardware advancements and to the implementation of the ReLU in most artificial neural networks⁸.

In the year 2012, a group of researchers from Stanford University published their results from training a neural network with unlabelled data: their experiment consisted in providing millions of face images downloaded from the Internet to a 9-layered network composed of 1000 machines and letting them analyse the data for 3 days. The results were astounding: not only it was possible to train a face detector without the need to label the images as containing faces or not, but the network was also sensitive to other information like cat faces and human bodies.

In 2017, there was another big step in the evolution of deep learning neural networks. Google researchers have developed and proposed a neural network architecture called “Transformer”: it is a model which is composed of two elements, an “Encoder”, whose main goal is to process the input information, and a “Decoder”, whose objective is to process the output sequence (both the Encoder and the Decoder are composed by multiple layers). The Transformer is trained by making use of semi-supervised learning: the Transformer learns thanks to a set of unlabelled data and then it is fine-tuned by making use of labelled data in order to make it perform better. However, the aspect which differentiates the Transformer from any form of neural network is the introduction of the so-called “Attention mechanism”: this mechanism, which consists in running multiple sequences in parallel, allows the Transformer to identify the context and the interdependencies of the input data by considering all the variables involved and by assigning a “weight” to each variable. Through the parallelization of the sequences, the Transformer learns at a higher pace, and it improves over time. This model is the basis for many of the Generative Artificial Intelligences which are available today. Since 2018, OpenAI started to develop its models of Generative Artificial Intelligence by making use of the GPT (Generative Pre-trained Transformer model): their first form of GenAI was ChatGPT, which is an “autoregressive language model”. The autoregressive language model is based on the concept of autoregression: autoregressive models are representative of random processes which are used to determine the future values given the current values available. ChatGPT became available to everyone from 30th November 2022⁹.

⁸The following article explains everything to know about the ReLU activation function:

<https://www.geeksforgeeks.org/relu-activation-function-in-deep-learning/>

⁹The following is the official announcement done by OpenAI regarding ChatGPT:

<https://openai.com/index/chatgpt/>

Current state of Artificial Intelligence

Artificial Intelligence can be defined as the capability of a digital computer or a computer-controlled robot to perform tasks associated with human cognitive processes like learning, comprehension, problem solving, decision-making and creativity (Copeland, 2025). As we saw earlier, Artificial Intelligence has forked out into multiple derivative fields:

1. Machine Learning (ML): a subset of Artificial Intelligence where its focus is on the creation of algorithms which allow to improve the machine's capability to make predictions or take decisions according to the data given (Stryker and Kavlakoglu, 2024).
2. Deep Learning (DL), which we already have discussed in the previous paragraph.
3. Expert Systems, which we already discussed in the prior paragraph.
4. Natural Language Processing (NLP): a subfield of computer science and AI making use of machine learning to give computers the ability to communicate and understand human language (Stryker and Holdsworth, 2024).
5. Computer Vision: a subfield of AI where machine learning and neural networks are used in synergy to derive important information from visual data (e.g., videos, photos), make recommendations or act when there is an anomaly (IBM, 2021).

However, as of today, there are multiple types of Artificial Intelligence which have developed in the course of these years, and we can classify them according to their capabilities or according to their functionalities.

If we consider their capabilities, there are 3 forms of Artificial Intelligence (IBM Data and AI Team, 2023):

- I. Artificial Narrow Intelligence (ANI): also known as Narrow AI, it consists in the training of a neural network to perform a single or narrow task.
- II. Artificial General Intelligence (AGI): it has the capability to exploit the accumulated experience and skills to perform new tasks in a different context without the need of human intervention.
- III. Super Artificial Intelligence: this form of AI – which is exclusively theoretical – should perform all cognitive tasks and surpass humans in terms of cognitive skills.

Now, if we consider AI in terms of functionalities, there are 4 kinds (IBM Data and AI Team, 2023):

- I. Reactive Machine AI: these are systems that do not have any form of memory of the tasks previously performed and they are designed to execute specific tasks.
- II. Limited Memory AI: it can recall previously obtained outcomes and observe specific situations over a given time span, allowing it to use time data for decision-making purposes.
- III. Mind AI: this AI model functions according to the “Theory of Mind¹⁰”. In such a context, the AI would be capable to simulate human-like relationships and actions but, in addition to that, it would be able to understand and interpret artworks or written essays.
- IV. Self-Aware AI: this theoretical AI, as the name implies, it will have the ability to be self-aware, hence it will have the capacity to understand its needs and wants and to feel emotions.

In the last decade, we saw the insurgence of Artificial Intelligence again thanks to the official launch of ChatGPT, which led to the birth of what it is known as Generative Artificial Intelligence (GAI, or GenAI): according to the previous classification, we may consider the GenAI models to be a form of Limited Memory AI (in terms of functionality) and probably one of the first forms of Artificial General Intelligence. It relies on the deep learning algorithms to identify and encode patterns and relationships between numerous amounts of data and use the information stemming from such patterns to understand the requests of the users and respond to them with content which is generated by such models: they can create text, images, video, sound, computer code, simulations and synthetic data in response to the users’ requests (Stryker and Scapicchio, March 2024).

Most of these GenAI models are based on a form of machine learning model called “Large Language Model” (LLM): this is a foundation model – i.e. a model trained on a vast dataset in order to fulfil a wide range of tasks (Caballar, 2024) - created to understand and generate natural language outputs. This is possible by how such model is designed: it is a model with a great number of neural nodes, which allows it to interpret the complexity of linguistics and to perform language-related tasks.

¹⁰ The Theory of Mind (ToM) is a model considering how emotions, thoughts, beliefs, desires and intentions affect the course of action of an individual. If you want to know more about the ToM and how such can be applied, here’s an article delves into the matter: <https://doi.org/10.1016/j.tics.2022.08.003>

Without the advancements in algorithms and neural networks, LLMs would not exist and GenAI would not exist.

As we have seen throughout this chapter, AI has evolved from a strictly theoretical concept to a system which is capable of performing complex cognitive tasks, where GenAI represents the most recent advancement: given its ability to create content, recognise patterns and make predictions across multiple domains, it makes it one of the most impressive feats of AI technology. However, the aspect that really puts things into perspective is the potential impact that such technology may have on cognitive-related jobs: due to their capacities of performing analytical and creative tasks, there are many doubts rising with regards to the nature of work and how the productive processes may change if human and artificial intelligence complement each other. In the following chapter, we will move from understanding the evolution of artificial intelligence to the analysis of its tangible impact on the labour market, by considering what are the latest uses of GenAI, its potential flaws, what are the consequences in implementing GenAI technologies on the labour market thus far and, finally, explore how public institutions have responded after this “AI boom”.

2. Artificial Intelligence and the Labour Market

Introduction of Artificial Intelligence in the Labour Market

We previously saw that “mechanical reasoning” has gone through an impressive evolution, but it was applied to only some sectors. However, with GenAI, we may expect a really fast adoption of such technology in a widespread manner, following a J-curve pattern (Brynjolfsson, Rock and Syverson, 2021), characteristic of all disruptive technologies¹¹: after an initial endowment of resources where there is no visible productivity gain at first. Nevertheless, once the results obtained from using such technology become visible, there will be a consequent growth in productivity leading to a widespread adoption of the new technology. However, GenAI is expected to have the fastest adoption rate due to two factors:

- I. The cost to gain access to GenAI: with respect to the innovations prior to AI, there's a low cost of access for GenAI models, sometimes there's no costs required for the firms (like in the case of Llama¹², an open-source AI model developed by Meta) or for the individuals (like in the case of ChatGPT's freemium option or Gemini's).
- II. The widespread use of this technology at such an early stage of its life: since ChatGPT's initial release¹³, people and firms started to use it in various contexts and its accessibility (since it is available on the Internet) made the adoption of such a technology faster and effortless.

This point is also backed up by the results of McKinsey's Global Survey on AI (Singla et al., May 2024): since McKinsey has started tracking AI adoption from organisations (i.e., 2017), we may see that the adoption of AI systems has increased

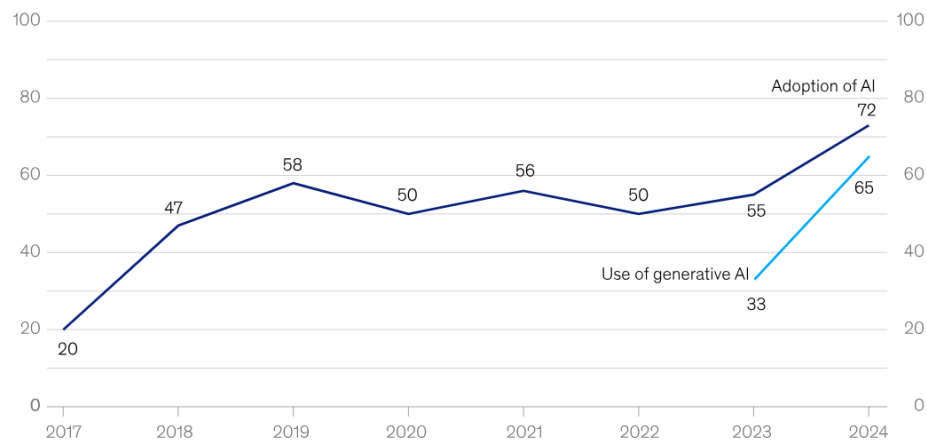
¹¹With “disruptive technologies”, we consider the innovations altering the status quo and implementing a new way to approach a given task (e.g., electricity and the Internet).

¹² This is the official webpage from which you may download the model: [Llama](#)

¹³ This is the official announcement: [Introducing ChatGPT | OpenAI](#)

by more than a twofold (2.6x increase by comparing 2017 and early 2024).

Organizations that have adopted AI in at least 1 business function,¹ % of respondents

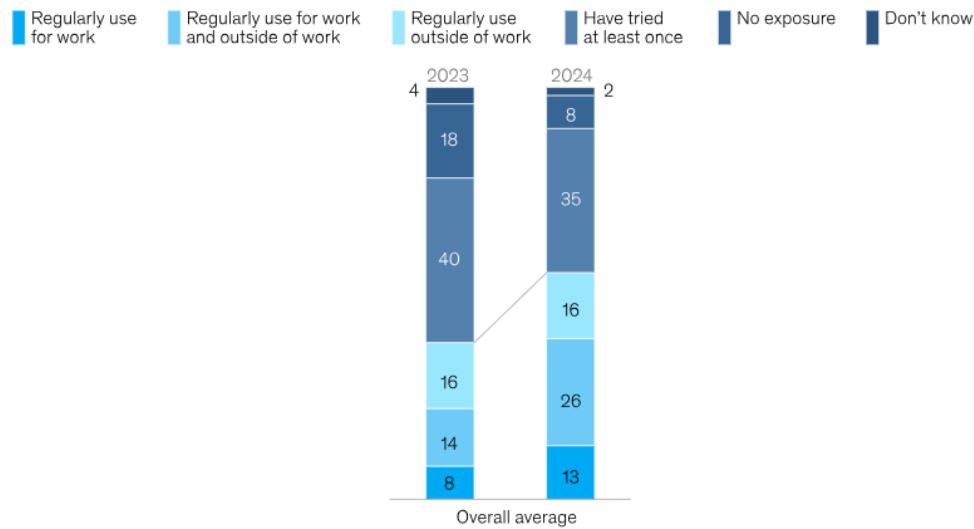


¹In 2017, the definition for AI adoption was using AI in a core part of the organization's business or at scale. In 2018 and 2019, the definition was embedding at least 1 AI capability in business processes or products. Since 2020, the definition has been that the organization has adopted AI in at least 1 function. Source: McKinsey Global Survey on AI, 1,363 participants at all levels of the organization, Feb 22–Mar 5, 2024

McKinsey & Company

Figure 1. “Organisations that have adopted AI in at least 1 business function”. Source: ‘The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value’. Singla Alex, Sukharevsky Alexandra, Yee Lareina, Chui Michael, Hall Bryce. McKinsey & Company, 30 May 2024. Accessed May 20, 2025. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024/>.

The increase in AI adoption during 2023 and 2024 was most probably due to the insurgence of GenAI: if we do a side-by-side comparison of the use of GenAI and of the adoption of AI systems, we can observe a positive correlation between the two (GenAI usage has increased by approximately 96,97% and the adoption of AI systems has also increased, but by approximately 30,91%).



Note: Figures may not sum to 100%, because of rounding.
 *In 2023, n = 1,684; in 2024, n = 1,363.

Source: McKinsey Global Survey on AI, 1,363 participants at all levels of the organization, Feb 22–Mar 5, 2024

McKinsey & Company

Figure 2. "Personal experience with generative AI tools, 2023-2024, % of respondents". Source: 'The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value'. Singla Alex, Sukharevsky Alexandra, Yee Lareina, Chui Michael, Hall Bryce. McKinsey & Company, 30 May 2024. Accessed May 20, 2025. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024/>.

In addition to such insight, the individuals who were interviewed by McKinsey between 2023 and 2024 declared that in early 2024 have used GenAI more than in 2023 (there was an average increase of approximately 44,74% in individuals using GenAI at work or outside work).

In short, we can see that GenAI is boosting the implementation of artificial intelligence technologies in our daily lives. Nonetheless, due to its polyhedric nature, GenAI can also be applied in many contexts: from writing summaries, to analysing a code script or a data array. Only recently firms started to see the potential of this technology and they started implement this technology in some of their productive phases.

One of the first cases was within the auditing sector: Ernst & Young has attempted in an experiment involving the UK and Irish branches to implement an AI system with the goal of analysing the accounts of specific client firms and if there were potential cases of frauds in the audit process. The first results were impressive: the algorithm has detected suspicious activities in 20% of the companies analysed, which were confirmed by the clients themselves (Wright, 2023).

Another interesting use case was with the so-called “Project Aurora”: this project, delivered by the BIS in partnership with a software house for financial crime compliance called “Lucinity”, is a “Proof of Concept” with the main objective of evaluating the AI’s ability to find transactions involving money laundering and if its implementation would be feasible.

Graph B1: Training, validation and evaluation of machine learning models

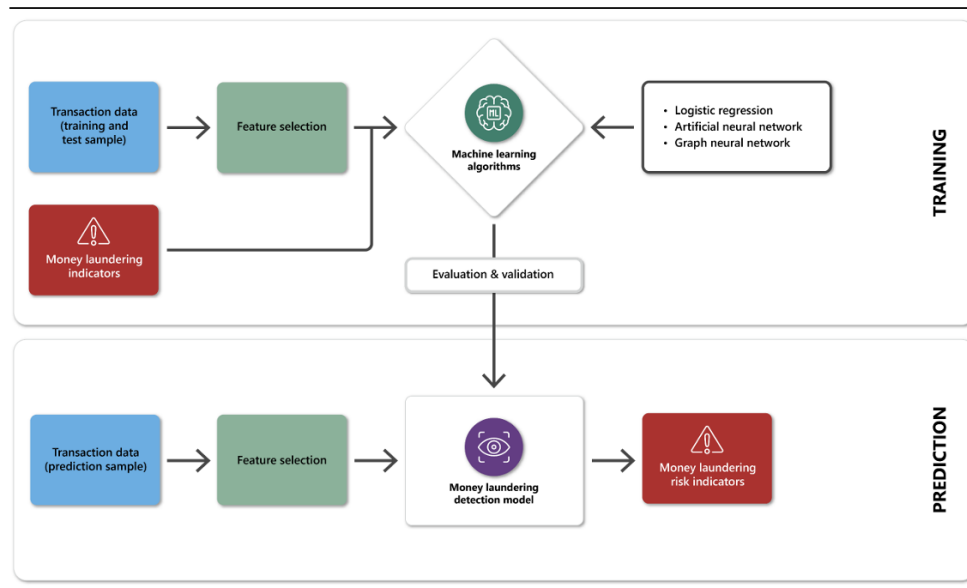


Figure 3. "Training, validation and evaluation of machine learning models". Source: 'Project Aurora: The Power of Data, Technology and Collaboration to Combat Money Laundering across Institutions and Borders'. Bank for International Settlements (BIS), May 2023. Accessed May 20, 2025. <https://www.bis.org/publ/othp66.htm>.

In order to test it, the BIS generated a synthetic data set representing an hypothetical list of transactions between financial institutions, individuals and businesses which come from the same country and from other countries - in order to simulate the transactions occurring inside national borders and across such - and they tested different monitoring scenarios with AI models in order to compare the performance in detecting suspicious individuals and networks in different scenarios and the results were mindboggling: with AI’s capability and the possibility to access a great set of informations regarding payments, it is possible to detect money laundering networks with ease with respect to the classical approach where financial institutions carry out the analysis on their own, which would require a great amount of energy and time (BIS Innovation Hub, 2023).

The GenAI can also be useful in the healthcare sector, specifically in screening various diseases: in the case of breast cancer, researchers have presented a model which not only it was able to surpass human experts on its own, but it was also

discovered that it could maintain a good level of performance while also reducing the workload of radiologists (McKinney et al., 2020).

As we can observe, AI can help humans in performing their existing tasks better and with greater efficiency, but there is a catch: the future of AI is promising, but there are still some flaws which must be corrected.

Starting with the most prominent one, which is the AI's training: in the sector, there is a raised concern regarding a phenomenon called "data poisoning". Data poisoning consists in a case where individuals with malicious intents, insert purposefully incorrect or misleading information in the dataset used in order to spread misinformation, undermine the functionality of the model or force it to spread sensitive information regarding the user or the about the company that created such model (Snow, 2024).

Another concern which is connected with training the AI model is ethics: if we give to such model a dataset which has some form of bias – e.g., data which emphasizes economic, racial, sexual, social or religious discrimination – then the model itself will have a biased reasoning, and it will behave in an unethical manner which may perpetrate discrimination or toxic stereotypes (Colback, 2020).

However, data poisoning may not only perpetrate bias, but it may also pose a cybersecurity threat: a research project – whose results were published in May 2024 – showed that by performing operations of buying expired domains and modifying the contents within the websites (split-view poisoning), or by modifying the snapshots of a given website, like Wikipedia, by overriding its content (frontrunning poisoning), hackers may inject malicious data, by making the AI model as form of "Trojan horse" (Carlini et al., 2023).

Nonetheless, there's also the aspect of copyright and privacy: if the model is trained with data which was used without the consent of the owner of such data, it will create breaches in the privacy of individuals – in the case that the data used for training was relative to the latter – or a copyright infringement, also known as "piracy" – in the case that the data provided to the model was stemming from works which require prior authorisation. In the year 2023, Mark Zuckerberg – Founder, chairman and CEO of Meta – was convicted into a class action lawsuit where novelists Christopher Golden and Richard Kadrey and comedian Sarah Silverman allegedly accused Meta of using their works without any prior consent by downloading such from "shadow libraries" – i.e. online databases where there are contents which are not accessible due to barriers on the accessibility of such, including academic,

literary and artistic works which are protected by copyright – in order to train their AI models (Brittain, 2025) (AP, 2024).

Last, but not least, there's another aspect of relevance when considering AI, which is "hallucinations": AI hallucination is a phenomenon where the model or a computer vision tool can "see" a pattern which is non-existent or impossible to perceive by humans, which leads to the provision of incorrect information or information which may sound credible, but instead it is based on false or non-existent information (IBM, 2023)¹⁴. In some contexts, hallucinations may be perceived by many common users as a bug, while lawyers perceive such aspect as a nuisance: in a study conducted by Stanford's "Regulation, Evaluation and Governance Lab" (RegLab) and by the "Institute for Human Centered AI", it was demonstrated that hallucinations in the legal sector are unsettling and omnipresent – due to the presence of constant reinforcement of incorrect legal assumptions and beliefs – due to the hallucination rates oscillating between 69 and 88 percent (Ho, 2024). However, in some cases, it is perceived as a valuable feature: John Thornhill, a Financial Times journalist, reported the perspective of a Harvard University professor who perceives AI hallucinations as a reflection of the human culture – which makes machines like humans who try to generate new syncretic outputs – and that AI may enhance human creativity if such is prompted properly and if it is used as a tool and not as an agent who may replace the human's cognitive capabilities.

Concisely, we can observe that GenAI not only is achieving adoption in record time, but it also obtained encouraging results in cognitive-focused sectors like medicine and finance. Even so, there are some aspects like privacy and cybersecurity, which will become becomes an imperative as GenAI evolves. During this "testing phase" we can observe that there are increasing concerns in how such technology may impact society, specifically in terms of occupations. The next paragraph will discuss about what are the potential effects of implementing GenAI on the labour market.

Socioeconomic implications of AI's implementation

As we have seen before, there is an increasing adoption of AI in the workplace, which has its upsides and downsides. However, during this phase, society as a whole (i.e., workers, firms and public institutions) is starting to raise concerns regarding its potential effects on the labour market. Unfortunately, since we are still in the early stages of implementing AI, we cannot be certain about which effects AI may

¹⁴This article extends the definition of AI hallucinations, and it provides examples and cases of hallucinations: [What is AI Hallucination? Understanding and Mitigating AI Hallucination - GeeksforGeeks](#)

generate over occupations and industries as a whole over longer periods of time, but there's an increasing effort in trying to understand the changes that occupations are undergoing and whether such technology can be classified as a "General-Purpose Technology" (Bresnahan and Trajtenberg, 1995), like the Internet or the steam engine: given its multi-faceted nature, it is highly likely that it will generate an overall increase in the general labour productivity, leading to a consequent increase in the labour demand and the creation of new tasks, which will lead to an even greater increase in labour demand. At the same time, GenAI may render specific tasks obsolete (like summarisation of documents or reports), implying the possible manifestation of an increased economic inequality between firms and individuals. Nevertheless, there is also the possibility that GenAI may not impact the employment sector as much and instead, it may ameliorate only the efficiency of execution of existing tasks.

As of today, in many working and academic papers concerning with studying AI's potential "disruptive effect", there are some effects which must be observed from a macroeconomic perspective: Displacement, Productivity and Reinstatement.

The displacement effect, as the name implies, stems from the increased productivity of machines, which leads to a relative decrease in human labour productivity, thus inducing a lower human labour demand, which leads to a negative shock on real wages and a positive shock on the levels of unemployment because now technology performs better.

The reinstatement effect generates new job placements, which will require new skills (in this case it may be the case of "prompt engineering") and thus to a decrease in the wage setting curve, leading to a negative shock on the levels of unemployment.

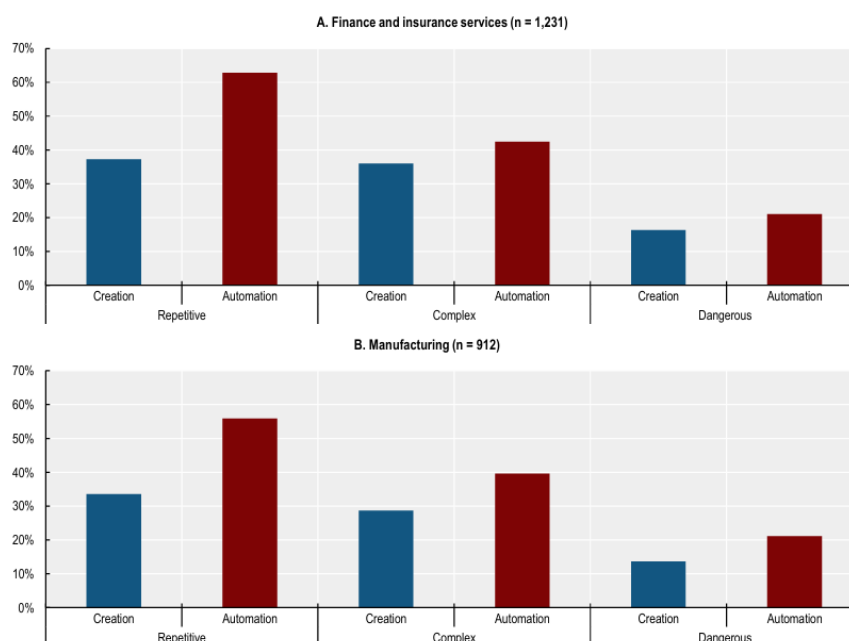
The productivity effect stems from the increase in human labour productivity due to their increased capability in performing a given task – thanks to Artificial Intelligence – thus leading to a higher overall productivity, which will impact the real wages positively and the levels of unemployment in a negative manner.

Definitions aside, in these last years, there were some clues regarding the impact on productivity and, for now, GenAI's implementation did not impact employment as much, but instead it has mentioned changes in the quality of the job performed.

Within OECD's 2023 Economic Outlook, Green et al. stated that the changes AI brought up are related to the tasks performed and the working environment, where

people possessing AI skills¹⁵ were the ones who received greater wage premiums: Alekseeva et al. (2021) estimated that in the US, for job postings requiring AI skills within the same hiring firm, the premium is equal to 11%, while for the same hiring firm and position it amounts to 5%. However, people lacking AI skills or performing a job not requiring them have not suffered from major variations in wages, which corresponds to the modest variations that occurred in productivity.

% of AI users



Note: AI users who said that AI had created or automated tasks in their jobs were asked: "Were most of these tasks repetitive? /complex?/dangerous?"

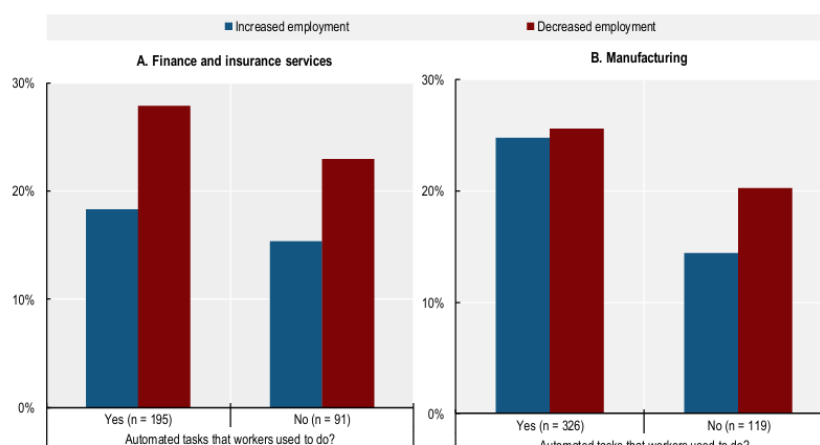
Source: OECD worker survey on the impact of AI on the workplace (2022).

Figure 4. "% of AI users who said that AI had created or automated tasks in their jobs and whether these were repetitive/complex/dangerous tasks". Source: 'The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers'. Lane Marguerita, Morgan Williams, Broecke Stijn. OECD Social, Employment and Migration Working Papers. Paris: OECD Publishing, 22 March 2023. Accessed May 20, 2025. <https://doi.org/10.1787/ea0a0fe1-en>.

This is because Artificial Intelligence has automated tasks which were tedious to perform, or even dangerous: Lane, Williams and Broecke (2023) analysed that the employers and workers that were surveyed by the OECD reported a greater level of automation of repetitive, complex and dangerous tasks with respect to how many they generated.

¹⁵ The OECD's report refers to them as a blend of skills in statistics, computer science and machine learning.

% of employers that have adopted AI, by whether AI has automated tasks



Note: Employers that have adopted AI were asked: "Thinking about your company, has artificial intelligence automated tasks that workers used to do?" They were also asked: "Has artificial intelligence increased, decreased or had no effect on overall employment in your company?" The figure does not include "Don't know" responses for either question.

Source: OECD employer survey on the impact of AI on the workplace (2022).

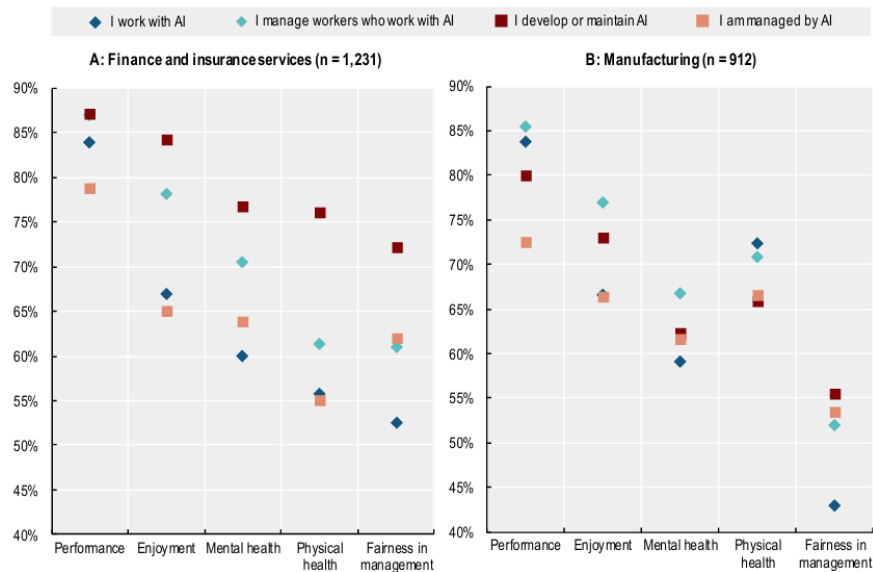
Figure 5. "% of employers that adopted AI who answered whether it has automated or not the tasks workers were used to do and whether AI has increased or decreased employment in the company". Source: 'The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers' Lane Marguerita, Morgan Williams, Broecke Stijn. OECD Social, Employment and Migration Working Papers. Paris: OECD Publishing, 22 March 2023. Accessed May 20, 2025. <https://doi.org/10.1787/ea0a0fe1-en>.

However, task automation cannot be considered as a clear causal link with lower employment: in the same paper, it can be seen that employers who answered that AI has automated some tasks were more likely to answer that it has decreased employment, but at the same time the likelihood of reporting a perceived increased employment was higher for those who reported a positive answer to the previously-cited question, confirming that we are still in a situation where automation has not been determined as a force that will increase or decrease employment.

Outside of the doubts related to automation, many AI users have reported a greater aid in the assistance during the decision-making process, whereas almost 80% have reported that AI is a great aid in performing faster and better decisions (both in

finance and manufacturing sectors).

% of AI users, by interaction type



Note: AI users were asked: “How do you think AI has changed your own job performance (performance)/how much you enjoy your job (enjoyment)?/your physical health and safety in the workplace (physical health)?/your mental health and well-being in the workplace (mental health)?/how fairly your manager or supervisor treats you (fairness in management)?” The figure shows the proportion of AI users who said that each of these outcomes were improved (a lot or a little) by AI. Workers who said that they interacted with AI in another way are not included in the figure.

Source: OECD worker survey on the impact of AI on the workplace (2022).

Figure 6. “% of AI users who were asked how AI has changed their job performance, enjoyment, mental health, physical health and fairness in management in their workplace”. Source: ‘The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers’ Lane Marguerita, Morgan Williams, Broecke Stijn. OECD Social, Employment and Migration Working Papers. Paris: OECD Publishing, 22 March 2023. Accessed May 20, 2025. <https://doi.org/10.1787/ea0a0fe1-en>.

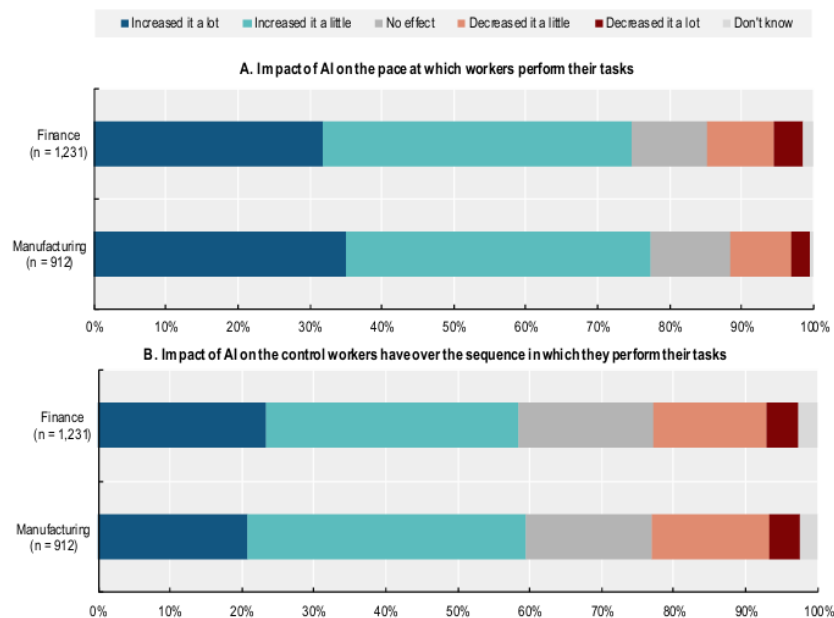
It was also reported from workers that AI has improved mental health and physical health, but this is highly dependent on whether they work with AI, develop, manage workers that work with AI and those managed by it: the workers in finance using AI reported a lower physical health improvement with respect to the manufacturing ones, but reported an approximately similar increase in mental health with respect to the workers belonging to the manufacturing sector. However, it should be noted that such results are also highly dependent on how Artificial Intelligence has been implemented in the workplace, i.e. what form of algorithmic management was implemented by the company.

Before moving forward, we should briefly describe what is algorithmic management: as the International Labour Organisation defines it, it is referred as “the set of algorithms making use of tracked data (stemming from workers) and other forms of

information (e.g., age, physical conditions) to organise, assign, monitor, supervise and evaluate the tasks performed¹⁶.

Now that we have defined algorithmic management, we should also consider that the latter may lead to greater efficiency in the tasks performed in the workplace, but it may systematise biases, possibly leading to an overall decrease in the quality of the job performed: if the AI algorithm is implemented in a workplace where biases are perpetrated, then the AI will also be biased and may generate negative externalities to the individuals affected. Another aspect which may influence the quality of the job performed is the pervasiveness of AI: these kinds of algorithms analyse constantly the data generated from human behaviour during work hours through monitoring and this may improve the efficiency and productivity of a firm but, at the same time, it may lead to breaches in the privacy of the workers involved.

% of AI users



Note: AI users were asked: "How has AI changed how you work, in terms of the pace at which you perform your tasks?/the control you have over the sequence in which you perform your tasks?"

Source: OECD worker survey on the impact of AI on the workplace (2022).

Figure 7. “% of AI users who answered on how AI has changed the pace at which the tasks in the workplace are performed Source: ‘The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers’. Lane Marguerita, Morgan Williams, Broecke Stijn. OECD Social, Employment and Migration Working Papers. Paris: OECD Publishing, 22 March 2023. Accessed May 20, 2025. <https://doi.org/10.1787/ea0a0fe1-en>.

The surveys performed by the OECD outline also that 75% of people working in finance and 77% of those working in manufacturing have experienced an increase in their work pace due to AI (Lane, Williams and Broecke, March 2023). In addition

¹⁶ Here you find the official definition of the ILO: [Algorithmic management in the workplace | International Labour Organization](https://www.ilo.org/gateway/topics/algorithmic-management-in-the-workplace/)

to how algorithmic management is implemented, we should note that the improvements in mental health are not equally distributed between labour sectors: OECD's 2023 Employment Outlook noted that 55% of the individuals working in the manufacturing sector and 54% of the individuals working in finance have declared a greater level of mental wellbeing.

According to the 2023 Employment Outlook of the OECD and BIS' own report on AI, the jobs which are going to be more affected by automation are "white collar jobs"¹⁷ – i.e. jobs requiring a great involvement of cognitive skills (e.g., Finance, IT Services, Management) – instead of "blue collar jobs"¹⁸ – i.e. jobs which require mainly manual skills: this is further backed up by the analysis performed by the International Labour Organization which considers the potential impact of GenAI on the quality and quantity of jobs (Gmyrek et al., 2023). In this paper, the ILO made use of LLMs which have the same capabilities as the latest GPT models (in this case, they used the GPT-4 model) and of an approach following the International Standard Classification of Occupation framework (an organisational tool whose main objective is to organise jobs into multiple clusters according to the job duties undertaken by a given job position)¹⁹ as their main data frame and designed some prompts in order to make the best estimation possible. Prior to the assessment of the predictions made by GPT-4, the ILO made a comparison between the ISCO definition of the role of a primary school teacher and its tasks with respect to GPT-4's prediction in order to understand whether the model understands how the ISCO classification works, and it provided a similar definition to the one from ISCO, but there was a caveat regarding the tasks described: the tasks that must have been described must be ten, which made the prompts generated by the AI model more generic than ISCO's because either (a) the model broke down complex tasks into simpler ones or (b) some additional tasks may have been derived in order to match the prompt's request. Outside from the previously described warning, they also ran some tests to ensure that the results generated by the AI model aren't biased in any shape or form: they performed a test of scoring consistency across tasks in order to observe whether the model predicts similar level of scores for different types of tasks across multiple test runs and an evaluation of the score variability at task level, which consists in analysing whether the range of scores predicted for the same task across multiple runs. These tests were

¹⁷ For those interested, here's the article defining the white-collar occupations: [White-Collar: Definition, Types of Jobs, and Other "Collar" Types](#)

¹⁸ For those interested, here's the article defining the blue-collar occupations: [What Is Blue Collar? Definition and Job Examples](#)

¹⁹ Here's the full description of the ISCO framework: [International Standard Classification of Occupations \(ISCO\) | International Standard Classification of Occupations \(ISCO\)](#)

performed by not varying the input provided to the model and by making 100 predictions for 5 tasks randomly selected from all tasks on ISCO-08 list: overall, the model was able to generate scores which are consistent across the board and with standard deviations which haven't exceeded 0,05. Tests aside, the overall result that the model has achieved were consistent with the conclusions drawn by the OECD: the roles which are considered as white-collar are the ones who are going to be more exposed to AI's impact, specifically the ones which involve clerical support²⁰ are the most exposed to Artificial Intelligence, where 58% of the workers in such category have an average exposure, while 24% of workers have great exposure. Another aspect which was considered by the ILO paper was the aspect of whether there will be a job augmentation or a job automation. Before discussing about the results that ILO obtained, we must distinguish between job augmentation and job automation:

- Job automation consists in the use of machines or computers to perform a given task without the need for human intervention²¹.
- Job augmentation, also known as job enlargement, consists in the widening of a job's scope by extending the duties and responsibilities associated with the same job²².

We may see that with job automation, there may be the destruction of existing positions, but it may also lead to the creation of new jobs while with job augmentation there's a consolidation of an existing position, by giving more autonomy to those who already cover such, which may allow to the improvement of the sense of job satisfaction and improve the existing skills of the worker²³. In order to assess whether there will be an augmentation or automation of a given work placement, the ILO performed an analysis of the distribution of the tasks according to the previously mentioned scores which were estimated by GPT-4: in order to determine whether there's a high likelihood of augmentation or automation potential, the mean and standard deviation of the scores were considered²⁴.

²⁰ For those interested, here's an article in Indeed where it explains what is a clerical occupation: [What Is the Definition of Clerical Work?](#)

²¹ Here's the definition of automation: [Automation Definition & Meaning - Merriam-Webster](#)

²² The following article gives a comprehensive definition of what is job enlargement: [Job Enlargement - Meaning, Importance, Process & Example | HRM Overview | MBA Skool](#)

²³ This article goes into detail about job enlargement and considers, for those who are interested, the pros and cons of this phenomenon: [What Is Job Enlargement? Meaning, Benefits and Examples | Indeed.com](#)

²⁴ In the paper, there's a high Standard Deviation if $\sigma > 0,5$ and there's a high mean if $\mu > 0,6$.

	Low Mean	High Mean
High SD	Augmentation potential	The big unknown
Low SD	Not affected	Automation potential

Table 1. “Grouping of occupations based on task-level scores”. Source: ‘Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality’. Gmyrek Pawel, Berg Janine, Bescond David. ILO Working Paper. Geneva: International Labour Office, 2023. Accessed May 20, 2025. <https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and>.

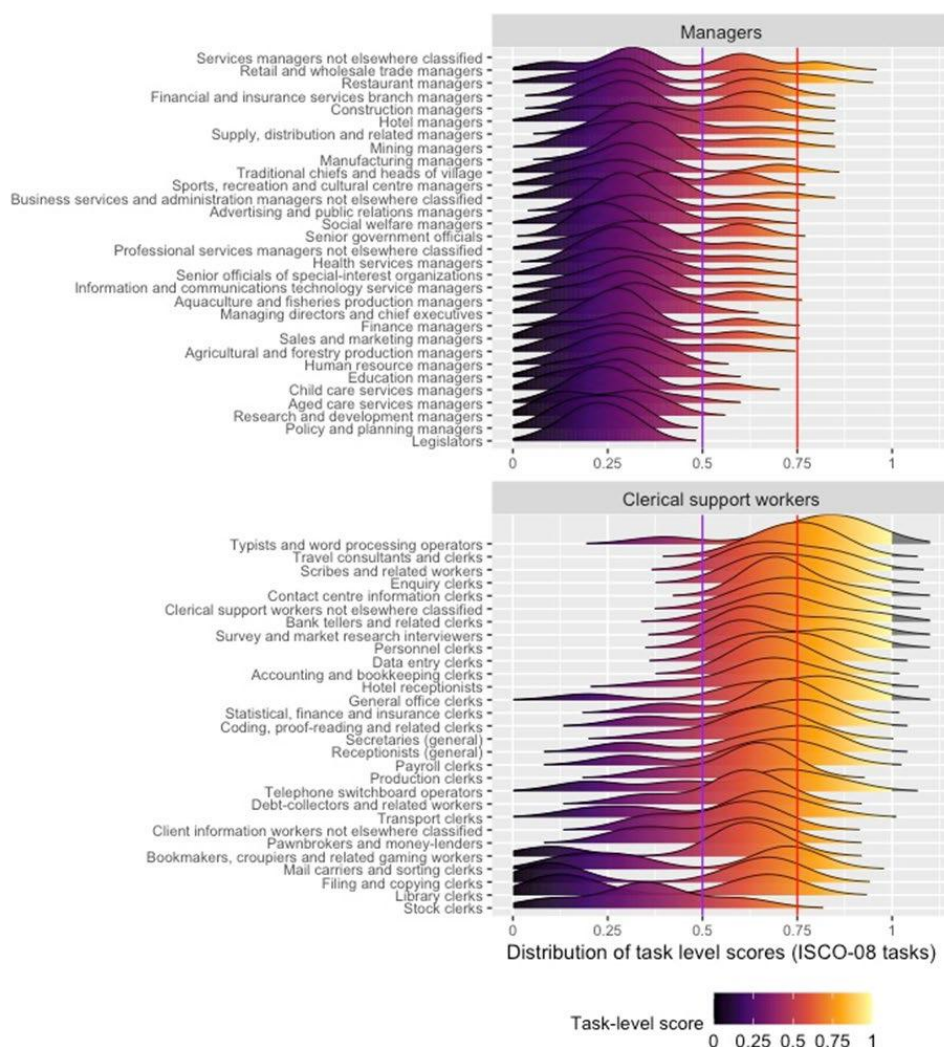


Figure 8. “Box plot of task-level scores by 4-digit ISCO code, grouped by the 1-digit ISCO code”. Source: ‘Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality’. Gmyrek Pawel, Berg Janine, Bescond David. ILO Working Paper. Geneva: International Labour Office, 2023. Accessed May 20, 2025. <https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and>.

Given the values obtained, we can observe that most of the clerical support tasks will be potentially exposed to automation, while many professionals and technical

operators will be most likely to be affected by augmentation.

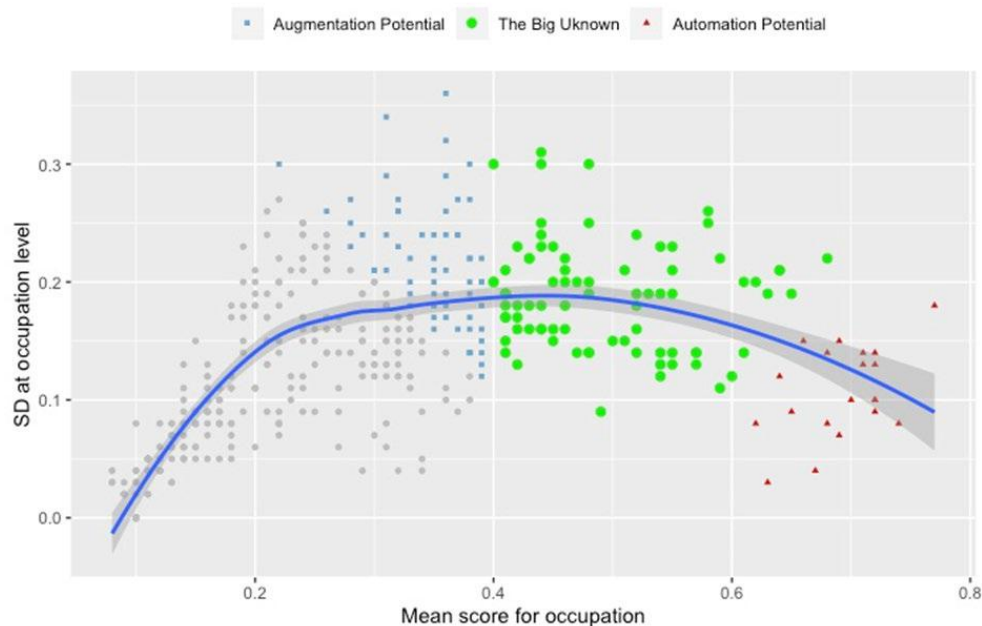


Figure 9. “Augmentation versus automation potential at an occupational level Source: ‘Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality’. Gmyrek Pawel, Berg Janine, Bescond David. ILO Working Paper. Geneva: International Labour Office, 2023. Accessed May 20, 2025. <https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and>.

There is also the group which is called by the authors of the paper as “The big unknown”: this is due to the peculiarity of each job which, according to the interaction they have with AI, there may be the generation of idiosyncratic effects. However, outside of the International Labour Organisation, also McKinsey & Company tried to assess the possible impact of GenAI on the existing jobs and its activities: due to GenAI’s capabilities of understanding and using natural language, according to their research, it lead to an increase in the potential for automation of many works involving cognitive capabilities (such works were defined in the paper as “knowledge work”) – this includes creativity-related jobs, office support, health professionals, managers and education-related works – by approximately 23,53% overall (Chui et al., 2023).

Now that we considered what AI may cause to given job clusters, we should also observe what are going to be the skill demands for workers who are going to be directly affected by AI, depending on whether the workers need to maintain these AI systems or not. If we consider the perspective of the workers performing AI maintenance, according to the OECD’s report, the most important skills are the ability to use Python, Big Data Management, Data Analysis and Visualisation, while skills like Machine Learning, Neural Networks and Decision Trees which are very

specific and may be required according to what form of AI must be implemented and maintained. In addition to the previously mentioned skills, many job positions requiring high level AI skills also require a specific set of soft skills like creative problem solving, communication, teamwork, negotiation, presentation, project management, mentoring and leadership. Instead, if we consider the ones who make use of AI, we may have different answers, but according to the research performed by Lane, Williams and Broecke (2023), 57% of the employers in the manufacturing sector and 48% of the employers in the financial sector have adopted AI systems and reported no significant need for upskilling or reskilling. However, even if it didn't vary the kind of skills required overall, AI has impacted the order of importance of given skills in some work contexts: in the case of the financial sector, there was a greater reliance on the existing skills possessed by the workers because AI has automated only tasks which were time wasting (e.g., data management and cleric-related tasks). This information provided by the OECD is confirmed by the Institute for Human-Centered AI's AI Index Report of 2024.

Top 10 specialized skills in 2023 AI job postings in the United States, 2011–13 vs. 2023

Source: Lightcast, 2023 | Chart: 2024 AI Index report

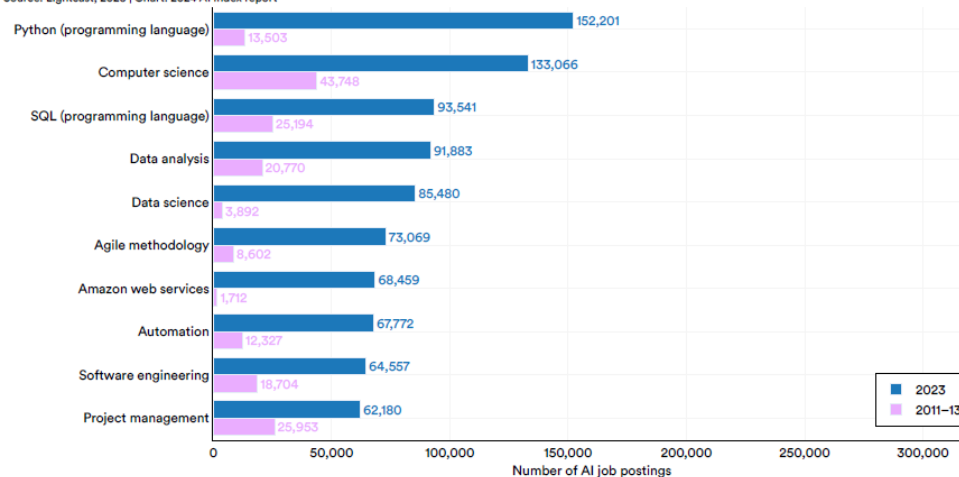


Figure 10. “Top 10 specialised skills in 2023 AI job postings in the United States, 2011-2013 versus 2023”
Source: ‘The AI Index 2024 Annual Report’ Maslej Nestor, Fattorini Loredana, Perrault Raymond, Parli Vanessa, Reuel Anka, Brynjolfsson Erik, Etchemendy John, Ligett Katrina, Lyons Terah, Manyika James, Niebles Juan Carlos, Shoham Yoav, Wald Russell, Clark Jack. *Artificial Intelligence Index Report*. Stanford: AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, April 2024. Accessed May 20, 2025. <https://hai.stanford.edu/ai-index/2024-ai-index-report>.

If we observe the top 10 requested specialised AI skills – which was obtained by comparing the job postings in the United States in the period between 2011-2013 with the postings in 2023 – we can conclude that firms are asking more for people who can program with Python, perform data analysis and who can use data science

software.

AI job postings (% of all job postings) in the United States by sector, 2022 vs. 2023

Source: Lightcast, 2023 | Chart: 2024 AI Index report

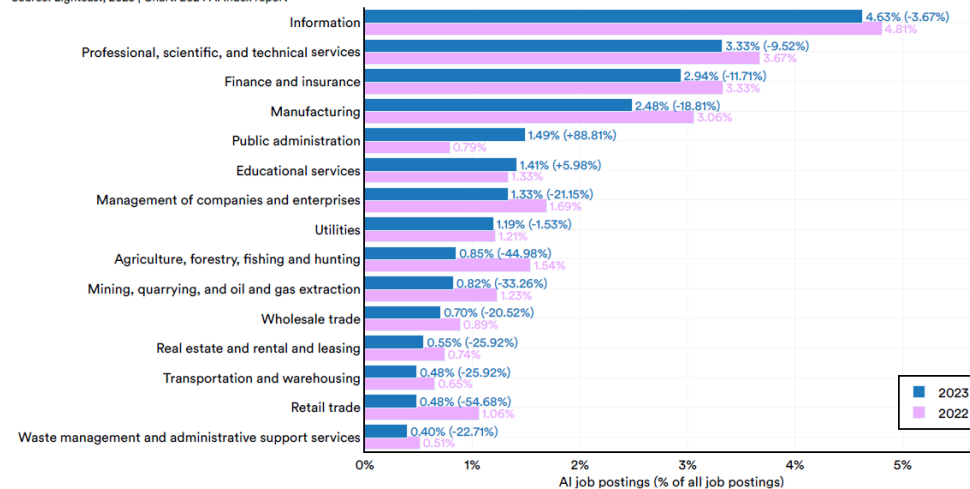


Figure 11. “AI job postings (% of all job postings) in the United States by sector, 2022 versus 2023” Source: ‘The AI Index 2024 Annual Report’. Maslej Nestor, Fattorini Loredana, Perrault Raymond, Parli Vanessa, Reuel Anka, Brynjolfsson Erik, Etchemendy John, Ligett Katrina, Lyons Terah, Manyika James, Niebles Juan Carlos, Shoham Yoav, Wald Russell, Clark Jack. *Artificial Intelligence Index Report*. Stanford: AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, April 2024. Accessed May 20, 2025. <https://hai.stanford.edu/ai-index/2024-ai-index-report>.

In addition to that, if we consider the AI job postings as a share of all job postings in the United States by sector between 2022 and 2023, we can conclude that almost every sector saw a drop in the postings where AI skills were required, with the exception of public administration (increased by 88,81%) and educational services (increased by 5,98%).

We can conclude that the socioeconomic implications of Artificial Intelligence go beyond an increase in overall productivity: there will be a potential increase in the productivity of individuals performing mind-intensive works, but it may also generate potential disruptions in jobs involving data and information management and it may raise some concerns in terms of privacy, job satisfaction and overall well-being if systems like algorithmic management tools were implemented. Given its disruptive capabilities, the impact of Artificial Intelligence will be heavily influenced not only by how such technology is implemented in the labour market, but also by how public institutions will respond: thanks to tools such as regulatory frameworks and education policies, the public administrations have a greater role on determining the most sustainable transition into an AI-centred economy from a social perspective. In the next paragraph, we will discuss about how public institutions are responding to the implementation of this novel technology.

Public institutions' role in tackling the effects of Artificial Intelligence

Since the rise of GenAI, people have started to become aware about the concept of Artificial Intelligence and form their own opinion about it: in a document presented by the “Policy, Elections and Representations Lab” (PEARL) at the Munk School of Global Affairs and Public Policy with the Schwartz Reisman Institute for Technology and Society (SRI) at the University of Toronto, both institutions performed a survey to understand what is the public opinion regarding AI and how such may impact society as a whole. It was conducted in parts of Europe, Asia, Oceania, North and South America, and Africa in order to represent the majority of the world’s population and the results were that:

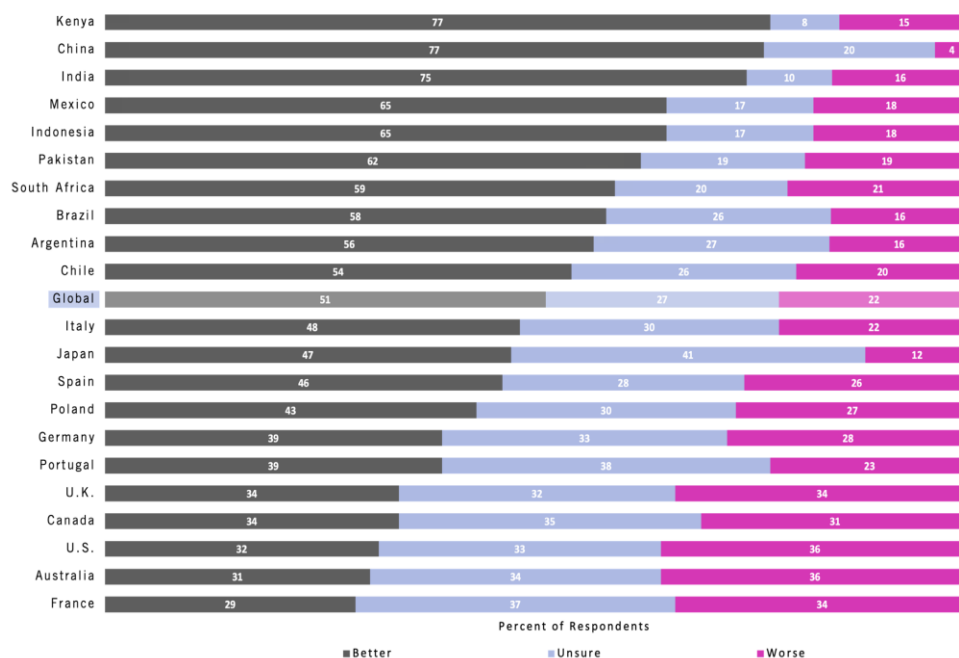


Figure 12. “Belief that AI will make the future better or worse (% terms)”. Source: ‘Global Public Opinion on Artificial Intelligence (GPO-AI)’. Loewen Peter John, Whiting-Lee Blake, Arai Maggie, Bergeron Thomas, Galipeau Thomas, Gazendam Isaac, Needham Hugh, Lee Slinger, Yussypovych Sofiya. Policy, Elections and Representation Lab (PEARL) and Schwartz Reisman Institute (SRI), 16 May 2024. Accessed May 20, 2025. <https://srinstitute.utoronto.ca/public-opinion-ai>.

Overall, 50% of the global population have a positive view of Artificial Intelligence and more or less 50% of such population considered that AI will bring a better future. The most optimistic country was India (43%) and the countries where there was a strong sentiment of AI being a “life-ameliorating technology” were Kenya and China (in both countries, 77% of the population considered AI as such), while the most pessimistic country was the United States (34%) and the countries having a strong

feeling about AI as a technology making the future worse are the United States and Australia (in both countries, 36% of the population thought so).

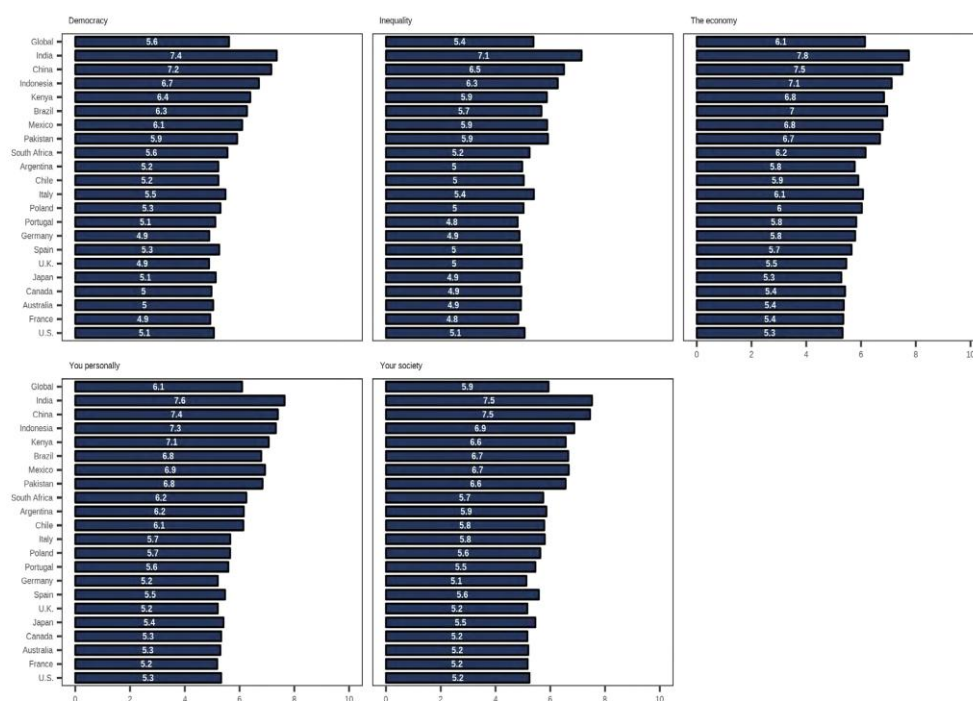


Figure 13. “Current impact of AI on democracy, inequality, economy, society and the individual (on a scale from 0 to 10: 0 is very negative, 10 is very positive)”. Source: ‘Global Public Opinion on Artificial Intelligence (GPO-AI)’: Loewen Peter John, Whiting-Lee Blake, Arai Maggie, Bergeron Thomas, Galipeau Thomas, Gazendam Isaac, Needham Hugh, Lee Slinger, Yuspovych Sofiya. Policy, Elections and Representation Lab (PEARL) and Schwartz Reisman Institute (SRI), 16 May 2024. Accessed May 20, 2025. <https://srinstitute.utoronto.ca/public-opinion-ai>.

On a global scale, people think that AI will neither have a positive nor a negative effect on democracy, inequality, the economy, the individual and society (respectively, 5.6, 5.4, 6.1, 6.1 and 5.9) while in 10 years from the year in which the survey was conducted (end of 2023), the results were approximately the same, implying that in 10 years it will not bring a great amelioration with respect to the present conditions.

Global opinions on products and services using AI (% of total), 2022 vs. 2023

Source: Ipsos, 2022–23 | Chart: 2024 AI Index report

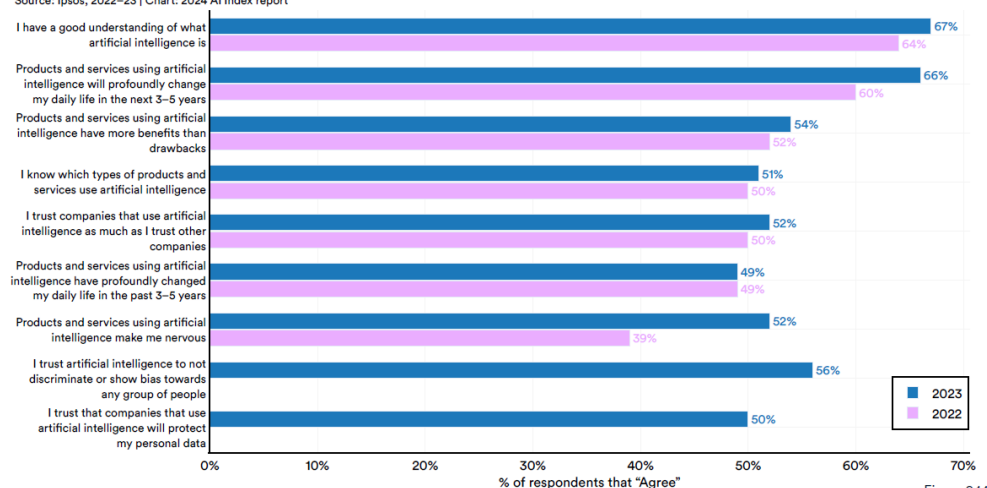


Figure 9.1.1

Figure 14. “Global opinion on products and services making use of AI (% of the total), 2022 versus 2023”. Source: ‘The AI Index 2024 Annual Report’. Maslej Nestor, Fattorini Loredana, Perrault Raymond, Parli Vanessa, Reuel Anka, Brynjolfsson Erik, Etchemendy John, Ligett Katrina, Lyons Terah, Manyika James, Niebles Juan Carlos, Shoham Yoav, Wald Russell, Clark Jack. Artificial Intelligence Index Report. Stanford: AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, April 2024. Accessed May 20, 2025. <https://hai.stanford.edu/ai-index/2024-ai-index-report>

If we compare the prior results with the ones summarised by the Human-Centered AI Institute of Stanford University – which stem from research performed by Ipsos – considering the results obtained in 2022 and 2023, we can observe that the global opinion had in 2023 an increased understanding of how artificial intelligence works and that the products and services which make use of AI will profoundly affect the lives of individuals in the short run²⁵, but we may also observe that globally, with this increased awareness there’s also a stronger sentiment of anxiety about AI.

So, we can observe that society has a somewhat positive opinion about AI and that it becomes increasingly aware of AI’s potential, but at the same time, it is perceived as a technology that will not bring an improvement to the economic system or to equity in general and that will probably bring important changes in the lives of individuals in the near future, which is why public institutions’ role is crucial, especially in the development of Artificial Intelligence: the OECD was one of the first public institutions that understood the implications of a technology which was developing with great celerity, while also posing risks to the workers’ fundamental rights (e.g., elimination of discrimination in respect of employment and occupation²⁶) and well-being. Given its position as a “soft law” institution (i.e. an institution whose main goal is to create a non-legally binding set of rules which influences the behaviour of the parties affected, instead of forcing a behaviour on parties in order

²⁵ With short run, we consider the period between three and five years.

²⁶ For those interested, here’s the definition of the ILO regarding the fundamental rights at work: [ILO Declaration on Fundamental Principles and Rights at Work | International Labour Organization](https://www.ilo.org/public/english/declaration/1998/declaration.htm)

to comply with the rules) (Sheehy, 2021), the OECD has adopted in 2019 the so-called “AI Principles” (which were updated in May 2024) whose main goal is, as the OECD describes it, to “guide the engaged parties in their efforts to develop a trustworthy AI and provide policymakers with recommendations for effective AI policies”. One of the most important words in the previous statement were “trustworthy AI”, a concept that can be summarised in the following key-points:

- Proactive engagement by stakeholders (i.e. all persons, legal or natural, who are going to be affected by AI systems, whether directly or indirectly) in responsible stewardship of AI by implementing and promoting these principles, according to their role: in this context, responsible stewardship is considered to be achieved when there’s a will to pursue beneficial outcomes for the planet and the people (e.g., reduce socio-economic, gender and other inequalities, protect natural environments in order to invigorate sustainable development).
- Respect for the rule of law, human rights and democratic values by all the actors who play an active role in AI system’s lifecycle (i.e. all the persons who are concerned with the development and implementation of AI systems).
- The actors should commit to transparency and explainability by performing disclosures with respect to the AI systems, which is done by granting meaningful information, depending on the context.
- The AI systems should be robust, secure and safe throughout the lifespan of such, to avoid unreasonable safety and/or security risks.
- The parties actively involved in the AI systems’ lifecycle should be accountable for their proper functioning according to the context and roles they have.

Another aspect which should be noted is the principles’ role in recommending effective policies, manifested in the following principles:

- Active investment by governments in the AI’s R&D and encouragement of private investment in R&D and open science, which induces innovation in trustworthy AI.
- Development of, and access to, an inclusive, dynamic, sustainable, and interoperable digital ecosystem for trustworthy AI by governments through investments in connectivity and computational infrastructure and the development of mechanisms for sharing knowledge on Artificial Intelligence.

- Governments should promote an environment supporting the transfer of knowledge – stemming from R&D – to the implementation phase of AI systems by developing and adapting policy and regulatory frameworks and assessment mechanisms in order to encourage innovation and competition in trustworthy AI.
- Governments must be actively participating with stakeholders in the preparation of the transformation of the labour's landscape and of society by equipping individuals with the skills needed to comprehend AI systems and by allowing them to use a variety of AI systems across multiple use cases.
- Governments must co-operate with stakeholders and developing countries to promote and evolve these principles in order to pursue the evolution of the concept of responsible stewardship of trustworthy AI.

We can observe that Governments have a central role in the creation of an AI which must not cause negative externalities to society as a whole: to be able to achieve such a noble goal, governments must intervene not only with financial investments but also with the creation of juridical frameworks. The main tool used until now by governments is soft law, which is manifested through the creation of ethical and technical frameworks and guidelines and of codes of conduct in order to promote the principle of “trustworthy AI” in the workplace: as the Employment Outlook outlines, the main advantage of soft law is its simplicity in the adaptation and adjustment process with respect to their “counterpart”, i.e. hard law (it groups all forms of legally binding instruments and laws giving rise to rights, duties and responsibilities and, most importantly, that can be legally enforced by a court)²⁷.

Soft law is used in contexts of international cooperation, co-ordination and situations where there must be a high degree of flexibility: due to AI's rapid adoption and development, it may be the best solution available. However, as outlined in the OECD's report, in order to create strong policies, there must be the right mix of soft law and legislation: soft law does not have the same level of enforcement that national law has, and it does not go through a democratic processes like parliamentary votes and discussions.

Hence, to keep up with the constant transformation that AI undergoes, governments must implement mechanisms that ensure a certain degree of flexibility to national law, i.e. by introducing criteria for a constant review of the juridical framework priorly

²⁷ Definition of hard law and soft law: [ECCHR: Hard law/soft law](#)

created which ensure the promotion of human values and fairness in the AI systems. A good example of how such can be achieved is if we consider the legal framework created in the European Union with regulations like the GDPR and the AI Act.

The General Data Protection Regulation builds on the basis that the Directive 95/46/EC²⁸ established in terms of circulation of data and data protections, with novelties in terms of the disclosure of the data collection and usage processes (which now must outline clearly how data are treated and for what purpose) and of the rights of the data subject. In the case of the latter, there is the addition of the following rights:

- “Right to erasure”, or “right to be forgotten”, allows a natural person to request the elimination of its personal data, without any delay, by the ones holding its data (i.e., the data controller) when the data is no longer necessary with respect to the purpose of the data collection or process, or in the case that the data processing and collection rely on explicit consent, which can be withdrawn, or when the data controller processed the data in an unlawful manner.
- “Right to rectification”, which allows the person generating data to the rectification, without any delay, of data which are concerned to them in case that the data collected are not accurate or in case there is a case of incomplete personal data.
- The “right to the restriction of processing” gives the possibility to restrict the data processed in case that the accuracy of the personal data is contested, when the processing of data is done unlawfully (i.e., when there wasn’t explicit consent from the data subject to process its personal data or when data processing is not necessary to protect the interests of the individual or for compliance to legal obligations) or when the individual explicitly rejects the processing of its personal data.
- The “Right to object” consists in the right to oppose, according to the situation of the data subject, of the processing of the data concerning them if the processing of the data collected isn’t necessary to accomplish a task carried out in the public interest, or when it isn’t necessary for the objectives of legitimate interest of the data controller or a third party (it occurs when these interests are overridden by the interests or fundamental rights and freedoms of the data subject which require protection of personal data, in

²⁸ For those curious, here’s the directive prior to the enforcement of the GDPR: [Directive - 95/46 - EN - Data Protection Directive - EUR-Lex](#)

particular where the data subject is a child). It must also be noted that in the case that data is processed for marketing purposes, the right to object of the individual becomes absolute, meaning that it can always exercise this right without any restrictions.

As we can observe, the rights granted to individuals allow for greater control over the data processed by the data controllers (which are usually companies) but at the same time, the GDPR allows firms to ameliorate their reputation and their relationships with customers. Furthermore, the GDPR can be considered as one of the founding blocks on which legislation on Artificial Intelligence would lay on due to AI's great dependence on data, but AI still represents a menace towards the European fundamental rights like the right to non-discrimination²⁹ and the freedom of expression³⁰. In order to make such technology human-centred, there is the need to create “guardrails” in order for the development of AI to be respectful of human values and rights: that is where the AI Act comes into play.

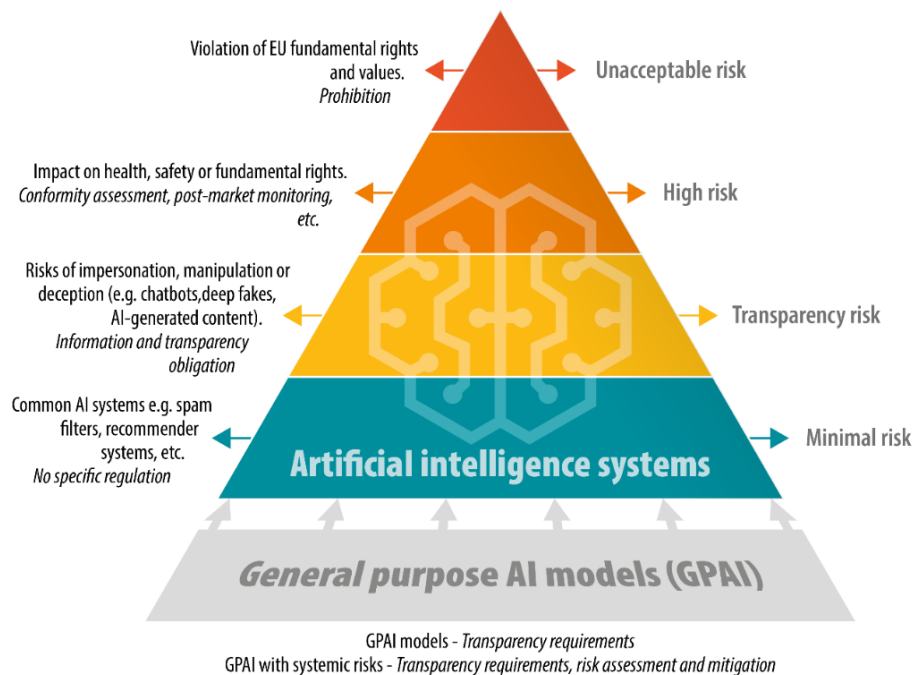


Figure 15. “EU AI act risk-based approach”. Source: European Commission. Accessed May 20, 2025. <https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai>.

The Artificial Intelligence Act is one of the first forms of regulation in such a field and it was approved in June 2024: its main goal is to implement a risk-based approach for the classification of the AI systems implying that there may be more stringent or less stringent regulations, restrictions and/or prohibitions depending on the level of

²⁹ Art 21.1, Charter of Fundamental Rights of the European Union

³⁰ Art 11.1, Charter of Fundamental Rights of the European Union

the risk³¹. In this act, all the models that follow AI practices which damage the fundamental rights and values of the European Union (e.g., deploy subliminal techniques who manipulate or deceive purposefully a human person with the goal of creating a bias in its behaviour, or exploiting the vulnerabilities of a natural person, or for social scoring purposes) are prohibited, the high-risk systems are those used as a safety component of a product which falls in the EU health and safety legislation or if it is deployed in Biometrics, education and vocational training, employment, workers' management, law enforcement, migration, asylum and border management or administration of justice and have stringent requirements in terms of transparency (the high-risk models require a disclosure of the policies implemented for human oversight, data governance, but also a mandatory compliance with all the requirements of safety outlined for obtaining the so-called CE marking³²³³). Then, as we can observe in the pyramid, there are also two levels of AI system risk, which are "Transparency" and "Minimal" risk: in the case of the former, these include AI systems conceptualised to interact with natural persons and these may pose the risk of deception or personification, even if they don't fall in the category of "high-risk" AI systems, which implies the submission of such to requirements of information and transparency requirements (e.g., in terms of how the data is collected and used to train the model, which must also follow the requirements already outlined in the GDPR in terms of data). In the case of "minimal risk" AI systems, there are no specific obligations to which they must be compliant with. Outside of the classification of AI systems, the most important aspect of this act is the introduction of the "regulatory sandbox": this is a controlled framework of rules and practices which offers the providers of AI systems the possibility to train, validate and test their models in real-life conditions according to the points outlined in the "sandbox plan", i.e. a document between the provider and the competent authority which outlines the goals, conditions, time period, methodology and the requirements for activities carried out in the previously cited sandbox. Moreover, the AI Act also outlines the need from AI model providers to supply the persons who operate such systems on their behalf, with the necessary upskilling and/or reskilling programmes and vocational training needed in order to acquire the AI literacy skills

³¹ Risk, in the AI Act, is defined as "the combination of the probability of an occurrence of harm and the severity of that harm".

³² Article 23.1(a), Artificial Intelligence Act

³³ For those interested, here's the definition of the requirements for the CE marking: [CE marking – obtaining the certificate, EU requirements - Your Europe](#)

required (depending on the role covered by such individuals and on the context in which these literacy skills will be utilised)³⁴.

As we can observe, both the AI Act and GDPR are solid tools that layout the framework for an ethical development of AI systems, but it may hinder innovation and investment in AI in the European Union territory: many of the “Big Tech” companies like Apple and Meta have expressed such concerns due to the burdens posed by a greater transparency requirement in data treatment and risk assessment procedures (Moen, Foy and Heikkilä, 2025).

AI’s adoption implies a profound yet nuanced effect on labour markets because it may displace some tasks, while augmenting the responsibility of existing roles, leading to shift in the perceived job satisfaction. However, there is also a heightened concern regarding the possible implication on the rights of individuals due to AI’s improper implementation, which is why there is also a greater push for AI regulation in order to safeguard the rights of workers, which allows for a “human-centred” development of Artificial Intelligence. Nonetheless, there is also another key uncertainty remaining to uncover: how will such transformations manifest in a measurable manner?

The next chapter will try to answer the prior question by performing an empirical analysis quantifying the potential impact of Artificial Intelligence over the labour market, by considering the multi-dimensional exposure of the Italian Labour Market to such technology.

³⁴ Article 4, Artificial Intelligence Act

3. The Italian labour market and AI

The rapid advancement of Artificial Intelligence (AI) has sparked in the last years a widespread discussion on what its potential effects on employment, productivity and on existing socio-economic disparities. As previously outlined in the first and second chapter, Artificial Intelligence has come a long way: from the theories focused on the concept of “mechanical reasoning” to the introduction of the Transformer model, AI was further and further integrated into the productive processes of multiple industries, which may generate positive outcomes in terms of productivity, but there may be potential threats to privacy and to cyber-security if public institutions do not intervene. While the previous discussions have addressed the broad implications of AI from a socioeconomic perspective, there is an urgent need for an empirical assessment of the impact that it may have on labour markets, especially in the case of Italy since there is not an ample amount of research on the matter.

The goal of this chapter is to bridge the previously cited void by providing a data-driven analysis of AI’s exposure across multiple dimensions – i.e., occupational, industrial, geographical and demographical – within the Italian labour market.

Research focus and objectives

The focus of this chapter is to quantify AI exposure in the Italian labour market and determine how it varied across different dimensions. To achieve this, we will evaluate AI’s impact by considering the following dimensions:

- I. Occupational Exposure
 - a. Which jobs are the most exposed to AI automation?
 - b. How do they compare with other estimations?
- II. Industrial Exposure
 - a. Which industries have faced the greatest AI-driven disruption?
 - b. How did the exposure change across the years considered?
- III. Geographical Exposure
 - a. How did AI impact the different regions of Italy?
 - b. Is AI exposure concentrated in specific geographic areas?
 - c. How does it change across time?
- IV. Demographic Exposure
 - a. Have AI-related technologies affected male and female individuals differently according to the job-related distributions?

- b. Were younger individuals more adaptable to AI-driven changes with respect to older workers?
- c. Were individuals with low levels of education more exposed to AI than those with high levels of education?

By addressing these questions, this study aims to provide concrete insights for policymakers, businesses, labour organisations and other stakeholders who want to navigate the changes that have occurred in the past in terms of AI exposure and observe which occupations may be the most exposed in the near future.

Methodological framework

To conduct our analysis, this chapter will construct its approach by considering – for most of the estimation process – the methodology constructed by Felten et al. (2021): in their paper, Felten et al. have created 3 indicators which allow to assess how AI will impact the labour market on an occupational, industrial and geographical sphere, i.e. the AIOE (AI Occupational Exposure), AIIE (AI Industrial Exposure) and AIGE (AI Geographical Exposure).

The formulas that were used in such paper are the following:

$$A_{ij}^{35} = \sum_{i=1}^{10} x_{ij}^{36}$$

$$AIOE_k^{37} = \frac{\sum_{i=1}^{52} A_{ij} L_{jk} I_{jk}}{\sum_{j=1}^{52} L_{jk} I_{jk}}$$

$$AIIE = AIOE * Ind. Emp.$$

$$AIGE = AIIE * County level employment$$

To assess the AIOE, Felten et al. have used data from the O*NET database and from the Electronic Frontier Foundation (EFF)³⁸: specifically, they considered 52 distinct abilities of each occupation from the O*NET database by considering their importance (on a scale from 1 to 5) and their prevalence (on a scale from 1 to 7), while

³⁵ A_{ij} considers the ability-level exposure: the i indicates the AI application, while j indicates the occupational ability

³⁶ $x_{ij} \in [0,1]$; x_{ij} is the application-ability relatedness score, where i indicates the AI application, while j indicates the occupational ability

³⁷ L_{jk} assesses the prevalence of a given ability (j) in each job (k). I_{jk} assesses the importance of the ability (j) in a given job (k).

³⁸ For those interested, here's the link to the history of the EFF: [A History of Protecting Freedom Where Law and Technology Collide | Electronic Frontier Foundation](https://www.eff.org/history)

Felten et al. have considered 10 AI applications for which the EFF measured major improvements from 2010 because it is believed that these will be the ones with the fastest growth and with higher likelihood to be used in the medium run. In our approach.

It should be noted that in the last years, there weren't many researches trying to assess the AI's impact on the Italian occupational fabric due to how recently GenAI arrived and due to the conformation of the economic fabric of Italy: due to the predominance of SMEs, there aren't sufficient private investments on Research and Development on a national level due to their limited capacity to spend which, for sectors which are exposed to international competitiveness like the high-tech sector, is fundamental (Hall et al., 2009).

In the years after ChatGPT's public announcement, the most recent efforts to assess the impact of AI in Italy and Europe are Guarascio et al. (2023) and Ferri et al. (2024).

The estimation performed by Guarascio et al. (2023) however, considered a wider perspective by analysing the European context: they estimated the AIOE by making use of the assumption that the AI-related workplace abilities of the American occupations are similar, if not the same, as their European Counterparts and by converting the O*NET-SOC occupational codes into the equivalent 4-digit ISCO codes. They also considered the creation of a 'Regional AI Exposure (AIRE)' indicator by following a methodology like the one suggested by Felten et al. (2021):

$$AIRE_{ijt} = \sum_{k=1}^{126} \frac{EMP_{kijt}}{EMP_{ijt}} * AIOE_k$$

where EMP_{kijt} denotes the number of employees in occupation k , in region j , in country i and year t and EMP_{ijt} is the total number of employees in region j , in country i , and year t .

The empirical research done by Ferri et al. instead, considered the impact of Artificial Intelligence on Italy by considering the AIOE formulated by Felten et al. (2021) and assessing the exposure of the Italian society by considering the data from the Occupational Sample Survey from the year 2013 and the Labour Force Survey conducted by the ISTAT during the year 2022: they made use of the Italian skills which are present in the Occupation Sample Survey – which match the 52 abilities of O*NET cited in Felten et al. (2021) – to assess the ability level exposure and to perform the calculations for the AIOE which was then used to assess the average AI exposure on a regional and provincial level. They also extended the analysis by

considering the average AI exposure levels according to the gender, age and educational level of the occupied individuals aged between 15-64 years.

In the end, we will make use of a hybrid approach:

1. We will consider the assumption that the AI-related workplace abilities denoted by the O*NET are, if different from the ones denoted by the Italian Occupations Sample Survey³⁹.
2. We will consider the top 20 occupations subject to a great AI exposure to assess not only which industries are the most exposed, but also to evaluate which regions are the most exposed and see if there may be any exacerbation of existing territorial, social and economic disparities.
3. The time frame considered will be ranging from the year 2008 to the year 2018: we chose this period because we want to understand how the AI exposure in general has changed according to the evolution of the AI applications⁴⁰ before and after 2010⁴¹.
4. To assess the AI exposure on an occupational and industrial level, we will make use of the methodology outlined by Felten et al. (2021) by making use of the methods used by them to estimate the AIOE and the AIIE, with some slight alterations to the AIIE formula⁴².
5. To assess the AI exposure on a territorial level, we will consider the AIRE indicator constructed by Guarascio et al. (2023) and we will construct an AIZE (AI Zone Exposure) indicator based on the AIRE constructed by Guarascio et al. (2023), which will be an aggregate of the regions considered in the AIRE, and it will consider the Northern, Central and Southern parts of Italy.
6. To perform a thorough analysis of the impact of Artificial Intelligence, we will also consider what is the exposure of AI with respect to the demographical dimension (i.e., we will consider gender, age and level of education of the occupied individuals), which will be quantified by the AIDE (AI Demographic Exposure).

³⁹ For those who want to read about the abilities denoted in the OSS, here's the link: [Occupations Sample Survey \(OSS\) - Inapp](#)

⁴⁰ In Felten et al. (2021), the researchers considered 10 AI applications for which the EFF has recorded significant progress from 2010 onwards.

⁴¹ The year from which the EFF has started tracking significant progress in the AI applications considered by Felten et al. (2021).

⁴² Specifically, we will obtain the industrial employment for a given period by considering the ratio between the number of employed in a given sector for a given year over the total number of employed for a given period.

7. The evaluation of the AIOE is based on the data used by Felten et al. (2021) and to convert the 4-digit US occupational codes to the Italian occupational codes (i.e., the ‘Classificazione delle Professioni 2011’, or CP2011) we will make use of the crosswalk⁴³ between the O*NET-SOC codes and the ESCO/ISCO occupational codes and then, consider the crosswalk between the ISCO and the CP2011. We will consider the CP2011 and not the CP2021 because the data which we will use (referring to the AIIE, which relies on the occupational codes), will consider a period in which the CP2011 was used (i.e., the period spanning 2008 and 2018). Also, since in our LFS dataset there is the presence of only the 3-digit CP2011, we will consider only the first 3 digits of the converted 4-digit CP2011 and aggregate those who have the same initial 3-digits.
8. For the economic activity codes, we will consider the Italian equivalent to the 4-digit NAICS for the period between 2008 and 2018, i.e. the ATECO 2007 codes. Once we have determined which employment matches with the ATECO code, we will make use of the 12-class aggregate of the ATECO 2007 codes to perform our estimations for the AIIE: this is due to the insufficient data for the variable which should consider the ATECO 2007 codes and because the variable considering the 12-class aggregate of ATECO 2007 has more observations than the former, ensuring a better estimation for the Italian AIIE.

Data sources and estimation formulas

Given the period that we want to cover, the datasets which will be used to assess the impact of AI on the Italian Labour Market will be the following:

- The Italian Labour Force Survey for the period between the year 2008 and the year 2018 (both years are included)⁴⁴.
- Data stemming from the Felten et al. (2021) repository, which can be found on GitHub⁴⁵.

The variables which will be considered from the Italian LFS⁴⁶ will be:

- ‘anno’, which is the year in which the observation was done.

⁴³ For those who want to check, here’s the crosswalk files made available in the O*NET website: [Crosswalk Files at O*NET Resource Center](#)

⁴⁴ For the curious individuals, here’s the link to the Istat’s section grouping the LFS data: [Labour Force Survey – cross-sectional quarterly data: file for research purposes – Istat](#)

⁴⁵ This is the GitHub repository used by Felten et al. (2021): [AIOE/Input at main · AIOE-Data/AIOE · GitHub](#)

⁴⁶ All the variables specified can be found [here](#) (you should seek for the first quarter of 2018).

- 'reg' (which will be renamed as 'region' when we will perform the estimation of the AIGE) considers the region.
- 'sg11' is the variable considering the gender of the individual being interviewed.
- 'rip3' which considers the 3 regional clusters of Italy.
- 'cletad' which embodies the age clusters (each cluster considers a 10-year interval in total).
- 'cond10' expresses in detail the working condition of the individual (i.e., whether he is employed, unemployed or out of the labour force).
- 'prof3' which is the group of 3-digit CP2011 occupational codes.
- 'cat12' which is the 12-class aggregate of the ATECO 2007 industrial codes.
- 'edulev' which expresses the maximum level of education attained.

To estimate the AIOE, we need to use the datasets from the GitHub repository cited in Felten et al. (2021).

For the AIIE, AIRE and AIZE's estimation, we will take inspiration from the 'AIOE, AIIE, and AIGE Construction.do' file present in the GitHub repository of Felten et al. (2021) and perform some modifications to adapt it to our use case:

- a. To estimate the AIIE, we will first need to consider from our LFS only the employed individuals for each year (in this case, the employed are those who have a value of 1 in the variable cond10) and generate the value of total employment according to the 12-class classification of ATECO 2007. Secondly, we will consider the dataset containing the top 20 exposed jobs and the converted occupational code (we will consider the 3-digit CP2011 code) and merge it with the LFS dataset by making use of the 12-class aggregate: we will also do a check to observe if there were some missing values stemming from the merge process. Once we saw that there are no observations missing, we move on by generating the level of employment according to the economic activity (done by considering the 4-digit ATECO 2007 codes).
- b. To estimate the AIRE and AIZE, we must consider the LFS database once again and filter it, by considering the employed individual for each year in the database (just like we did for the estimation of the AIIE) and generate the employment rate according for each region and the 12 class ATECO 2007 classification for the AIRE, while for the AIZE we will consider the employment rate according for each zone (North, Centre or South / Mezzogiorno) and the 12 class ATECO 2007 classification.

To estimate the different AIDE coefficients, we will follow the steps outlined in the following points:

- a. Firstly, to estimate the AIDE according to the gender (AIDE-S) we will consider the top 20 exposed jobs and match them with the individuals who perform these jobs. Once we performed the matching, we will perform an estimation of an AIDE which will be weighted according to the number of employed people according to the profession performed and the gender.
- b. Secondly, to estimate the values of the AIDE according to age groups (AIDE-A), we will consider the individuals which have 15 years of age or more. The estimation will be done in a similar way to the previously described AIOE, but instead of considering the gender, we will consider the age group of belonging.
- c. Finally, to estimate the values of the AIOE according to the level of education attained (AIDE-E), we will consider 6 levels of education: No education, Primary, Lower Secondary, Upper Secondary (2-3 years or 4-5 years)⁴⁷, and Tertiary education. The estimation process will be like the previous two, but instead we will consider the educational level group in which the individual belongs.

In addition to the prior, given the period that we want to cover (i.e. the years 2008-2018), we will estimate the AIOE, AIIE, AIRE, AIZE and AIDE by considering the data for each year.

The formulas which are going to be used in this chapter to assess the previously cited indicators are going to be the following:

$$AIOE_k = \frac{\sum_{i=1}^{52} A_{ij} L_{jk} I_{jk}}{\sum_{j=1}^{52} L_{jk} I_{jk}}$$

$$AIIE_{bt} = \sum_k \left(AIOE_k * \frac{EMP_{kbt}}{EMP_{bt}} \right)$$

$$AIRE_{rt} = \sum_b \left(AIIE_{bt} * \frac{EMP_{brt}}{EMP_{rt}} \right)$$

⁴⁷ The '2-3 years' in upper secondary education considers the first 2-3 years of high school, which are mandatory. While the '4-5 years' in upper secondary education considers the whole high school path.

$$AIZE_{zt} = \sum_b \left(AII E_{bt} * \frac{EMP_{zt}}{EMP_t} \right)$$

$$AIDE - S_{gt} = \sum_k \left(AIO E_k * \frac{EMP_{kgt}}{EMP_{gt}} \right)$$

$$AIDE - A_{at} = \sum_k \left(AIO E_k * \frac{EMP_{kat}}{EMP_{at}} \right)$$

$$AIDE - E_{et} = \sum_k \left(AIO E_k * \frac{EMP_{ket}}{EMP_{et}} \right)$$

Empirical outcomes

Before going into detail and show the results obtained, we should note that the AI exposure scores can be positive or negative: if they are above zero, then it means that the aspect in question is exposed to the evolution and/or introduction of AI-related technologies while if they are below zero, it implies the opposite.

Disclaimer aside, we can start talking about the AIOE: once we have used the data repository outlined in Felten et al. (2021) and converted the O*NET-SOC occupational codes to the CP2011 classification of the twenty most exposed occupations, we have obtained the following table, which sums up the AIOE scores for each of the occupations in question.

	cp2011...	cp2011...	cp2011_3d	cp2011...	cp2011...	occ_title_cp2011	aioe
1	1	11	113	1131	11310	Dirigenti della magistratura ordinaria	1.431381
2	2	25	251	2513	25141	Specialisti in contabilità	1.432205
3	2	24	241	2417	24173	Epidemiologi	1.436074
4	2	25	253	2532	25323	Geografi	1.436085
5	2	26	261	2615	26151	Docenti universitari in scienze storiche e filosofiche	1.437277
6	3	33	332	3322	33220	Tecnici del lavoro bancario	1.440083
7	2	25	251	2513	25132	Specialisti dell'organizzazione del lavoro	1.440772
8	1	12	123	1231	12310	Direttori e dirigenti del dipartimento finanza ed amministrazione	1.446018
9	2	25	253	2533	25331	Psicologi clinici e psicoterapeuti	1.456643
10	1	11	112	1124	11242	Rettori di università, direttori di istituzioni dell'Alta Formazione e di enti di ricerca	1.460934
11	3	34	346	3461	34610	Tecnici dei servizi giudiziari	1.462757
12	2	21	211	2113	21131	Matematici	1.472102
13	3	33	331	3312	33121	Contabili	1.484061
14	4	43	431	4311	43110	Addetti alla gestione degli acquisti	1.48762
15	2	25	252	2524	25240	Magistrati	1.496275
16	2	25	251	2512	25120	Specialisti della gestione e del controllo nelle imprese private	1.502769
17	3	33	334	3342	33420	Agenti di commercio	1.508961
18	2	21	211	2113	21132	Statistici	1.516253
19	2	25	251	2514	25143	Specialisti in attività finanziarie	1.525841
20	2	24	241	2414	24140	Laboratori e patologi clinici	1.527445

Table 2. “Top 20 occupations in terms of the AI Occupational Exposure scores (ascending order)”

Moving on to the results for the AII E, we can compare the results obtained across multiple time periods and across industries: we can observe that from our estimations, the industries which are considered as the most exposed to AI-related technologies in Italy (with respect to the twenty most exposed occupations based on

the AIOE metric) are five, i.e. “commerce and trade” (corresponding to the activity with the number 4), the “financial and insurance activities” (matched with the number 8), the “real estate, business services and other professional and entrepreneurial activities” (matched with the number 9), “public administration and defence” (matched with the number 10) and “education, health and other public services” (matched with the number 11).

Moving on, by observing the time series for all the industries involved in our analysis, we can observe that there are 3 activities which are considered to be exposed to AI-related technologies (i.e., the activities denoted by the number 4,9 and 11), while those that are the least exposed overall to AI-related technologies are only two: the “finance and insurance activities” and the “public administration and defence” sector. We can also conclude that the “Commerce and trade” sector was the one with the greatest change in terms of exposure from 2010 onwards: the other sectors, outside of the “education, health and other related public services” sector, have experienced an overall stability prior to the year 2010 and after the year 2010. The only ones who have experienced a significant change were the “Commerce and Trade” sector and the “education, health and other public activities”.

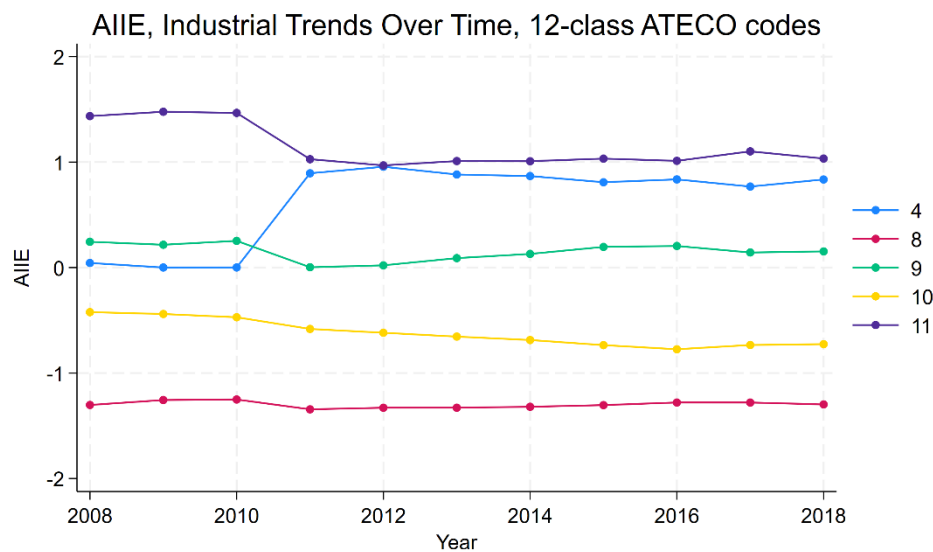


Figure 16. “AI Industrial Exposure (2008-2018) across the industrial sectors considered in Italy (classified according to the ATECO 2007 12-class industries)”. Data source: Italian Labour Force Survey (2008 – 2018).

If we observe the values obtained for the AIRE and AIZE, we can see some interesting results in terms of exposure:

if we focus on the AIZE, we can observe that across time periods, all the regional clusters have experienced an upward trend in terms of AI exposure since 2010. However, the cluster which had the highest exposure towards AI was the zone of

Southern Italy, while the one which experienced the least exposure to AI was the zone of Central Italy, whereas Northern Italy falls between the two in terms of exposure.

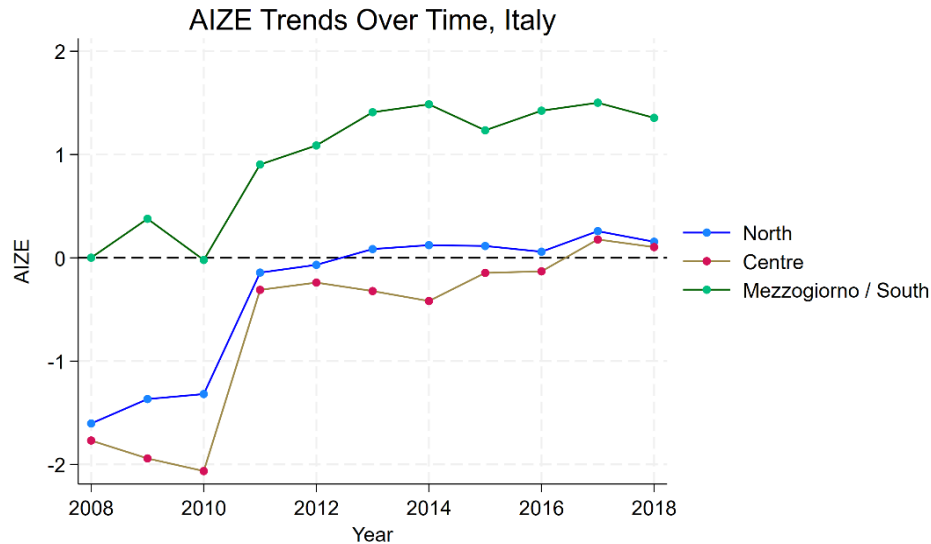


Figure 17. “AI Zone Exposure (2008-2018) in Italy”. Data source: *Italian Labour Force Survey (2008 – 2018)*.

If we go deeper, and observe the AIRE across the periods considered, we can conclude that overall, the Italian regions have experienced a generalised increase in exposure between 2010 and 2012. From 2012 onwards, many of the regions had a steady trend in terms of exposure. Now, if we also consider the regional clusters, but by looking at each individual region in the three clusters, we can observe that for the vast majority of regions in Southern Italy, from 2011 onwards, have experienced an important upward trend in terms of exposure for the period we considered (which matches with the trend for the “Mezzogiorno” zone that we observed previously), whereas we cannot say the same for the regions belonging to the Central and Northern zones of Italy: this can be observed by comparing the AIRE exposure on the heatmap for the periods 2010-2013 and 2014-2018, where we can observe that in terms of scores, Southern Italy has achieved the highest AIRE scores over the period

of

analysis.

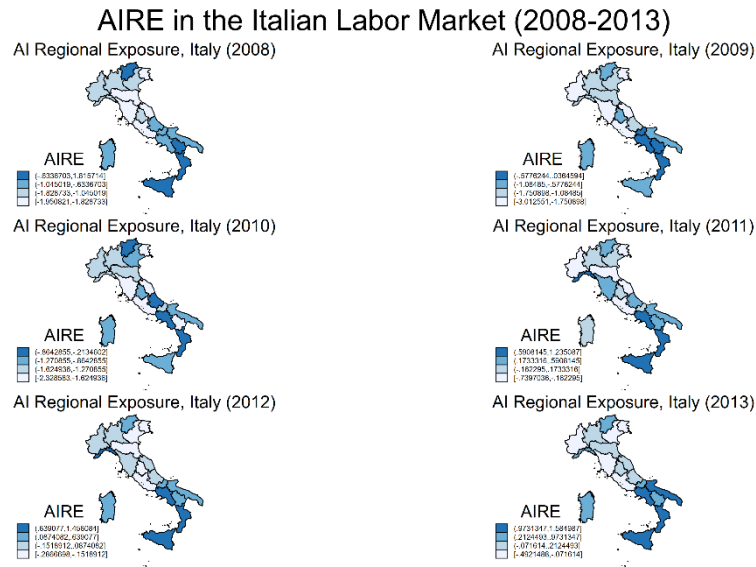


Figure 18. “AI Regional Exposure across Italian regions (2008-2013)”. Data source: Italian Labour Force Survey (2008 – 2018).

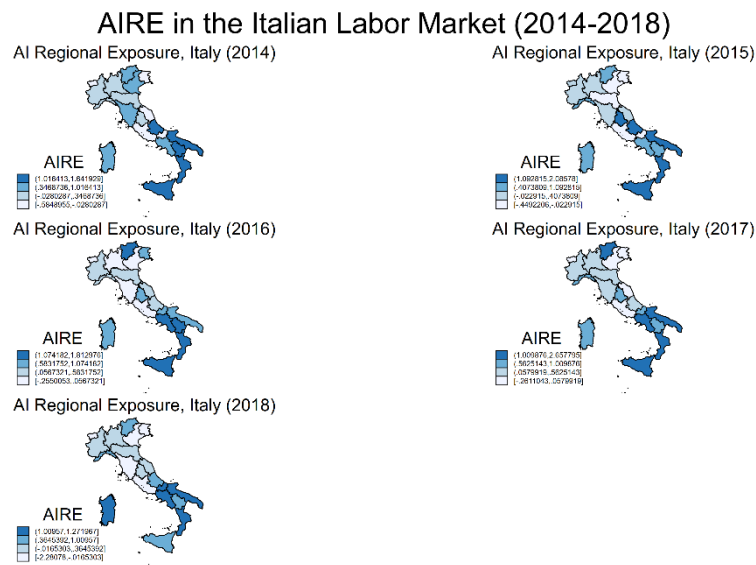


Figure 19. “AI Regional Exposure across Italian regions (2014-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

Finally, we can consider what is the AI exposure in the Italian labour market by considering the demographic sphere:

starting off with the analysis of the AI Demographic Exposure according to the level of education attained (AIDE-E), we can conclude that those with no education and primary education are the ones experiencing the greatest level of volatility and average exposure across the period considered. For those that have attained a level

of education equal to lower-secondary and above experience a lower volatility in terms of exposure. However, if we consider that the jobs require, in most cases, at least upper-secondary education, we will consider only those with an education above the lower-secondary level: by comparing the different time series for each level of education, we can observe that as the level of education increases, the overall levels of exposure tend to decrease and that also the overall volatility for each job tends to get smaller and smaller.

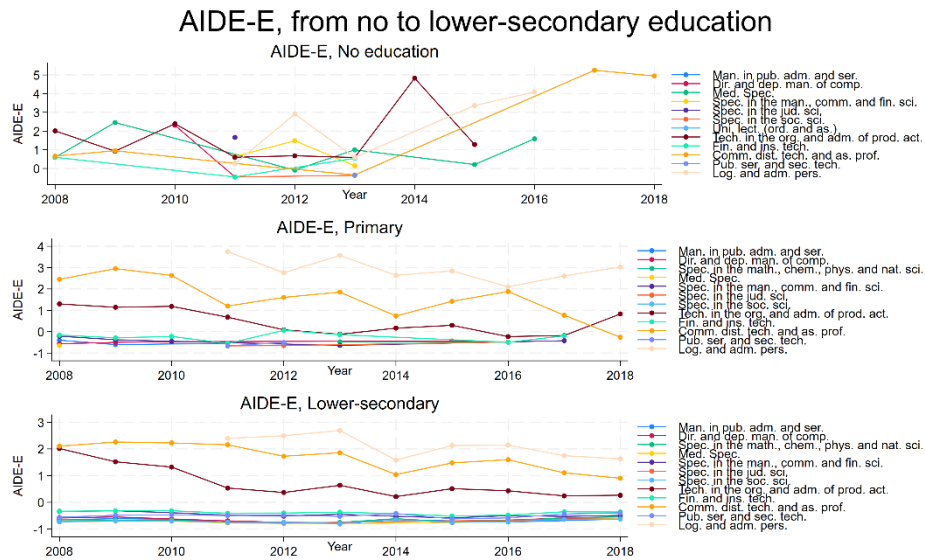


Figure 20. “AI Demographic Exposure – Education. Individuals considered: those that do not have a degree, those who have a primary education and those who have a lower-secondary education (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

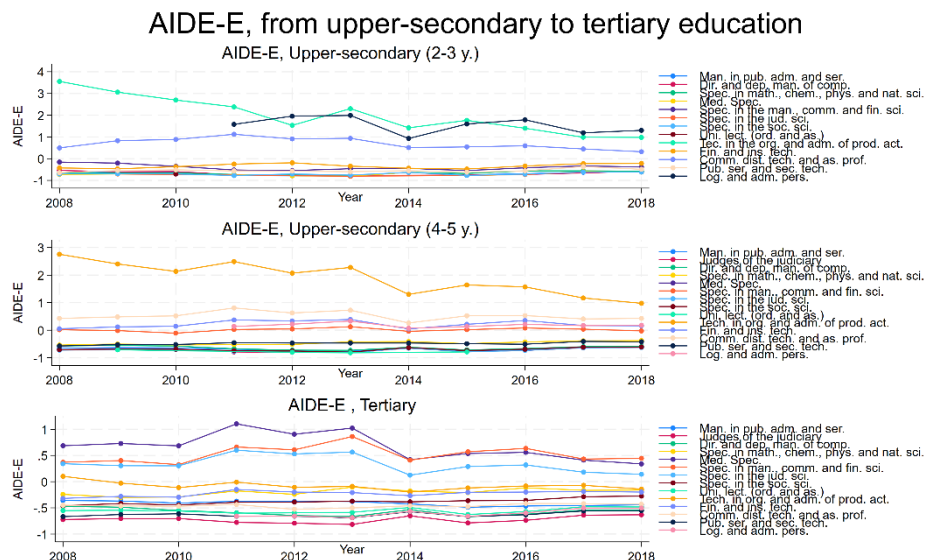


Figure 21. “AI Demographic Exposure – Education. Individuals considered: those who have an upper secondary education and those who have tertiary education(2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

Moving on to the AI Demographic Exposure according to the age class (AIDE-A), we can observe that if we consider the individual professions and compare the exposure level across different age classes, there are many jobs which register for the period considered an overall negative exposure to AI-related technologies: it is the case with the “managers in the public administrations and services”, “judges of the judiciary”, “university lecturers” and the “directors and departmental managers of companies”, where, more or less, all age classes had negative exposure and a downward sloping trend. Contrary to the prior, there are some positions like the “specialists in managerial, commercial and financial sciences” – where almost all age classes have a positive exposure, except for those who have an age between 15-24 – or like the “technicians in organisation and administration of productive activities”, where all age classes have a positive exposure for the entire period, but with a downward sloping trend for the all classes except those with over 75 years of age, where there’s an approximately stable trend. It should be noted the following: (a) there are the “medics” with an age between 65-74 years who are positively exposed to AI technologies, with an upward sloping trend and (b) the “logistics and administrative personnel”, whose age falls between 15-24 years of age, has experienced an upward sloping trend in terms of exposure, which makes it the most exposed

Man. in pub. adm. and ser. (health, education and research included)

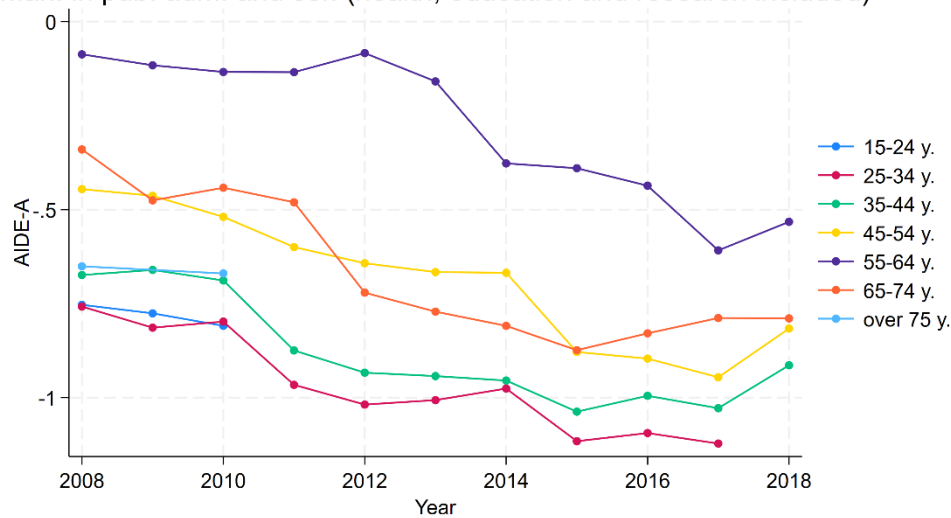


Figure 22. “AI Demographic Exposure – Age: managers in public administration and services (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

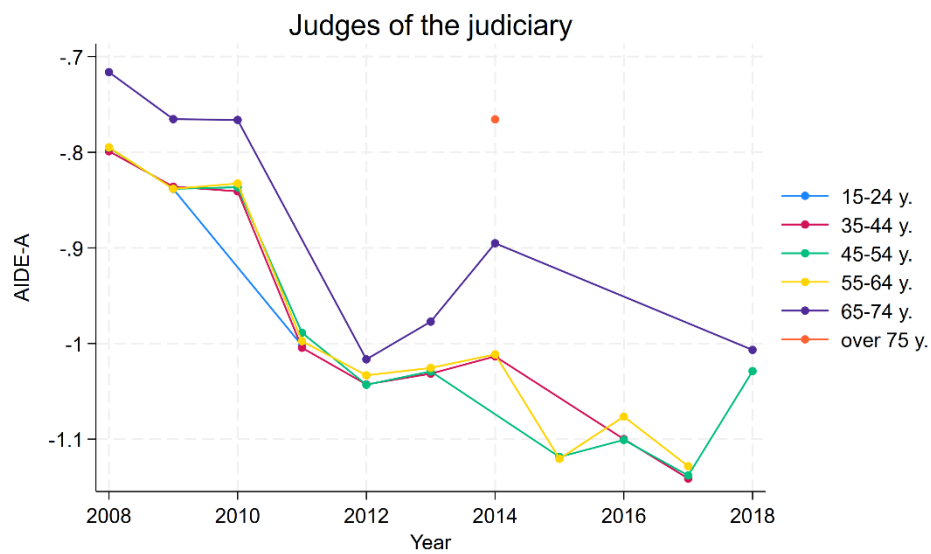


Figure 23. “AI Demographic Exposure – Age: judges of the judiciary (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

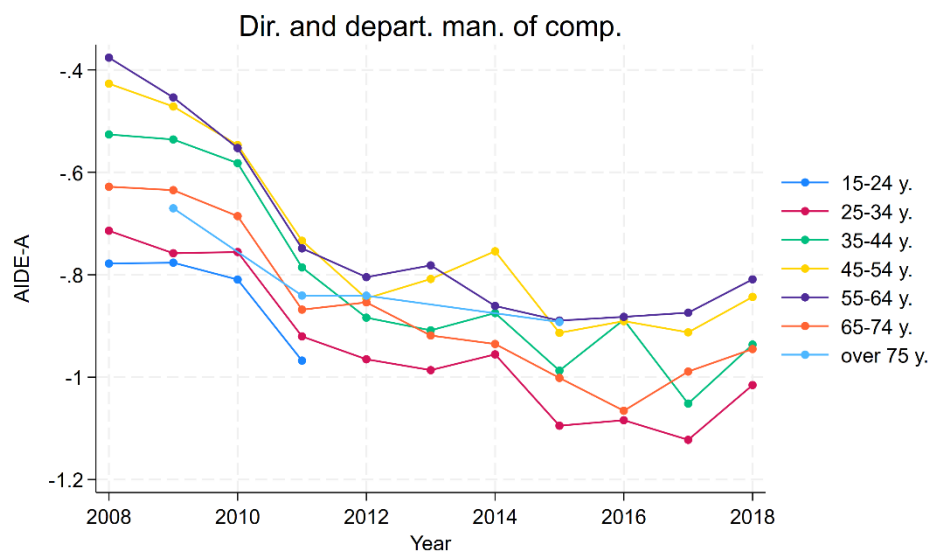


Figure 24. “AI Demographic Exposure – Age: directors and departmental managers of companies (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

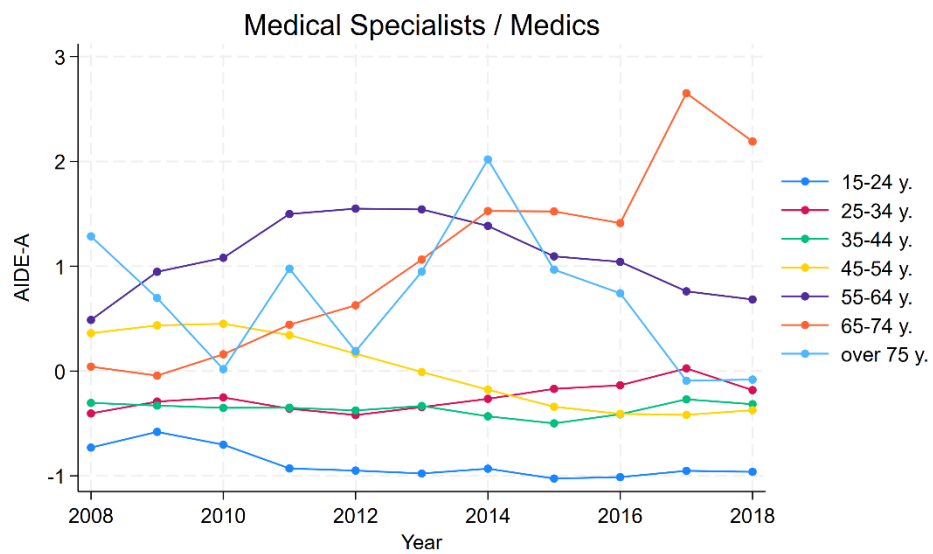


Figure 25. “AI Demographic Exposure – Age: medical specialists / medics (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

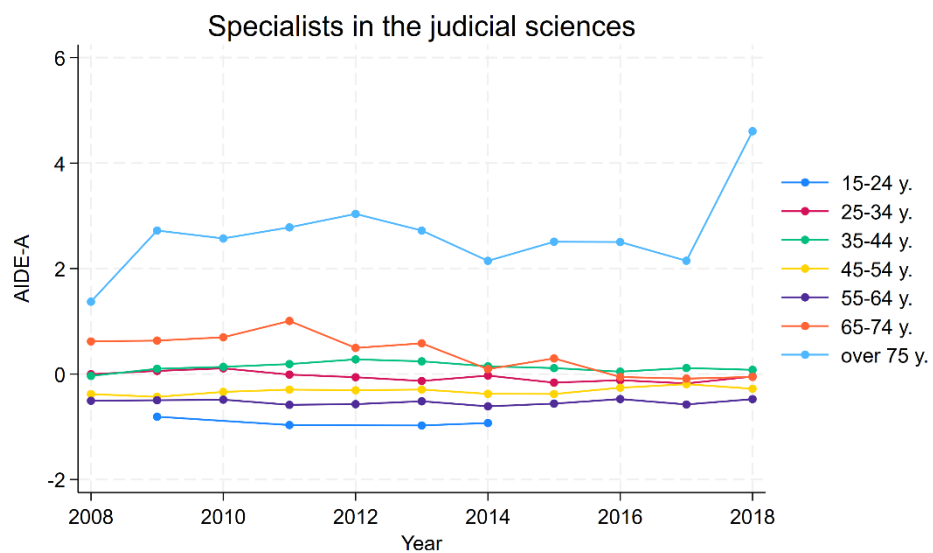


Figure 26. “AI Demographic Exposure – Age: specialists in the judicial sciences (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

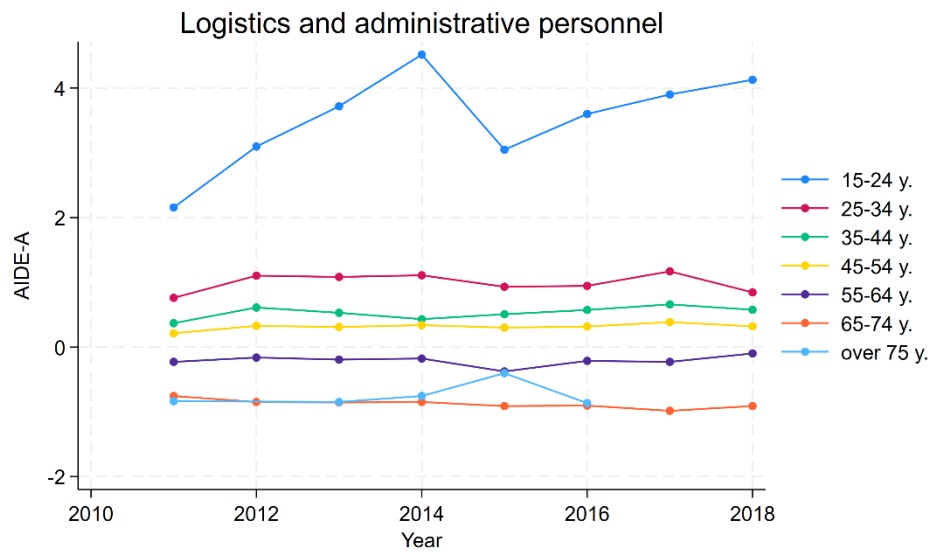


Figure 27. “AI Demographic Exposure – Age: logistics and administrative personnel (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

Last but not least, there’s also the aspect of AI exposure according to the gender: by doing a side-by-side comparison in terms of exposure perceived by males and females, we can observe that for a good part of the occupations, the males have a greater exposure to AI with respect to females. However, it should also be noted that for some positions where both males and females are exposed more or less in the same way to AI (like in the case of male and female judges), but there are also some notable cases like in the cases of “Technicians in the organisation and administration of production activities”, where females are way more exposed to AI than their male counterpart or like in the case of the specialists in the judicial and social sciences, where the gap between female and male widened, making the females relatively more exposed to AI than males.

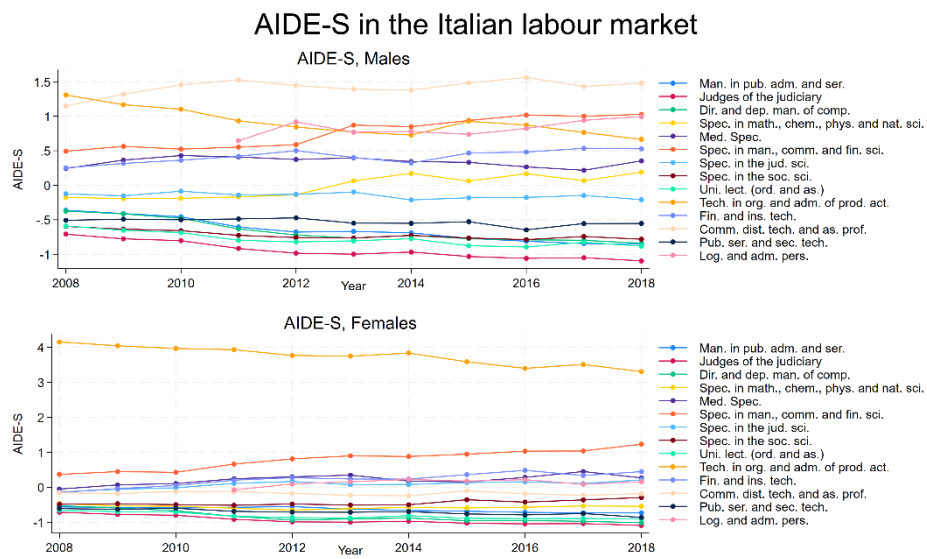


Figure 28. “AI Demographic Exposure – Sex: Males and Females (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

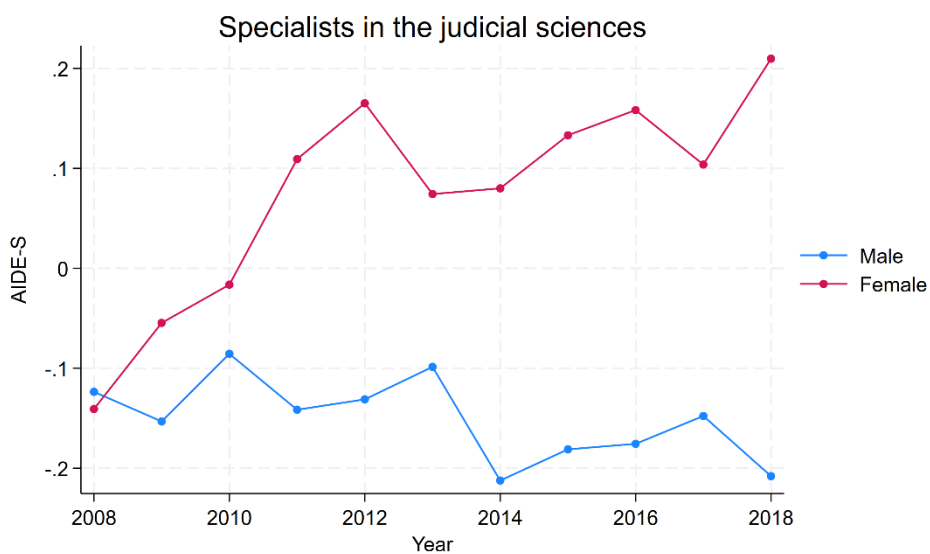


Figure 29. “AI Demographic Exposure – Sex: Specialists in the judicial sciences (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

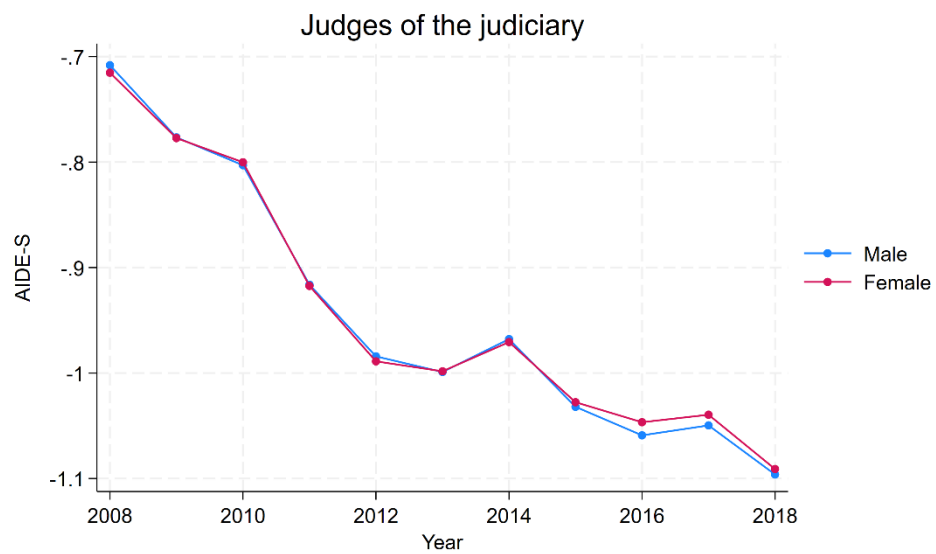


Figure 30. “AI Demographic Exposure – Sex: Judges of the judiciary (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

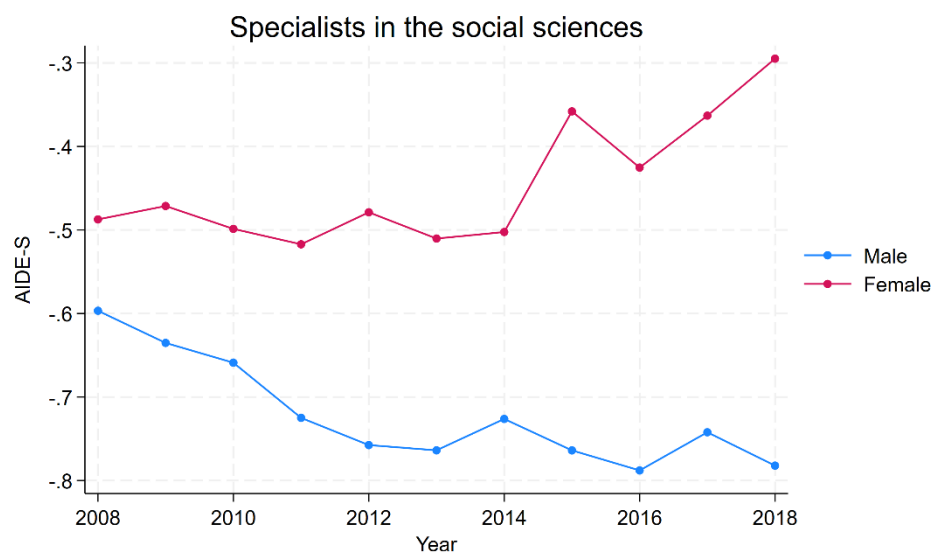


Figure 31. “AI Demographic Exposure – Sex: Specialists in the social sciences (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

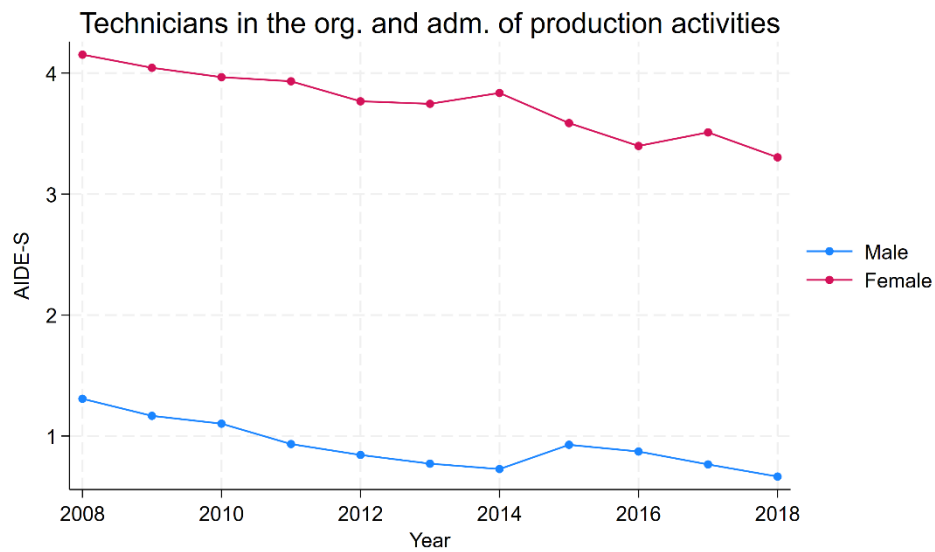


Figure 32. “AI Demographic Exposure – Sex: Technicians in the organisation and administration of production activities (2008-2018)”. Data source: Italian Labour Force Survey (2008 – 2018).

Discussion of the results obtained

Returning to our initial research questions, this study has yielded several important results. First, our analysis revealed that contrary to popular narratives regarding the job displacement of individuals performing blue collar jobs, those that demonstrated the highest exposure scores were knowledge-intensive occupations, suggesting that AI technologies may complement or substitute for cognitive tasks previously thought to be resistant to automation. Now, if we compare our results with the ones that the International Labour Organisation has attained when trying to estimate the “average occupational exposure score”, we can see that our estimations match with the results obtained by ILO (Gmyrek et al., 2023), thus enforcing the fact that Artificial Intelligence technologies will impact more the white-collar occupations.

Moving to our industry-level analysis, we can observe that some industries had a linear trend. Given that we have considered the twenty most exposed occupations based on the AIOE, and that the AIIE – as we specified previously – depends on the AIOE scores, the industries that are going to be considered in our analysis will be, as we stated in the third chapter, the financial, professional services and public services sectors (i.e., the knowledge-intensive industries). Out of these industries, we can conclude that during the period considered, three industries had a “positive exposure” to AI⁴⁸: “commerce and trade”, “real estate, business services and other professional activities” and the “education, public health and other public services”.

⁴⁸ It means that the AIIE > 0 and that they are exposed to AI’s evolution.

Those that have registered, for the period considered, a “negative exposure” to AI⁴⁹ were the financial and insurance sector and the “public administration and defence” sectors. The results obtained across time, however, suggests that relative to the sectors involved, the AIIE scores of the financial, insurance, public administration and defence sectors may be negative due to the fact that some sectors (like “finance and insurance”) already rely on technology for many of the tasks performed in the industry, which may lead to a lower AIIE in general. While for the sectors that have registered a high AIIE, it may be due to the aspect that the occupations pertaining to the industries are sensible to the tasks that the Artificial Intelligence is ought to “replicate”.

Now we can shift our focus to the geographical exposure to AI according to the zones and regions of Italy and we can already deduct that there’s a strong disparity on a territorial level: if we observe the trends that zones had, we can see the South having the highest exposure to AI with respect to Central and Northern Italy. Central and Northern Italy experienced a low exposure to AI due to a higher concentration of knowledge-intensive industries and occupations over time, which led to greater levels of innovation and consequently, to a greater economic growth. The same cannot be said however for the South, especially due to the brain drain that still suffers until now. This problem – mainly caused by government corruption, short-term labour contracts and skill mismatch – led many highly skilled workers to migrate towards Central or Northern Italy, or even move out of the country in search of a job which matches the skills that the workers possess (Abler et al., 2023): this leads to the decrease in innovation potential, which may explain why the AI Zone Exposure was that high for the period considered. The exposure that Southern Italy has is also confirmed by the AI Regional Exposure heat maps: for the period considered, all the regions of the “Mezzogiorno” were always the most exposed every single year (with respect to Central and Northern Italy).

However, if we compare the results obtained with the research performed by Ferri et al. (2024), we can see major discrepancies in terms of regional exposure: their approach was really similar to the one that we have used, but the major difference is that they performed an analysis by considering all the occupations present in the Italian territory, while in our case we magnified our analysis on the most exposed jobs, which has amplified greatly the signal of AI exposure and its volatility, as a result. In addition to the prior, the picture that the paper by Ferri et al. depicts a context that highly matches with the actual occupational reality of Italy (the regions

⁴⁹ It means that the AIIE < 0 and that they’re not as exposed to AI’s evolution.

of Central and Northern Italy are the most exposed due to the concentration of industrial sectors and services in these regions), while in our case, the picture is “flipped upside down”: given that we consider only the occupations with the greatest exposure scores, it will highlight the regions which have the highest concentration of such jobs, without considering how the other occupations we have excluded are “smoothing out” the exposure scores.

Finally, we can move to the demographic-level analysis:

- a. Firstly, if we consider the exposure according to the age group, we can observe that the employed individuals with over 55 years of age are exposed to AI in many occupations (with some exceptions): the results obtained make sense since the group of individuals with more than 55 years is more likely to be the one which doesn’t have the skills required to adopt and use AI and/or the one which doesn’t engage actively in training (OECD,2023, pages 164-166).
- b. Moving to the analysis according to the level of education attained, if we restrict our focus to the individuals that attained an upper-secondary education by completing the whole course of study and to those that attained tertiary education since most jobs considered require at least the attainment of an upper-secondary education qualification, we can observe that the latter are those who experience a lower level of exposure to AI with respect to the former: it implies that even if AI will have an impact on jobs requiring high levels of educational preparation, on a relative level, the individuals with at least a bachelor degree or higher, are those that are less affected by the possible implementation of AI technologies.
- c. Finally, we can analyse the AI exposure according to the gender of the individuals: in occupations like in the case of “directors and department managers” or of “STEM specialists”, the males are more exposed to AI with respect to females. However, if we observe the occupation of “judges”, we can observe that males and females are exposed to AI equally, while in the case of “specialists in managerial, commercial and financial sciences” or of “technicians in the organisational and administration of production activities”, females are more exposed to AI with respect to males. This “AI exposure gender gap” may be due to multiple factors: the kind of degree that the male or female has attained, the exposure to continuous training and learning, and the soft skills that the individual possesses may be some of them, but there may be aspects which cannot be quantified easily.

Conclusions

This thesis has investigated the complex relationship between artificial intelligence technologies and the Italian labour market by using and expanding existing methodologies to measure and analyse exposure patterns across occupations, industries, regions and demographics. The research was motivated by the need to move beyond one-dimensional narratives about AI's impact on employment towards a more nuanced understanding of how AI's capabilities interact with the diverse skill requirements and structural characteristics of labour markets.

Contribution to academic literature

This research contributes to the literature in several ways: from a methodological standpoint, it extends the framework constructed by Felten et al. (2021) to account for the specific characteristics of the Italian context, demonstrating how international approaches can be adapted to different national settings. Empirically, it provides one of the first mappings of AI exposure across highly exposed Italian occupations, industries, and regions over a time span of eleven years, creating a foundation for more targeted research and policy development based on the evolution of AI exposure and how it may change with the advancements of AI. Conceptually, it advances our understanding of how AI interacts with labour markets over a lapse of time by highlighting the multidimensional nature of exposure and vulnerability.

Potential drawbacks

Despite these contributions, this research has several limitations that should be acknowledged. The AIOE methodology, while representing a significant advance over simpler approaches, still relies on expert assessments of AI capabilities that may evolve rapidly as the technology develops. In addition to the prior, there is also the fact that focusing on exposure rather than realized impacts implies that the findings should be interpreted as identifying potential vulnerabilities rather than predicting specific job losses or gains.

Another aspect of relevance is the estimation of the AIRE and AIZE: as we previously explained, there is a great noise in exposure scores due to the exclusion of multiple occupations from the analysis, leading to a “noisy” representation of the occupational reality in Italy. The analysis we performed demonstrated that there’s still some room for improvement in terms of estimating the AI exposure of jobs on a geographical level: the metrics are highly sensitive to whether we exclude a

significant number of occupations and, consequently, to which industrial sectors we consider in our analysis.

These limitations, however, suggest several promising directions for future research: longitudinal studies tracking changes in occupational tasks, skill requirements, and employment patterns over time could provide insights into how AI is actually reshaping work. More granular analyses of occupations and tasks could help identify the precise mechanisms through which AI complements or substitutes for human labour.

Potential implications

These results have significant implications for policy design. Labor market policies will need to become increasingly targeted and responsive to the specific vulnerability profiles of different occupational groups and regions: the educational systems must evolve to develop the types of skills that complement rather than compete with AI capabilities, with particular attention to critical thinking, creativity, people skills, and adaptability. In addition to the development of the educational systems, there should be the creation of a policy incentivising the enterprises to invest in continuous training and learning: through this policy, the individuals will have the opportunity to keep up with the new technologies and, at the same time, develop skill which are transversal. Regional development policies should explicitly consider AI exposure in their design, potentially incorporating strategies to help vulnerable regions develop complementary specializations or build the infrastructure necessary to capture AI's productivity benefits: it may be the case of tax exemptions or tax credits for innovative enterprises that start an activity, operate and develop new AI technologies in the territory of the south of Italy, thus stimulating innovation and, possibly, reverse the brain drain. However, in order to tackle a complex issue like the brain drain of the south of Italy, there must be the development of a policy mix which invests in innovation, infrastructures and education.

Final remarks

In conclusion, this thesis has demonstrated that AI's impact on labour markets is likely to be highly differentiated across occupations, industries, and regions. While these findings highlight legitimate concerns about potential displacement and inequality, they also point to opportunities for initiative-taking policies that can shape AI's integration into the economy in ways that promote inclusive growth. The key challenge for policymakers, educators, and business leaders will be to recognize

and respond to this heterogeneity, developing targeted approaches that address specific vulnerabilities while capitalizing on the complementarities between human and artificial intelligence.

Bibliography

Abler Alexandra, Ebert Alice, Drewes Haley, Hoxha Eneida, Otto M. Jonah. 'Analysing Youth Unemployment and Brain Drain in Southern Italy'. *The Strategic Management of Place at Work, Future of Business and Finance*, 25 June 2023, 137-58. https://doi.org/10.1007/978-3-031-29463-1_7.

Arnold Martin. 'Central Banks Urged to Keep Pace with "Game Changer" AI'. *Financial Times*, 25 June 2024. <https://www.ft.com/content/ccecf5e1-4e49-4110-93d5-bcb627c59562>.

Arnold Martin. 'ECB "Infinity Team" Launches AI Experiment to Speed up Basic Tasks'. *Financial Times*, 28 September 2023. <https://www.ft.com/content/58e4cafe-cb57-4bca-ad4f-b43a98d658df>.

Berg Janine, Snene Mehdi, Velasco Lucia. 'Mind the AI Divide. Shaping a Global Perspective on the Future of Work'. United Nations Office of the Secretary General's Envoy on Technology; International Labour Organization Research Department, 2024. <https://www.ilo.org/publications/major-publications/mind-ai-divide-shaping-global-perspective-future-work>.

Bergmann Dave, Stryker Cole. 'What Is Artificial General Intelligence (AGI)?' IBM Think, 17 September 2024. <https://www.ibm.com/think/topics/artificial-general-intelligence>.

BIS. 'Artificial Intelligence and the Economy: Implications for Central Banks'. *Annual Economic Report*. Bank for International Settlements, 25 June 2024. <https://www.bis.org/publ/arpdf/ar2024e3.htm>.

BIS. 'Project Aurora: The Power of Data, Technology and Collaboration to Combat Money Laundering across Institutions and Borders'. Bank for International Settlements, May 2023. <https://www.bis.org/publ/othp66.htm>.

Bresnahan F. Timothy, Trajtenberg M. 'General Purpose Technologies "Engines of Growth"?' *Journal of Econometrics* 65, no. 1 (January 1995): 83-108. [https://doi.org/10.1016/0304-4076\(94\)01598-T](https://doi.org/10.1016/0304-4076(94)01598-T).

Brittain Blake. 'Meta Knew It Used Pirated Books to Train AI, Authors Say'. *Reuters*, 9 January 2025. <https://www.reuters.com/technology/artificial-intelligence/meta-knew-it-used-pirated-books-train-ai-authors-say-2025-01-09/>.

Bronwyn H. Hall, Francesca Lotti, Jacques Mairesse. 'Innovation and Productivity in SMEs. Empirical Evidence for Italy'. *Small Business Economics* 33, no. 13–33 (June 2009). <https://doi.org/10.1007/s11187-009-9184-8>.

Brynjolfsson Erik, Rock Daniel and Syverson Chad. 'The Productivity J-Curve: How Intangibles Complement General Purpose Technologies'. *American Economic Journal: Macroeconomics* 13(1) (January 2021): 333–72. <https://doi.org/10.1257/mac.20180386>.

Caballar Rina. 'What Are Foundation Models?' IBM Think, 11 October 2024. <https://www.ibm.com/think/topics/foundation-models>.

Carlini Nicholas et al. 'Poisoning Web-Scale Training Datasets Is Practical'. San Francisco, CA, USA: IEEE, 2024. <https://doi.org/10.48550/arXiv.2302.10149>.

Chui Michael, Roberts Roger, Yee Lareina, Hazan Eric, Singla Alex, Smaje Kate, Sukharevsky Alex, Zimmel Rodney. 'The Economic Potential of Generative AI: The next Productivity Frontier'. McKinsey & Company, 14 June 2023. [https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#/.](https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#/)

Colback Lucy. 'The Impact of AI on Business and Society'. *Financial Times*, 16 October 2020. <https://www.ft.com/content/e082b01d-fbd6-4ea5-a0d2-05bc5ad7176c>.

Copeland B.J. 'Artificial Intelligence'. *Britannica*, 21 January 2025. <https://www.britannica.com/technology/artificial-intelligence>.

Felten Edward, Raj Manav, Seamans Robert. 'Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses.' *Strategic Management Journal* 42, no. 12 (28 April 2021): 2195–2217. <https://doi.org/10.1002/smj.3286>.

Ferri Valentina, Porcelli Rita, Fenoaltea Enrico Maria. 'Lavoro e Intelligenza artificiale in Italia: tra opportunità e rischio di sostituzione', Inapp Working Paper, 125 (13 September 2024). <https://oa.inapp.gov.it/handle/20.500.12916/4389>.

Gmyrek Paweł, Berg Janine, Bescond David. 'Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality'. ILO Working Paper. Geneva: International Labour Office, 2023. <https://www.ilo.org/publications/generative-ai-and-jobs-global-analysis-potential-effects-job-quantity-and>.

Guarascio Dario, Reljic Jelena, Stöllinger Roman. 'Artificial Intelligence and Employment: A Look into the Crystal Ball'. Working Paper. Luiss institute for European Analysis and Policy (LEAP), 20 October 2023. <https://leap.luiss.it/publication-research/publications/d-guarascio-j-reljic-r-stollinger-artificial-intelligence-and-employment-a-look-into-the-crystal-ball/>.

Ho E. Daniel. 'Hallucinating Law: Legal Mistakes with Large Language Models Are Pervasive'. Stanford University Human-Centered Artificial Intelligence, 11 January 2024. <https://hai.stanford.edu/news/hallucinating-law-legal-mistakes-large-language-models-are-pervasive>.

Holdsworth Jim, Scapicchio Mark. 'What Is Deep Learning?' IBM Think, 17 June 2024. <https://www.ibm.com/think/topics/deep-learning>.

Householder S. Alton. 'A Theory of Steady-State Activity in Nerve-Fiber Networks: I. Definitions and Preliminary Lemmas'. The Bulletin of Mathematical Biophysics 3 (June 1941): 63–69. <https://doi.org/10.1007/BF02478220>.

IBM. 'Deep Blue'. IBM Heritage. Accessed 20 January 2025. <https://www.ibm.com/history/deep-blue>.

IBM. 'Understanding the Different Types of Artificial Intelligence'. IBM Think, 12 October 2023. <https://www.ibm.com/think/topics/artificial-intelligence-types>.

IBM. 'What Is a Neural Network?' Think. Accessed 20 January 2025. <https://www.ibm.com/think/topics/neural-networks>.

IBM. 'What Is Computer Vision?' IBM Think, 27 July 2021. <https://www.ibm.com/think/topics/computer-vision>.

IBM. 'What Is Unsupervised Learning?' IBM Think, 23 September 2021. <https://www.ibm.com/think/topics/unsupervised-learning>.

Keynes Soumaya. 'How to Get Big Numbers When Predicting AI's Effect on Growth'. Financial Times, 10 May 2024. <https://www.ft.com/content/8ee7fe88-ef5a-405a-9cac-914612fd4c89>.

Lane Marguerita, Morgan Williams, Broecke Stijn. 'The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers'. OECD Social, Employment and Migration Working Papers. Paris: OECD Publishing, 22 March 2023. <https://doi.org/10.1787/ea0a0fe1-en>.

LeCun Yann et al. 'Backpropagation Applied to Handwritten Zip Code Recognition'. *Neural Computation* 1, no. 4 (1 December 1989): 541–51. <https://www.doi.org/10.1162/neco.1989.1.4.541>.

Loewen Peter John, Whiting-Lee Blake, Arai Maggie, Bergeron Thomas, Galipeau Thomas, Gazendam Isaac, Needham Hugh, Lee Slinger, Yusepovych Sofiya. 'Global Public Opinion on Artificial Intelligence (GPO-AI)'. Policy, Elections and Representation Lab (PEARL) and Schwartz Reisman Institute (SRI), 16 May 2024. <https://srinstitute.utoronto.ca/public-opinion-ai>.

Maslej Nestor, Fattorini Loredana, Perrault Raymond, Parli Vanessa, Reuel Anka, Brynjolfsson Erik, Etchemendy John, Ligett Katrina, Lyons Terah, Manyika James, Niebles Juan Carlos, Shoham Yoav, Wald Russell, Clark Jack. 'The AI Index 2024 Annual Report'. Artificial Intelligence Index Report. Stanford: AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, April 2024. <https://hai.stanford.edu/ai-index/2024-ai-index-report>.

McKinney, S.M., Sieniek, M., Godbole, V. et al. 'International Evaluation of an AI System for Breast Cancer Screening'. *Nature*, no. 577 (2020): 89–94. <https://doi.org/10.1038/s41586-019-1799-6>.

Moens Barbara, Foy Henry, Heikkilä Melissa. 'EU Pushes Ahead with Enforcing AI Act despite Donald Trump Warnings'. *Financial Times*, 4 February 2025. <https://on.ft.com/4jFLBWT>.

OECD. 'OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market'. OECD Employment Outlook. Paris: Organisation for Economic Co-operation and Development, 2023. <https://doi.org/10.1787/08785bba-en>.

OECD Council. 'REVISED RECOMMENDATION OF THE COUNCIL ON ARTIFICIAL INTELLIGENCE'. Meeting of the Council at Ministerial Level. OECD, 3 May 2024. <https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449>.

Parikh Tej. 'Erik Brynjolfsson: "This Could Be the Best Decade in History – or the Worst"'. *Financial Times*, 31 January 2024. <https://www.ft.com/content/b71759fe-397b-4688-bc81-b082edb25f31>.

Quoc V. Le et al. 'Building High-Level Features Using Large Scale Unsupervised Learning'. Vancouver, BC, Canada: IEEE, 2013. <https://doi.org/10.1109/ICASSP2013.6639343>.

Romei Valentina. 'IMF Warns of "Profound Concerns" over Rising Inequality from AI'. Financial Times, 17 June 2024. <https://www.ft.com/content/b238e630-93df-4a0c-80d0-fbfd2f13658f>.

Rosenblatt Frank. 'The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain.' Psychological Review 65, no. 6 (1958): 386–408. <https://www.doi.org/10.1037/h0042519>.

Sheehy Benedict. 'Soft Law'. Encyclopedia of Sustainable Management, 11 December 2021, 1–4. https://doi.org/10.1007/978-3-030-02006-4_102-1.

Singla Alex, Sukharevsky Alexandra, Yee Lareina, Chui Michael, Hall Bryce. 'The State of AI in Early 2024: Gen AI Adoption Spikes and Starts to Generate Value'. McKinsey & Company, 30 May 2024. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-2024/>.

Snow Jackie. 'As Generative AI Takes Off, Researchers Warn of Data Poisoning'. Wall Street Journal, 14 March 2024. https://www.wsj.com/tech/ai/as-generative-ai-takes-off-researchers-warn-of-data-poisoning-d394385c?mod=saved_content.

Stryker Cole, Holdsworth Jim. 'What Is NLP (Natural Language Processing)?' IBM Think, 11 August 2024. <https://www.ibm.com/think/topics/natural-language-processing>.

Stryker Cole, Kavlakoglu Eda. 'What Is Artificial Intelligence (AI)?' IBM Think, 9 August 2024. <https://www.ibm.com/think/topics/artificial-intelligence>.

Stryker Cole, Scapicchio Mark. 'What Is Generative AI?' IBM Think, 22 March 2024. <https://www.ibm.com/think/topics/generative-ai>.

Swaine R. Michael, Freiburger A. Paul. 'ENIAC'. Britannica, 11 December 2024. <https://www.britannica.com/technology/ENIAC>.

The Associated Press. 'Mark Zuckerberg Faces Deposition in AI Copyright Lawsuit from Sarah Silverman and Other Authors', 27 September 2024. <https://apnews.com/article/ai-copyright-lawsuit-zuckerberg-deposition-sarah-silverman-meta-df4dec4aef8924d38d258212e0654a3d#:~:text=SAN%20FRANCISCO%20%28AP%29%20%E2%80%94%20Meta%20CEO%20Mark%20Zuckerberg,copyright%20infringement%20to%20train%20its%20artificial%20intelligence%20technology>.

Thornhill John. 'Why AI Hallucinations Can Be a Good Thing'. Financial Times, 1 February 2024. <https://on.ft.com/3u8iGWD>.

Turing Mathison Alan. 'Computing Machinery and Intelligence'. Mind, 1950, 433–60. <https://doi.org/10.1093/mind/LIX.236.433>.

Vaswani A. et al. 'Attention Is All You Need.', 2017. <https://doi.org/10.48550/arXiv.1706.03762>.

Venkataramakrishnan Siddharth. 'Financial Services Counting on AI for a Productivity Boost'. Financial Times, 26 March 2024. <https://www.ft.com/content/9ffe888e-2f78-4f59-9536-2e31f5bde8b7>.

Waskan Jonathan. 'Connectionism'. Internet Encyclopedia of Philosophy. Accessed 20 January 2025. <https://iep.utm.edu/connectionism-cognition/#:~:text=Connectionism%20is%20an%20approach%20to,%2C%20neuron%2Dlike%20processing%20units>.

Wright Robert. 'EY Claims Success in Using AI to Find Audit Frauds'. Financial Times, 3 December 2023. <https://www.ft.com/content/b18961f1-c65c-433b-8dd4-05196fa0e40a>.

Zwass Vladimir. 'Expert System'. Britannica, 10 February 2016. <https://www.britannica.com/technology/expert-system>.