Decoding AI's Evolution Using Big Data: A Methodological Approach

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Abstract: This study presents a novel approach to measuring the impact of Artificial Intelligence on occupations through an analysis of the Atlante del Lavoro dataset and web job postings. By focusing on data preparation and model selection, we provide real-time insights into how AI is reshaping job roles and required skills. Our methodological framework enables a detailed examination of specific labour market segments, emphasizing the dynamic nature of occupational demands. Through a rigorous mixed-method approach, the study highlights the AI impact on sectors such as ICT, telecommunications, and mechatronic, revealing distinct skill clusters and their significance. This innovative analysis not only delineates the convergence of digital, soft, and hard skills but also offers a multidimensional view of future workforce competencies. The findings serve as a valuable resource for educators, policymakers, and industry stakeholders, guiding workforce development in line with emerging AI-driven demands.

1 INTRODUCTION

The integration of artificial intelligence into work processes is set to significantly influence various types of workers, leading to changes in wage structures and skill requirements. Public policies will, therefore, play a critical role in promoting training and ensuring that workers are adequately prepared for the transformations in the labour market. This study aims to provide an innovative analysis of the labour market, focusing on the measure of the impact of AI-related skills across different economic sectors. By utilizing data from the Atlante del Lavoro[1] and online job postings (provided by Lightcast[2]), this study explores the competencies demanded in job postings and characterizes professional profiles, offering a detailed perspective on the emerging labour dynamics in sectors significantly impacted by AI.

To explore this relationship, we apply big data principles, focusing on five key dimensions: volume, by leveraging a large dataset of online job postings for comprehensive labour market analysis; velocity, with near real-time processing to capture dynamic changes in AI skill demands; variety, by combining structured data from Atlante del Lavoro with unstructured job postings for a multifaceted view; veracity, using NLP techniques to ensure data accuracy and reliability; and value, providing actionable insights for policymakers, training institutions, and industry stakeholders on AI-related skills and their economic impact. Through rigorous quantitative analysis and qualitative interpretation, we aim to characterize emerging professional profiles and elucidate the nuanced interplay between AI adoption and skill demand. This approach allows for a granular examination of labour market trends, with particular emphasis on sectors experiencing significant AI-driven transformations.

AI's labour market impact includes job displacement, creation, and transformation. Studies indicate AI automates routine and non-routine tasks, altering work and skill demands. (Lane et al., 2023) highlight how AI transforms roles by automating repetitive tasks, increasing the need for cognitive and socioemotional skills. Generative Pre-trained Transformers (GPT) further revolutionize labour by automating tasks requiring natural language understanding. GPT is widely used in customer service, content creation, and data analysis, enhancing productivity (Eloundou et al., 2023). As GPT reshapes job roles, new training programs are essential for effective AI collaboration. (Squicciarini and Nachtigall, 2021) investigations confirm that the majority of workers developing and maintaining AI possess these specialized skills, although not all workers involved in AI

[1]https://atlantelavoro.inapp.org/
[2]https://lightcast.io

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have these skills to the same extent. The demand for these specialized AI skills has grown significantly in recent years, particularly in the United States, with similar trends observed in Canada, Singapore, and the United Kingdom. Job advertisements increasingly demand AI skills alongside transversal competencies such as social skills and management abilities, indicating their complementary nature.

Our approach innovatively analyzes the effects of AI on job competencies by integrating large-scale job posting data with the Atlante del Lavoro framework. This method provides a detailed view of evolving skill demands and AI-related skills across sectors. Advanced text mining techniques capture emerging trends in real-time, offering more immediate insights than traditional surveys. The dynamic mapping of AI adoption and skill demand reveals subtle shifts in job roles, often missed by conventional methods.

The study begins with a review of the state of the art in research on AI's impact on the labour market. This section will introduce the current understanding and highlight gaps that this research aims to fill. Following this, section 3 presents the data used in our analysis. The data section also covers the preprocessing steps undertaken to ensure the accuracy and relevance of the data for our study. In the section 4, we detail our innovative approach that integrates both qualitative and quantitative data to evaluate the impact of AI on work activities. Advanced Machine Learning and NLP techniques are employed to estimate AI's impact efficiently. This section provides a comprehensive description of the data preparation and model selection processes, highlighting the nuances of our methodological framework. The results section presents our findings on the impact of AI in specific sectors such as ICT, telecommunications, and mechatronic. The conclusion discusses the implications of our findings, the limitations of the study, and suggests directions for future research.

2 RELATED WORK

Recent studies indicate a significant acceleration in the adoption of Artificial Intelligence (AI) across various sectors of the economy. The PwC AI Barometer[3] reports that 52% of companies have expedited their AI adoption plans, with 86% anticipating AI to become a mainstream technology within their organisations by 2024. This trend is corroborated by the OECD AI surveys (Lane et al., 2023), which found that 24% of businesses across OECD countries are currently utilising AI technologies. Notably, there exists a substantial disparity in adoption rates based on firm size, with large firms being ten times more likely to adopt AI than their smaller counterparts.

(Brynjolfsson and McAfee, 2014) highlight AI's dual effect on the workforce: automation of routine tasks and creation of new roles requiring advanced skills. This underscores the complex interplay between technological innovation and labour market shifts, with both job displacement and new opportunities emerging. (Autor, 2015) delved into the polarization of the labour market caused by technological advancements. The research indicates that AI and automation technologies tend to replace middle-skill jobs that involve routine tasks, while simultaneously increasing demand for both high-skill jobs that require creative and cognitive abilities and low-skill jobs that involve non-routine manual tasks. This polarization highlights the need for targeted educational and training programs to equip workers with the skills necessary to thrive in an AI-driven economy. (Frey and Osborne, 2017) utilize a Gaussian process classifier to estimate automation probabilities for 702 occupations, based on O*NET data. The study highlights sectoral automation risks, though it focuses on current technology and technical feasibility, neglecting future advancements and workforce adaptability.

Recent empirical investigations have delved into the specific competencies. (Alekseeva et al., 2021) conducted a comprehensive analysis of job postings, revealing a marked upsurge in demand for AI-centric skills, encompassing proficiency in programming languages such as python, expertise in big data management, and capabilities in model development. Complementing this work, (Acemoglu et al., 2022) explored the intricate relationship between AI technology adoption and evolving workforce skill demands. Their findings underscore the symbiotic nature of technical proficiencies and soft skills in the contemporary labour landscape, highlighting the complex interplay between technological advancement and human capital development in shaping employment dynamics.

The methodological approaches for analyzing the impact of AI on job postings have also evolved. (Manca, 2023) utilized advanced NLP techniques to parse and analyze large datasets of job advertisements, providing real-time insights into emerging skill demands. This approach enables a more dynamic understanding of labour market trends, as opposed to traditional static analyses.

(Eloundou et al., 2023) integrate expert judgments with datasets from O*NET, ILO, and the World Bank, assessing generative AI's impact on 923 occupations

[3]https://www.pwc.com/AIJobsBarometer

across 199 countries. The broad scope and AI exposure scoring system are strengths, though expert reliance and rapid AI evolution pose limitations. Despite extrapolation challenges, the study offers valuable insights for global labour markets. (Weichselbraun et al., 2024) employs a deep learning-based approach to anticipate future job market demands by assessing the automatability and offshorability of skills. The authors use a combination of Support Vector Machines (SVMs), Transformers, and Large Language Models (LLMs) to classify skills and estimate their future relevance. Their findings highlight the increasing demand for skills related to automation and offshoring, driven by trends like the Gig economy and technological advancements.

3 DATA

The Atlante del Lavoro is the Italian classificatory and informative device for work and qualifications, created based on the descriptive sequences of the Classification of 24 Economic Professional Sectors (SEPs). The Atlante del Lavoro was developed as part of the construction of the National Repository of Education and Training Titles and Professional Qualifications, as stipulated by Legislative Decree No. 13 of January 16, 2013[4]. It aims to systematize and correlate the competencies of qualifications from the public lifelong learning offerings with work activities. The sectors were generated by intersecting two independent ISTAT classifications, both in terms of the object represented and the constructive criteria used: the classification of economic activities (ATECO 2007[5]) and the classification of professions (CP 2011, updated in 2023 with CP 2021[6]).

All the codes constituting the aforementioned statistical classifications, at their maximum extension, have been aggregated in the Atlante del Lavoro Economic Professional Sectors (SEPs) to meet the empirical need to identify a "perimeter" where sets of work processes and activities with relative internal homogeneity (intra-sectoral) and sufficient external distinction (inter-sectoral) can be placed and ordered in their information field. The Economic Professional Sectors (SEPs) are articulated into work processes, process sequences, activity areas, and individual activities described following the typical logic of the value chain model (Mazzarella et al., 2017). These descriptors are constantly updated to meet the need to track the evolution of constantly changing work activities.

The INAPP[7] study utilized online job advertisements to calculate skill rates and assess the relevance of these skills for the descriptors within the Atlante del Lavoro, which detail each segment of work. Three indicators were defined to measure the evolution of work dynamics in processes, sequences, and area of activities (ADAs), quantifying the skill rate for each system component (Mezzanzanica et al., 2018). These indicators measure the incidence of digital, soft, and hard non-digital skills on the Atlante del Lavoro's descriptive elements:

$$Skill\_Rate_t = \frac{f_t}{f_s + f_d + f_h}$$

Where t denotes the skill type (digital, soft, or hard non-digital), with f_t representing the frequency of type t, f_s the frequency of soft skills, f_d the frequency of digital skills, and f_h the frequency of hard non-digital skills in the dataset. Three indicators were identified, relating to classes of macro-competencies based on ESCO skills[8], extracted from the job postings database. These indicators measure and monitor over time the degree of digitalization, the demand for soft skills, and the demand for technical/hard skills within Economic Professional Sectors (SEPs), Processes, Sequences, and Area of Activities (ADAs).

The working method can be summarized in the following steps:

(i) Job advertisements are used as measurement tools to elaborate all indices on macro-competencies. Each job advertisement is classified according to the CP 2011 standard, at the 5-digit level.

(ii) Ads are linked to Area of Activities (ADAs) through the associated profession. It should be noted that only advertisements classified according to the occupations belonging to the area of activity contribute to the calculation of indicators. During the association between area of activity and job advertisements, the correspondence between a single area of activity and the occupations may not be one-to-one: each profession can be associated with multiple activities. In this case, if the same profession is associated with multiple areas belonging to the same sequence, the job advertisements for this sequence are considered only once.

(iii) Job advertisements associated with each area can be further filtered based on the industry codes

[4] https://www.gazzettaufficiale.it/eli/id/2013/02/15/13G00043/sg

[5] https://www.istat.it/en/classification/ateco-classification-of-economic-activity-2007/

[6] https://www.istat.it/en/classification/classification-of-occupations/

[7] https://www.inapp.gov.it/en/homepage

[8] https://esco.ec.europa.eu/en/classification

associated with the process Sequence to which the area belongs. The industry sectors filter, in some cases, reduces the expressive capacity of the database, but when present, it refines the match.

(iv) Job advertisements associated with each area report the required skills, categorized according to the ESCO classification and grouped by macro-competency classes.

The skills rate, broken down into macro-competence areas, monitors the results within the area of activity, sequence, or process through successive aggregations and it tracks the evolution of jobs over time.

3.1 Job Postings Dataset

The Lightcast database currently consists of over 21 million online job postings for Italy. After thorough data cleaning, it contains more than 8 million validated job postings. These postings, often in semi-structured or unstructured text, require rigorous scientific, methodological, and technical work to extract useful information. Covering the entire national territory, they provide a rich data source for analyzing various dimensions (occupations, industry sectors, regions, and skills) (Vrolijk et al., 2022).

The processing phases are: (i) Data Collection: Extracting job postings via API, bulk extraction, and scraping. (ii) Data Treatment: Structuring data to meet shared standards. (iii) Text Processing: Preparing unstructured texts for classification. (iv) Classification: Extracting professions and skills from job postings.

Occupations are extracted from texts using a combination of machine learning algorithms that train the classifier based on previously classified and expert-validated occurrences. Skills are extracted using feature extraction techniques and mapped to the ESCO standard. Each skill is then associated with a macro-competence class: digital, soft, or hard-no-digital, defined by the working group using ESCO and O*NET classification pillars. Hard skills are specific job abilities, while soft skills are interpersonal and environmental interaction abilities. Digital skills within hard skills include ICT tool usage to complex system design. Soft skills include thinking, social interaction, knowledge application, and attitudes and values. For each occupation, the required competencies are analyzed, and the frequency of soft, hard non-digital, and digital skills is calculated.

(Lovaglio, 2022) introduces a methodology for analyzing labour market trends using web-scraped job vacancies, revealing the growing importance of digital skills across sectors. Despite potential biases in online recruitment, the approach provides real-time insights. Similarly, (Vermeulen and Amaros, 2024) and (Enrique and Matteo, 2024) assess the validity of Lightcast job posting data compared to national statistics across Europe (2019–2022). Their benchmarking highlights discrepancies but emphasizes the complementary value of online postings for tracking labour demand trends.

4 METHODOLOGY

The methodology involves selecting a representative sample from the Atlante del Lavoro using stratified sampling by Economic Professional Sector (SEP). Sector experts then evaluated the AI impact on sampled work activities. Next, NLP techniques were applied to efficiently analyze the data corpus and estimate AI's impact across all activities. Finally, work activities were classified based on AI impact estimates, enabling a clear assessment of sectoral transformations. This methodology partially draws from (Frey and Osborne, 2017) study. A 5% random sample of areas of activity was extracted using stratified sampling to ensure fair sector representation. The sample comprises 48 Area of Activities (ADAs), with each of the 24 Economic Professional Sectors (SEPs) represented by 2 ADAs (see Table 1).

To ensure the reliability and consistency of the labeling effort, we assessed inter-rater agreement among the five industry experts who evaluated the AI impact on various work activities. Each expert independently assigned scores ranging from 1 to 5, reflecting the perceived impact of AI on specific activities. To gauge the consistency of these assessments, we calculated inter-rater agreement using the Fleiss' Kappa method. The calculated Fleiss' Kappa value of 0.2128 suggests fair agreement among the raters. This indicates some level of consistency in their evaluations, but the variability implies differences in their assessment criteria (see Table 2).

To efficiently analyze the impact of AI on all work activities, a methodology based on advanced machine ,earning techniques was adopted. Initially, Sentence BERT (Bidirectional Encoder Representations from Transformers, (Reimers and Gurevych, 2019)), a natural language representation model, was used to create a data corpus containing descriptions of work activities and their related embeddings. Subsequently, the dataset was divided into training and test sets to train and evaluate the ML models. Various models were explored, including XGBoost (Chen and Guestrin, 2016), linear and polynomial regression, neural networks, and support vector machines

Table 1: Sample of the area of activities evaluated by the experts.

Sector	Area of Activity description
Chemistry	Operation and control of plants/machines in the production of sterile and non-sterile drugs
Chemistry	Processing of plastics and rubber
Construction	Execution of foundations and tunnels
Construction	Painting works
Extraction of gas, oil, coal, minerals, and stone processing	Environmental recovery of disused extraction areas
Extraction of gas, oil, coal, minerals, and stone processing	Preparation and squaring of blocks
Wood and furniture	Selection and storage of lots
Wood and furniture	Packaging of curtains and drapes
Mechanics, production, and maintenance of machinery, plant engineering	Maintenance and repair of mechanical and structural components of aircraft
Mechanics, production, and maintenance of machinery, plant engineering	Maintenance and repair of household appliances and electrical devices

Table 2: Sample of AI Impact Evaluation on work activities from the experts.

Sector	Description	Expert evaluation
Social and Health Services	Implementation of clown therapy interventions	1
Tourism Services	Operational management of bathing services	2
Tourism Services	Operational management of ski slopes and implementation of rescue interventions	3
Printing and Publishing	Handcrafted production of prints using lithographic processes	3
Printing and Publishing	Digital archiving of the publishing house's documentary heritage	5

(SVM), in order to estimate the impact of AI on work activities. Among the various models tested (see Figure 1), those that showed the best performance were selected for subsequent analysis. The performances, computed on the test set and reported in table 3 indicate that the Gradient Boosting model performs best, with an R^2 of 0.417, meaning it explains 41.7% of the variance in the data. The Gradient Boosting model utilizes XGBoost. Key parameters include the number of trees (100), which dictates the ensemble's size, and the learning rate (0.1), controlling how much each tree contributes to the model. The regularization (Lambda: 10) adds penalties to prevent overfitting, and the depth of trees (10) controls tree complexity, balancing model expressiveness and overfitting risk. Subsampling parameters are set to 1.0, meaning the entire dataset and all features are used at each step.

Table 3: Comparison of model performance metrics evaluated on the test set.

Model	MSE	RMSE	MAE	R^2
Gradient Boosting	0.400	0.633	0.490	0.417
Linear Regression	0.494	0.703	0.641	0.282
Neural Network	0.703	0.838	0.635	-0.022
SVM	0.503	0.709	0.587	0.268

Based on the estimates obtained through models, work activities were classified according to their relative AI impact. Activities were divided into categories, including areas with high impact (score $>$ 3.5), medium impact (score $>$ 2 and $\leq$ 3.5), and low impact (score $>$ 1 and $<$ 2). This categorization provides a clear overview of AI's influence on different work activities and sectors.

5 RESULTS

The results of the analysis provided a detailed overview of the impact of AI on work activities across various economic sectors.

5.0.1 AI Impact

Initially, we examined the number of activities classified based on AI impact, distinguishing between high impact (category A), medium impact (category B), and low impact (category C). The results indicate that the most significant number of activities fall into category B (564 activities), followed by category C (254 activities), while category A includes 84 activities.

Analyzing the industry sectors and their respective areas of activity with significant AI impact, data shows considerable variation across sectors (Table 4). For instance, in the "Digital Services" sector, most ADA (63.64%) are classified as high impact; in "Printing and Publishing" and "Construction" 45.45% and 4.17%, respectively. The strong AI presence in ICT related services drives demand for specific skills such as programming, data analysis, and AI itself. Sectors with medium AI impact, like printing and manufacturing, require professionals to adapt

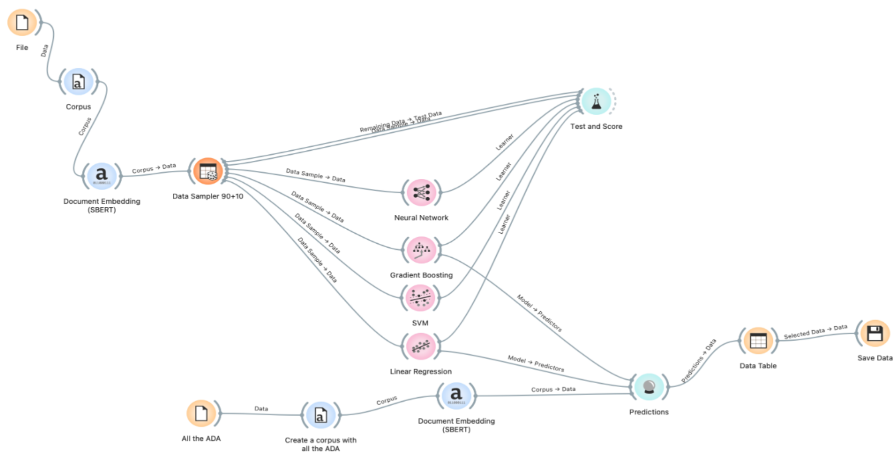

Figure 1: The text mining process to evaluate the AI impact on all the area of activities. The process begins with document embedding using SBERT[9], followed by a data split for training and testing. Four models (Neural Network, Gradient Boosting, Support Vector Machine, and Linear Regression) are trained and evaluated using test data. The best-performing model generates predictions, which are output for further analysis.

their skills to optimize work processes using AI technologies. Even in sectors with limited AI impact, such as education, professional development must address digitalization demands, preparing the workforce for future innovations.

The analysis highlights the need for continuous adaptation of the education and skill development system in response to technological evolution. Training should focus on transversal digital skills, such as critical thinking, problem-solving, and communication, in addition to AI-specific skills and their applications in various sectors (Pedone A. 2024, Conforti D. 2024).

To complete the study, we explored the link between digital skills (using the digital skills rate at the Area of Activity level) and the AI impact on ADA. A polynomial model was used to calculate the coefficient of determination (R^2), which measures how much variation in AI impact is explained by digital skills. The R^2 of 0.2095 indicates that 20% of the variability in AI impact is explained by digital skills. The adjusted R^2 was 0.2078, suggesting the model is appropriate and does not overfit. While a correlation exists, the relatively low R^2 suggests that other factors contribute to explaining AI impact variability, indicating the need for further research (Figure 2).

5.0.2 Digital Services

The analysis of the ICT sector highlights several key findings. The sector shows a high susceptibility to AI-driven changes, with a significant portion of activities impacted by AI. Skill demands are shifting towards AI-related competencies, with a notable emphasis on machine learning, NLP, and data analytics. Digital

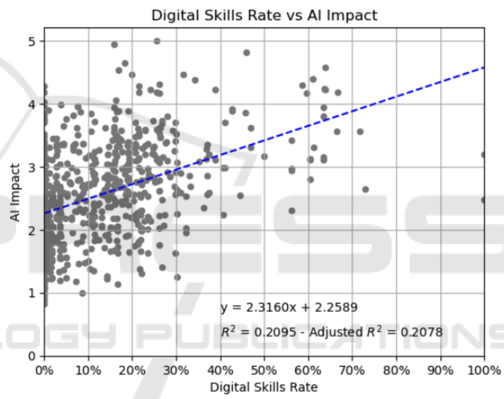

Figure 2: Digital Skills Rate and AI Impact. The digital skills rate is represented on the horizontal axis of this scatter plot, while the vertical axis presents the AI impact.

skills dominate the sector, and soft skills are increasingly valued, especially for roles managing AI. These insights stress the need for an adaptable ICT workforce, capable of continuous upskilling to keep pace with AI advancements (Table 5).

Job postings in 2023 already highlight AI-related skills such as Apache Spark, Machine Learning, NLP, Computer Vision, PyTorch, Deep Learning, Keras, Generative AI, Cognitive Computing, and Large Language Modeling. To attract talent in the ICT sector, it is important to introduce policies focused on upskilling and reskilling the workforce. These initiatives enhance existing employee skills, making the region more competitive and appealing to potential talent. Continuous learning ensures that the workforce stays adaptable, filling skill gaps and positioning the region as a hub for innovation and professional growth (Gatti et al., 2022).

Table 4: AI Impact on the economic sectors.

Industry	A (High Impact)	B (Medium Impact)	C (Low Impact)
Agriculture, forestry and fishing	2.00%	58.00%	40.00%
Food production	4.76%	69.05%	26.19%
Wood and furniture	0.00%	21.74%	78.26%
Paper and papermaking	0.00%	75.00%	25.00%
Textiles, clothing, footwear and fashion system	0.00%	27.50%	72.50%
Chemistry	0.00%	76.00%	24.00%
Extraction of gas, oil, coal, minerals and stone processing	0.00%	43.33%	56.67%
Glass, ceramics and building materials	0.00%	28.57%	71.43%
Construction	4.17%	41.67%	54.17%
Mechanics, machine production and maintenance, plant engineering	11.32%	63.21%	25.47%
Transport and logistics	7.35%	89.71%	2.94%
Commercial distribution services	0.00%	90.00%	10.00%
Financial and insurance services	2.08%	81.25%	16.67%
Digital Services	63.64%	36.36%	0.00%
Telecommunication and postal services	38.46%	61.54%	0.00%
Public utilities services	18.18%	68.18%	13.64%
Printing and publishing	45.45%	45.45%	9.09%
Education, training and employment services	9.38%	90.63%	0.00%
Social and health services	4.17%	79.17%	16.67%
Personal services	0.00%	29.41%	70.59%
Recreational and sports services	0.00%	62.50%	37.50%
Cultural and entertainment services	11.11%	64.81%	24.07%
Tourism services	9.68%	83.87%	6.45%
Common area	20.55%	73.97%	5.48%

Table 5: ADA SEP – High AI Impact Digital Services and corresponding digital skills rate.

Area of activity	AI Impact	Digital Skills Rate
Engineering ICT Systems	4.57	64%
Improving ICT Processes	4.46	20%
Innovation in ICT	4.4	61%
Data Science and Analytics	4.38	34%
Sustainability Management in ICT	4.29	59%
Monitoring Technological Trends	4.23	64%
Information and Knowledge Management	4.23	64%
Problem Management in ICT	4.18	67%
Defining IT Strategy and Aligning with Business	4.16	60%
User Experience Design	3.95	63%
Application Development	3.8	63%
Developing Cybersecurity Strategy	3.62	47%
Providing ICT Services	3.57	66%
Supporting System Changes and Evolutions	3.55	72%

5.0.3 Telecommunications

In the telecommunications sector, AI significantly impacts work activities, as shown by the digital skill rate of area of activity analyzed for this SEP (Table 6). The highest AI impact is seen in Network Architecture Design and Planning (5.00), requiring a 26% digital skill rate. Installation, Configuration, and Testing of TLC Systems have a high AI impact (4.64) with an 18% digital skill rate. Network Management and Supervision also show significant AI impact (4.18) with a 26% digital skill rate. Conversely, Online Shipping Service Programming has a lower AI impact (3.88) with a 19% digital skill rate, while TLC System Maintenance Assistance has a moderate AI impact (3.87) with an 8% digital skill rate.

Job postings in the telecommunications sector highlight the demand for AI-related skills, such as Machine Learning, K-Means Clustering, Deep Learning, and Natural Language Processing. Technologies like Apache Spark, TensorFlow, PyTorch, and Keras are widely adopted, emphasizing the need for skills in data analysis, ICT system management, and project management methodologies.

Table 6: ADA SEP – Telecommunications and Postal Services with High AI Impact and Corresponding Digital Skills Rate.

Area of activity	AI Impact	Digital Skills Rate
Network Architecture Design and Planning	5.00	26%
Installation, Configuration, and Testing of TLC Systems	4.64	18%
Management, Supervision, and Control of TLC System Components and Networks	4.18	26%
Programming and Control of Online Shipping Services	3.88	19%
Assistance/Maintenance of TLC Systems	3.87	8%

5.0.4 Mechatronic

In the mechatronic, AI integration is revolutionizing several operational activities (Table 7). Key areas include programming and automating electronic systems, utilizing AI platforms to optimize production processes, and improving assembly line efficiency. AI solutions in electrical/electronic installation on boats integrate smart sensors and control algorithms, enhancing system safety and reliability. Aerospace sector AI optimizes production of components and vehicles through advanced modeling and virtual simulations. Building automation systems use machine learning algorithms to optimize energy consumption and occupant comfort.

Job postings in this sector frequently mention roles such as electromechanics, industrial engineers, telecommunication technicians, and aerospace engineers. Skills in Machine Learning, Apache Spark, Computer Vision, and Natural Language Processing are highly sought after, indicating a growing need for AI competencies to enhance automation, safety, and efficiency in industrial and electronic systems.

6 CONCLUSIONS

The analysis investigated AI's impact across various labour segments in the Atlante del Lavoro using online job vacancies. Results revealed differing AI impacts, categorized as high, medium, and low, with a correlation between digital skills and AI impact on work activities. Analysis of selected sectors focused on high-impact area of activities, identifying key professions and AI-related skills. A clear distinction was found between AI application roles, which require digital literacy and domain-specific expertise, and AI development roles, which demand specialized skills like Python, SQL, and machine learning. These findings underscore the varied skillsets needed across AI's influence on the labour market.

In Digital Services, AI automates repetitive tasks, requiring new skills for designing intelligent applications like Robotic Process Automation (RPA) and data analysis tools. In telecommunications, AI automates network management, enhances customer interactions through NLP, and improves predictive analytics for network maintenance. In the mechatronics sector, AI-driven robots boost efficiency, and machine learning predicts equipment failures, while simulators optimize production processes and predictive maintenance reduces downtime. In addressing the feasibility of satisfying the required shift in skills, it is important to acknowledge the gap between the demand for advanced AI skills, such as deep learning, and the realistic capacity for most workers to acquire them. While reskilling efforts can help non-technical workers adopt AI-related competencies, expecting a significant portion of the workforce to master complex areas like deep learning is unrealistic. Recent studies suggest that non-technical workers are better suited to focus on skills such as AI collaboration, data literacy, and problem-solving, which are more attainable and still highly relevant in an AI-driven environment (see (Whelan and Redmond, 2024)).

The study has limitations, such as potential biases from relying on online job vacancies and overlooking future AI advancements. The analysis is not exhaustive across sectors, and digital skills measurement may miss emerging trends. Expert evaluations introduce subjectivity, and the study's focus on a specific timeframe and region limits broader applicability. Economic shifts and sectoral AI adoption rates are not fully considered. However, the study emphasizes the need for investment in training programs, identifying two key skill areas: technical competencies for AI system development and general skills for AI adoption and interaction.

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Table 7: ADA SEP – Mechatronic with High AI Impact and Corresponding Digital Skills Rate.

Area of activity	AI Impact	Digital Skills Rate
Programming Electronic Systems for Automation Control	4.53	17%
Installation of Electrical/Electronic Systems on Boats	3.82	7%
Manual and Automated Machine Forming	3.75	0%
Installation and Repair of TV Reception and Signal Systems	3.75	0%
Designing Renewable Energy Source (RES) Systems	3.73	27%
System Integration for Optimizing Aerospace Components and Vehicles Production	3.73	25%
Customer Installation, Commissioning, and Testing	3.71	12%
Design of Thermohydraulic Systems (e.g., civil, industrial, HVAC)	3.69	27%
Installation/Maintenance of Industrial Electrical Systems	3.61	14%
Management and Improvement of Aerospace Production Processes and Logistics	3.61	21%
Building Automation Systems Setup and Management	3.59	26%
Installation/Maintenance of Civil and Commercial Electrical Systems	3.57	11%

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