

AI4Labour: Reshaping Labour Force Participation with Artificial Intelligence

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Abstract

The emergence of Industry 4.0 in the post-Covid era has forced companies to adopt new procedures heavily relying on technologies. While automation and the adoption of new technologies can be helpful in many ways, it also jeopardizes certain jobs, rendering the training of large numbers of workers obsolete. AI4Labour is an H2020 European Project aiming to predict which of these jobs will be at risk of automation in the near future, in order to allow individuals, companies, institutions and policymakers to prepare themselves for the transition. The challenges that AI4Labour faces are **therefore** threefold. First, being able to predict the occupations or tasks that might be replaced by others in the near future. Second, enhancing the relation between task tasks and skills with education and training options, to enable workers to learn new skills or earn the required qualification for the job at hand. Finally, recommending training options to workers for the new skills required by the market. As a result, the innovative skill-based modelling and skill development methodology designed in this project will help reduce the possible negative AI-based impacts on the labour force.

Keywords

Labour market, NLP, Automation, Skill, Task, Training, Knowledge Graph

1. Introduction

Over the past decade, the progress of computing power has been nothing short of remarkable. This progress has led to the emergence of a new era in manufacturing systems called Industry 4.0. Industry 4.0 is characterized by the integration of advanced technologies such as the Internet of Things (IoT), cloud computing, and big data into the manufacturing process. The integration of these technologies has led to the creation of smart factories, which are highly automated and efficient. This has resulted in significant productivity gains and cost savings for manufacturers.

However, the impact of Industry 4.0 is not limited to manufacturing alone. The integration of advanced technologies into other sectors of the economy is expected to have a profound impact on the socio-economic dynamics of society. The recent COVID-19 pandemic has highlighted the vulnerability of the modern labour force to changing conditions. Many workers have been laid off or furloughed due to the economic impact of the pandemic. This has led to a renewed focus on the role of technology in shaping the future of work.

As studies on the future of work predict that 30% cent of global working hours could be automated by 2030 [1], it is becoming increasingly important to consider the role of Artificial Intelligence (AI) in taking on monotonous and repetitive aspects of work currently done by humans. This could allow for a greater focus on strategic or analytical work. However, this also raises concerns about the displacement of workers due to automation.

To address this challenge, the AI4Labour project¹ titled “Reshaping labour force participation with Artificial Intelligence” seeks to predict occupations that will be automated in the near future, as well as the skills needed to attain long-lasting occupations. The project aims to design an innovative skill-based modelling and skill development methodology powered by AI techniques. This methodology will be the foundation for a web portal that will serve as a recommendation tool for individuals, companies, institutions, and policymakers.

The goal of the AI4Labour project is to help workers adapt to the changing demands of the labour market and acquire the skills needed to succeed in the future. By predicting the types of jobs that will be in demand in the future and the skills needed to obtain them, the project aims to help workers stay ahead of the curve and avoid being left behind. The project also aims to help companies and policymakers make informed decisions about the types of skills and training needed to build a workforce that is resilient and adaptable to change. In order to make this easily accessible, a final recommendation portal will be publicly available.

The rest of the paper is organized as follows. Section 2

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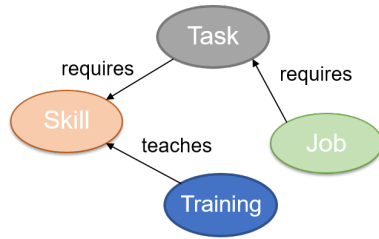


Figure 1: Relation among the different basic concepts of the project.

introduces the terminology and the use case of the project. Section 3 presents the main tasks tackled in the project, grouped as data gathering (Section 3.1), skill modelling (Section 3.2) and recommendation portal (Section 3.3). Section 4 breaks down the participants in the project, both on the industry and research sides. Finally, Section 5 presents the efforts related to the dissemination of the results, while Section 6 summarizes and closes the paper.

2. Context

Before going deeper into the different tasks of the project, it is necessary to clarify both the terminology used in the project and the use case.

2.1. Terminology

In the context of the project, we can distinguish four core concepts, described below:

- Job: an occupation in the labour market. Each job entails a series of tasks to be performed.
- Task: a piece of work to be undertaken in a certain job, such as managing people, writing reports or documenting business processes. Each task requires a set of skills to be carried out correctly.
- Skill: ability that allows a person to undertake certain tasks. Some examples of skills are the ability to speak languages or to handle certain tools. They can be acquired via training activities.
- Training: an activity that allows a person to acquire certain skills. Training activities include MOOCs (Massive Online Open Courses), internal company training or university degrees, among others.

The interaction among these basic concepts is depicted in Figure 1.

2.2. Use case

Figure 2 represents the use case of the project, where we have to detect which tasks will be soon automatized and

recommend users a training option that allows them to obtain a new job. Below we clarify each of the steps in this scenario.

1. We have two employees, Alice (P1) and Bob (P2), who have certain skills that allow them to perform certain tasks in certain jobs (J1 and J2, respectively).
2. Nevertheless, while Alice's job looks safe for now, automation will soon be able to perform the tasks required for Bob's job (J2).
3. Therefore, we inform Bob that there is a high probability of he will soon be losing his job.
4. Luckily, there is one job for which Bob has almost all the skills required (J3), and he would only need to acquire a new one (S8).
5. We inform Bob of this situation and recommend him a course he could take in order to acquire this skill.
6. Bob takes the course.
7. Now Bob acquires the skill and is able to perform the tasks in J3.
8. Bob gets J3 and the impact of automation is minimized.

3. The Project

We summarize below the main tasks tackled in the project, which we can split into different groups (data gathering, skill modelling and recommendation portal). Figure 3 shows the workflow of the project.

3.1. Data Gathering

A fundamental part of the AI4Labour project includes the design of surveys to help to detect undesired situations or changes in the labour market. One of these possible situations is gender bias: there may be gender differences in the predictions, such as some jobs being more often associated with a particular gender than with the other, being these either male- or female-associated jobs primarily disappearing, and, if so, considering an equitable approach to take this into account when making recommendations [2]. Also, different surveys have been designed to gather information regarding the new skills required for several jobs, leveraging the knowledge, experience and contacts of our industrial partners.

In addition to the information retrieved from these surveys, we also rely on previous and ongoing efforts for data gathering, such as the available occupations and skills databases O*NET² and ESCO³.

²<https://www.onetonline.org/>

³<https://esco.ec.europa.eu/en>

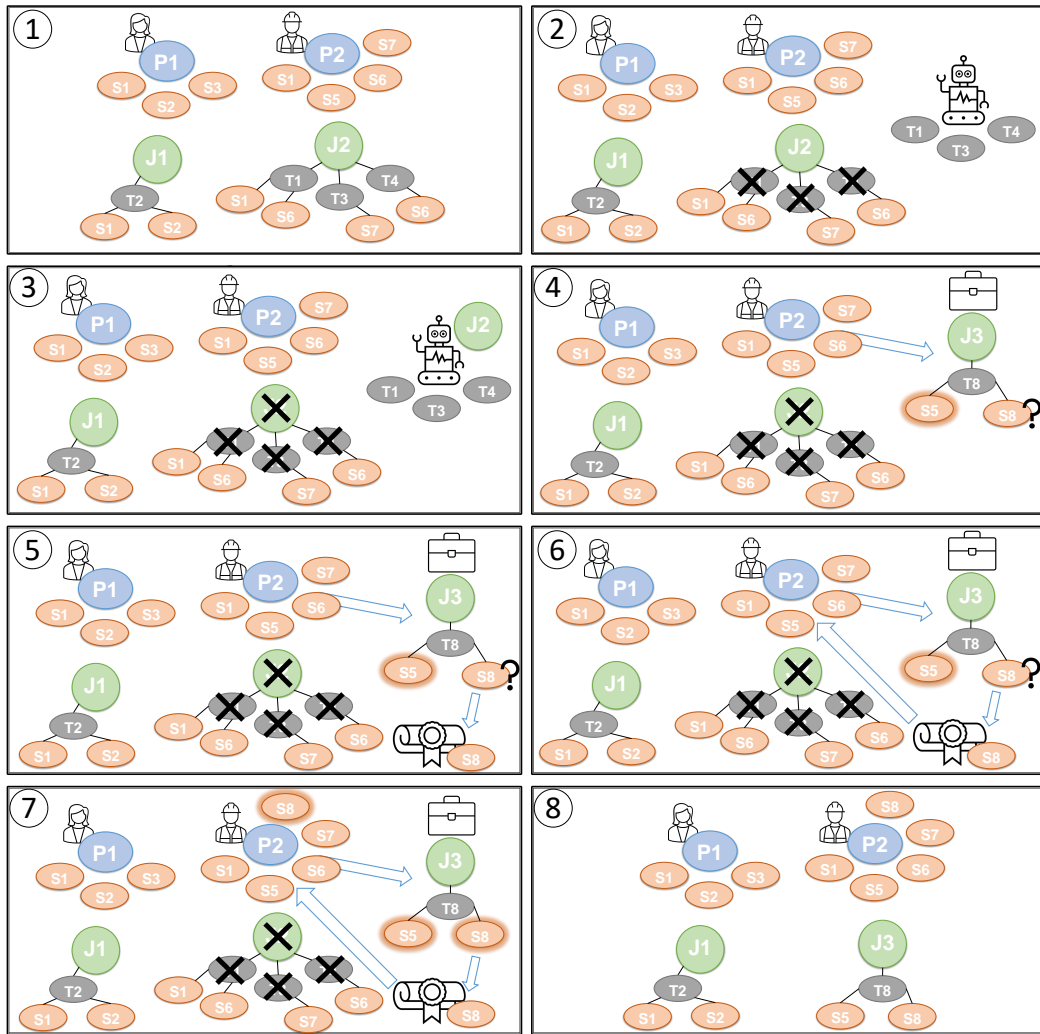


Figure 2: Use case of the project step by step.

The Occupational Information Network Database, known as O*NET, is the primary source of information on occupations in the United States, and it is developed with the support of the US Department of Labor/Employment and Training Administration. This comprehensive database contains standardized and occupation-specific descriptors on nearly 1,000 occupations across the US economy, and it is updated periodically. Each occupation is defined through a set of worker-oriented descriptions, which include knowledge, skills, and abilities that a worker should have, as well as a range of activities and tasks they should perform.

Similarly, the European Commission's multilingual classification of Skills, Competences and Occupations, called ESCO, is a project led by the Directorate-General for Employment, Social Affairs and Inclusion. It is freely available to access and consult, and it can also be downloaded through the ESCO API, which provides access for software agents to analyze the data. ESCO contains descriptions of 3000 occupations and more than 13,000 skills related to these occupations, translated into 27 languages, including all official EU languages, as well as Icelandic, Norwegian, and Arabic.

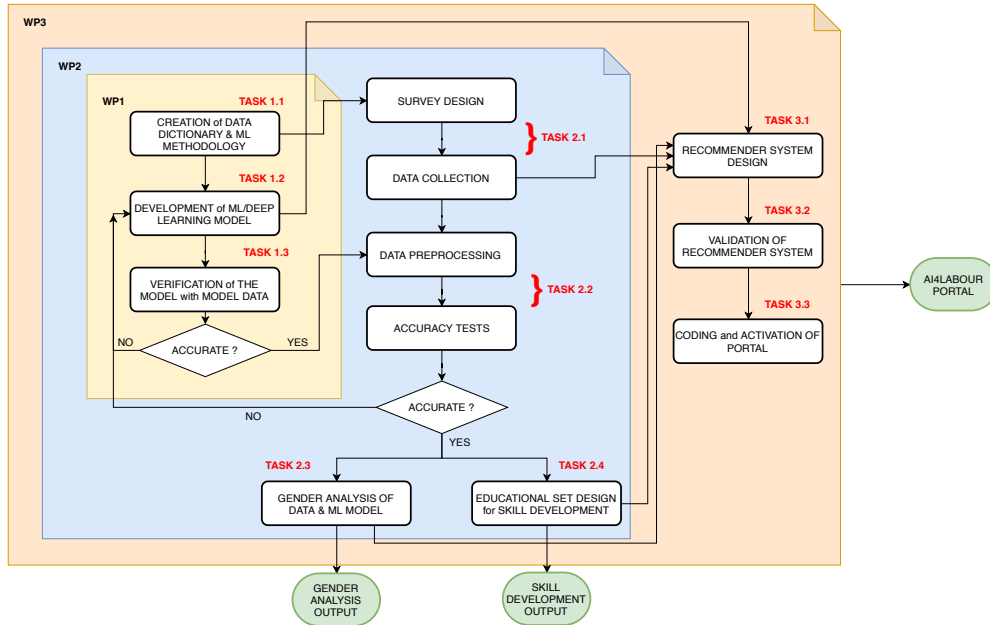


Figure 3: Overview of the tasks in the AI4Labour project.

3.2. Skill Modelling

We are currently using the previously mentioned data sources ESCO and O*NET for two different tasks. First, for training the natural language models that relate skills and tasks, since the input by the industrial partners would not be enough for training and testing. This process involves different steps, such as semantic similarity between the different jobs/skills naming among different countries, task/skill matrix building to assign weights to their relations, and skill clustering and naming.

Once all this information is acquired, it will be represented in an ESCO compliant format, building a Knowledge Graph able to support different applications, such as QA systems or pattern detection.

Second, as useful as the previously mentioned resources are, they do not include information about the training required to acquire the different skills necessary for the performance of the labour activities mentioned. Unfortunately, we have not found either in the literature or industry any training repository that includes the skills or tasks they cover. That is why it has been necessary to extract that information directly from the sources; in the context of the project, different code snippets have been created in order to extract course listings (with their respective skills) from different MOOC platforms. In the future, we plan to work on extracting this information from university teaching guides; however, given the absence of a global repository (and the difficulty of finding

these documents, which are usually "hidden" on university websites and in very different formats), we will focus for the time being on those of the centres participating in the project.

Once we have models able to relate the different pieces of information of interest for the project (see Figure 1), we are ready to use them for user recommendation.

3.3. Recommendation portal

The models created in the previous step allow to:

1. Predict which task will be automatized, and therefore the jobs that are at risk.
2. Based on the input of the user, find the most similar skills/tasks/jobs to theirs in the database.
3. Tell the user if their job is at risk, and if this was the case, recommend available training to increase their possibility to get a new job related to their skills.

These functionalities will feed a portal that allows the user to input their data (current job and skills) and get the risk prediction and training recommendation.

4. Consortium

We can divide the partners in the AI4Labour project into research institutions and industrial partners. This division responds to the purpose of this Marie Skłodowska-

Curie Research and Innovation Staff Exchange project itself, which seek to promote exchanges between companies and research centres and only funds secondments between companies and research centres, never between organizations of the same category.

4.1. Research institutions

KHAS Kadir Has Üniversitesi⁴ is the leader of the AI4LABOUR project. Their research focuses on topics such as Gender and Women's Studies, but also leads the technical developments in the project.

University of Wolverhampton This English university⁵ work focuses on addressing real-world problems, such as the health of ageing populations and sustainable development, in a variety of different ways.

ITCL Instituto Tecnológico de Castilla y León⁶ is a Spanish research institute whose research covers areas such as Energy Technologies, Artificial Intelligence/Electronics, or Simulation (Virtual and Augmented Reality).

University of Limerick , in particular the Kemmy Business School at this university⁷ bring their expertise on strategic HRM, Strategy-As-Practice and Strategic Change, as well as some key areas which underpin organisational strategy such as the Digital Transformation of Work, People Analytics and MNC Leadership/Management.

UPM Universidad Politécnica de Madrid⁸, and more specifically the Ontology Engineering Group, works in different areas of information extraction and management, such as the representation of knowledge (e.g., Ontology Engineering, Linked Data) or Natural Language Processing.

4.2. Industrial Partners

Among the business partners, we find companies operating in different fields.

Arçelik Better known in Europe for being the parent company of *Beko*, this international Turkish company⁹ designs intelligent and networked products at the intersection of AI, software and hardware. As a result of their cooperation with global and competent partners

in research and development, they develop cloud-based platforms in the fields of voice, vision and health and are supported by machine and deep learning techniques.

ICBE The Irish Centre for Business Excellence¹⁰ is a centre based in Limerick (Ireland) that facilitates members to access solutions to organisational challenges. Their principal aim is to promote and develop business excellence through benchmarking, knowledge-sharing forums, and training and development.

DataLobster The France-based company DataLobster¹¹ optimizes operations and maintenance, services and develops digital transformation strategies for globally renowned companies.

5. Dissemination

One of the main objectives of the project is to make AI-related information accessible to layman people, companies and any agent in society. Due to this, a big effort of the project is devoted to the organization of dissemination activities, such as seminars and workshops. Besides the website of the project and the broadcast of a newsletter, also some seminars have been and will be organized, including topics such as "Machine/Deep Learning Applications at Industry", "Skill Gap in Industrial Manufacturing between Today and Tomorrow" or "AI and Data Analytics", as well as workshops on automation, Industry 4.0, education and AI, or gender. Updated information about these events can be found in the webpage of the project¹².

6. Conclusion

In conclusion, the progress of computing power and the emergence of Industry 4.0 is expected to have a profound impact on the socio-economic dynamics of society. The recent COVID-19 pandemic has highlighted the importance of technology in shaping the future of work. The AI4Labour project aims to help workers, companies, and policymakers navigate these changes by predicting the types of jobs and skills that will be in demand in the future and designing the required training to develop these skills.

The results of the project are publicly available both in its Cordis profile¹³ and the webpage of the project¹⁴, and the whole consortium is open to collaboration in order to positively impact the labour market.

⁴<https://www.khas.edu.tr/en>

⁵<https://www.wlv.ac.uk/>

⁶<https://itcl.es/>

⁷<https://www.ul.ie/>

⁸<https://www.upm.es/>

⁹<https://www.arcelikglobal.com/en/>

¹⁰<https://icbe.ie/>

¹¹<https://www.data lobster.io/>

¹²<http://www.ai4labour.com/index.php/events/>

¹³<https://cordis.europa.eu/project/id/101007961/results>

¹⁴<http://www.AI4Labour.com/>

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References

- [1] J. Manyika, S. Lund, M. Chui, J. Bughin, J. Woetzel, P. Batra, R. Ko, S. Sanghvi, Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages, 2017. URL: <https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages>.
- [2] AI4Labour, D.2.2. Report on gender analysis of survey data and model, Technical Report, led by University of Wolverhampton, 2022.