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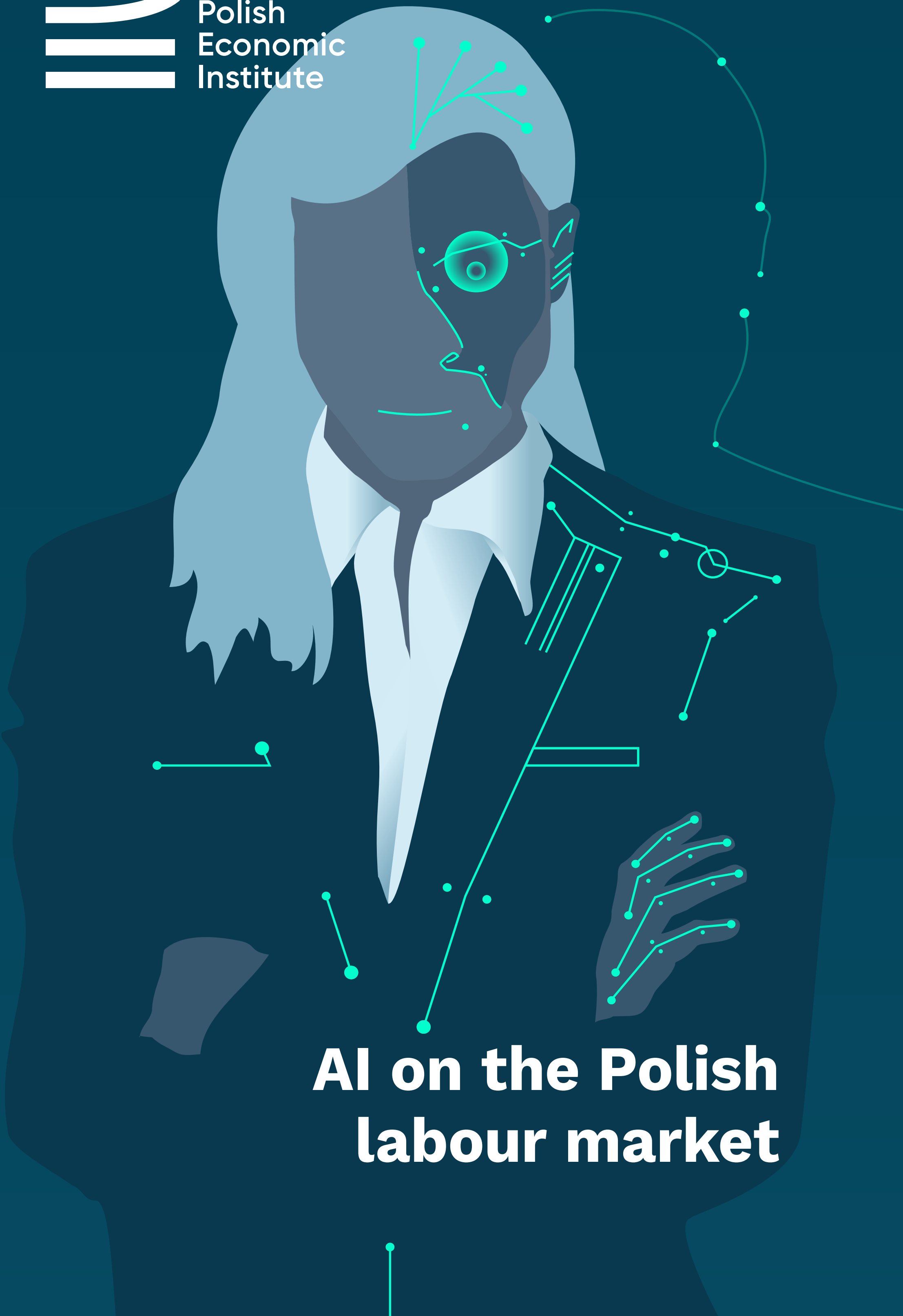

AI on the Polish labour market

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1.66 M

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2.16 M women and 1.53 M men

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82 %

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25.8 %

the percentage of Poles believing that the use of artificial intelligence will have a positive impact on the number of jobs on the market, while **33.4 %** believe it will have a negative impact, while around 40 % have no opinion

more than 65 %

the percentage of respondents in Poland who declared that they have used an AI chatbot at least once, and **almost 2 % declared daily** use

1 in 5

Poles fear that automation of tasks using AI could lead to job cuts in the public sector

Key findings

- Artificial intelligence (AI) has the potential to significantly transform the Polish labour market - simplifying or eliminating some tasks, increasing the productivity of some workers, and increasing the pressure to acquire new skills or retrain almost everyone. In our analysis, we use a methodology used previously for US data to estimate the impact of AI on the Polish labour market (and additionally, we distinguish the impact of large language models and image generation algorithms).
- **The 20 occupational groups most exposed to AI include mainly professional occupation**s - financiers, lawyers, some civil servants, administrative professionals or programmers. On the other hand, the professions least exposed include labourers doing simple jobs in various sectors, cleaners and janitors, and machine operators.
- **Women are more likely than men to work in occupations where AI is highly likely to be used**. This may be because AI is more likely to affect industries where women make up a higher proportion of the workforce, and women are less likely to take on manual jobs and are more likely to be better educated than men.
- **AI will also have a much greater effect on professions that require university-education**. 44 % of people in such professions work in the 20 occupations most likely to be affected by AI, and they account for as much as 82 % of all those working in these occupations. For them, the use of AI could mean an increase in productivity and earnings - which could translate into increased inequality in Poland.
- **Those working in the Masovian, Lesser Poland and Pomeranian voivodeships are most exposed to AI, while those in the Świętokrzyskie, Lublin and Kuyavian-Pomeranian voivodeships least**. This is probably due to the presence of agglomerations and jobs of specialised non-physical workers in the voivodeships with the highest exposure, as well as the more frequent presence of technology and science centres.

- **The figures presented should not be interpreted as the number of jobs that will be replaced by AI**. People working in jobs exposed to AI can expect that some of their tasks will be enabled by AI tools. This can mean both an opportunity to make work easier, acquire new skills and increase productivity, and a risk of downsizing and having to look for a new profession. Depending on actions taken at the individual, institutional and state level, **the long-term effect could mean more quality jobs, increased inequality or the emergence of technological unemployment**.

- The results of our analysis indicate significant differences in the extent to which individuals and groups of people will be affected by AI in the workplace. From the point of view of public policy, this implies the need for differentiated tools that take into account the effects of AI implementation on social cohesion, economic development and spatial development in Poland.

Introduction

The dynamic development of artificial intelligence (AI, Artificial Intelligence) is significantly changing the landscape of the labour market. AI has the potential to automate many tasks that previously required employee involvement.

This can lead to both positive and negative impacts across professions, sectors and regions (Cazzaniga et al., 2024). Automation enables increased efficiency and productivity and allows firms to complete tasks in less time and at lower cost (Acemoglu et al., 2016; Acemoglu, Author, Johnson, 2023). It can also lead to job losses in occupations that are most vulnerable to automation, raising concerns about job security and the need for workers to retrain (Felten, Raj, Seamans, 2021).

Artificial intelligence is already widely used in many sectors, including industry, logistics, finance or services. Examples include automated warehouse management systems, advanced algorithms for analysing financial markets and chatbot-based customer service systems. Despite the benefits associated with the application of AI, there are still numerous challenges to overcome. These include ethical issues related to algorithmic biases, abuse of privacy, blurring of responsibility or the carbon footprint that is generated when training models. In the case of generative AI models (i.e. programmes that create new content based on a query), there are new issues, such as hallucinating models (generating answers that sound convincing but are false or not based in reality). Many people also fear that their workplace will be replaced by artificial intelligence and automated tasks, which could lead to social and economic inequalities (Digital Poland, 2023).

The aim of our study is to understand the impact of AI on the Polish labour market from the perspective of different occupations, socio-demographic characteristics of workers, sectors and regions. We transfer foreign models to Polish realities and analyse which occupations are most vulnerable to automation, to what extent specific sectors of the economy may benefit from the implementation of AI and which regions may experience the greatest changes in employment structure. As part of the study, we conducted a detailed literature analysis, quantitative data analysis and an empirical survey.

In the first chapter of the report, we present a literature review on the impact of AI on the labour market, including the latest trends and forecasts for Poland and the world. In the second chapter, we take a closer look at data on Poles' awareness, opinions and competences. In the next chapter, we present the results of our research, including occupational, sectoral and regional analysis to identify the areas most affected by automation. In the final discussion, we discuss challenges and recommendations for public policy and business strategies that can help mitigate the negative effects of automation and fully exploit the potential of AI.

Chapter 1. Artificial intelligence in the labour market

Automation and the labour market

The development of information technology has started another phase of the debate on the impact of emerging technological solutions on the labour market and raised questions on whether they will change the nature of existing occupations (Felten, Raj, & Seamans, 2021; Mokyr, Vickers, & Ziebarth, 2015). Frey and Osborn's (2017) article, which describes the vulnerability of different occupations to automation and computerisation and assesses which occupations are most likely to be replaced by technology, inspired researchers to attempt to further explore the relationship between modern technologies and the labour market. **Crucially, the impact of automation should be considered in two ways - as a complementary or substitutive factor to manual labour (Council of Economic Advisers, 2024; Felten, Raj, Seamans, 2021)**.

In the case of the substitution effect of automation on the labour market, it can be expected that work previously performed by humans will be partly or fully performed by machines or software. Thus, total employment (whether calculated at company, industry or country level) may decrease. However, the results of the European Labour Market Survey by Doorley et al. (2023) indicate that while progressive robotisation had a negative impact, it was not a significant one. There are also indications that automation has translated negatively into wages across all demographic groups (Doorley et al., 2023). This has meant an increase in income inequality because some of the technologies have been highly complementary to better-educated workers (Autor, Goldin, Katz, 2020; Autor, Katz, Kruger, 1998; Autor, Levy, Murnane, 2003; Goldin, Katz, 2009), and because many of the tools have been used to automate work, with unequal impacts on different types of workers (Acemoglu, Autor, Johnson, 2023; Autor, Levy, Murnane, 2003).

AI and productivity

Currently, the use of AI is driven by large, high-productivity companies (their number in the economy is relatively small). They are significant employers, which translates into their real impact on the labour market (Acemoglu et al, 2022; Council of Economic Advisers, 2024; Kochhar, 2023). **In contrast, optimistic estimates put the impact of widespread AI use at 0.1-1.5 percentage points of annual productivity growth in high-income countries, with slightly lower values estimated for emerging markets (Goldman Sachs, 2024; McKinsey, 2023)**. However, it is also pointed out that these estimates may be too optimistic (Acemoglu, 2024), and how and to what extent artificial intelligence is used may prove crucial (Doellgast, Wagner, O'Brady, 2023). At the same time, irrespective of the conscious implementation by companies, AI has an impact on the processes that take place within them (Council of Economic Advisers, 2024). The discussion about the impact of AI on productivity is reminiscent of discussions about the role of ICT a decade ago. While some researchers have indicated that digital technologies have created new goods and services and increased productivity in some areas (Brynjolfsson, McAfee, 2014), there are also research findings suggesting that the productivity gains that have resulted from these technologies have been well below expectations (e.g. Acemoglu et al., 2016; Acemoglu, Autor, Johnson, 2023).

AI and inequality

Recent changes in technology due to the development of artificial intelligence are complementary to the knowledge and skills of better-educated workers (Cazzaniga et al., 2024). Workers performing manual non-routine tasks have been less affected by recent technological changes, positively affecting the productivity of those performing non-routine cognitive tasks. Since workers performing such tasks (manual and cognitive) are often at the extremes of the income distribution and workers performing routine tasks in the middle, information technology can lead to labour market polarisation (Autor, Dorn, 2013). Research for the US shows that changes in labour market income by decile of the income distribution were U-shaped between 1980 and 2005, although they occurred unevenly over short periods, with concentrations of employment and wage growth alternating on one side or the other of the distribution (Mishel, Schmitt, Shierholz, 2013). Between 2015 and 2019, employment growth was mainly concentrated in the highest-income occupations, and real earnings growth was widespread, although slightly stronger in low-income occupations (Council of Economic Advisers, 2024).

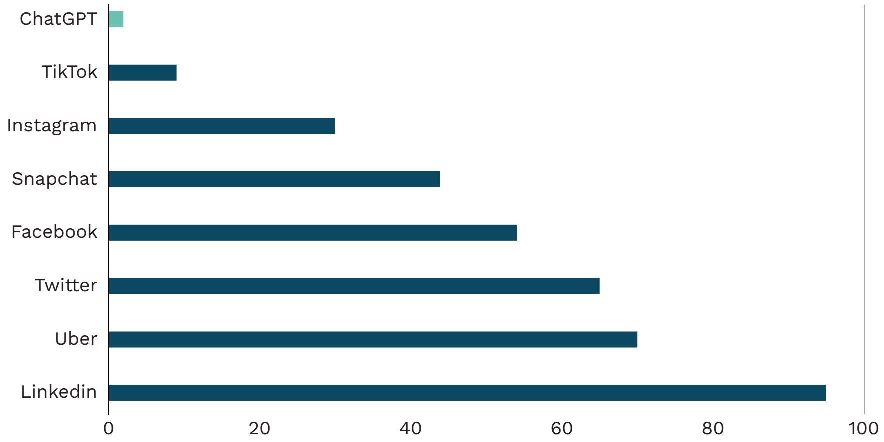
Looking at the demographics, it can be concluded that women are more likely to be affected by AI than men. This is due to their high employment in service and sales positions. In doing so, they are a group that can benefit more from the benefits associated with AI technology, but are also exposed to substitution impacts. At the same time, people with an education above secondary level are more likely to be affected by AI than less educated people. The impact of AI on the labour market may take on a more polarised character in developed countries, where some occupations may be replaced by AI, but at the same time some may gain in productivity (Pizzinelli et al., 2023).

Changes occurring through the increasing use of AI could lead to greater capital accumulation by the wealthy. This would reinforce the rise in income and wealth inequality that results from the increased returns to capital that accrue to high earners. The main reason for the increase in capital income and wealth inequality is that AI leads to labour displacement and an increase in demand for AI capital and increases returns to capital and asset value (Cazzaniga et al., 2024).

GenAI and the labour market

With the release of the ChatGPT app in November 2022, large language models became available to a wider non-specialist audience. The language model from OpenAI has quickly gained popularity with users. ChatGPT set a record by gaining 100 M users in just two months (Hu, 2023). Another 73 M users arrived in the next three months (O'Connell, 2023), translating into 1.8 billion visits per month by April 2023 (Gupta et al., 2023). These figures prove that ChatGPT is the fastest growing app ever.

Figure 1. Time required to reach 100 M app users (in months)



Source: Prepared by PEI.

Recent advances in machine and deep learning have expanded traditional AI tasks such as prediction, classification or recommendation towards generating unique, realistic and creative content, both textual and pictorial (Banh, Strobel, 2023), thereby increasing the number of skills in which AI mimics humans.

Generative artificial intelligence (GenAI) has provided new perspectives for augmenting and automating tasks at work (Banh, Strobel, 2023), especially in terms of ease of use through commercialised tools. Access to GenAI tools can bring tangible benefits to specific professional groups, e.g. reducing task completion time for programmers by up to 56 % (Peng et al., 2023), or increasing the productivity of low-skilled workers in customer service and copywriting (Brynjolfsson, Li, Raymond, 2023; Noy, Zhang, 2023). **Despite the positive rationale, the real impact of artificial intelligence on productivity may prove to be small and translate into only an additional 0.55-0.71 % of total factor productivity and about 0.92 % of US GDP over 10 years (Acemoglu, 2024)**.

The rapidly changing nature of GenAI requires conceptualisation of the properties and capabilities of this technology (Dwivedi et al., 2023; Strobel et al., 2024). In Table 1, we indicate the main differences between artificial intelligence and GenAI.

Table 1. Differences between AI and GenAI

Criterion	Artificial intelligence (AI)	Generative artificial intelligence (GenAI)
Simplified definition	computer software that relies on highly sophisticated algorithmic techniques, can be adaptive, most often used to find patterns in data and make predictions, content or recommendations based on them	a subset of AI focused on creating new data or content
Scope	wide range of applications, including analysis, decision-making, process automation	generation of original content such as text, images, music
Examples of applications	image recognition, natural language processing, recommendation systems	text generation (e.g. ChatGPT), image generation (e.g. DALL-E)
Objective	automation and optimisation of processes, analysis of existing data	creation of new, original content
Approach	analysis and interpretation of existing data	creation of new data based on patterns collected from training data
Examples of models	image classifiers, chatbots, recommendation systems	language models (GPT), image generators (DALL-E, Midjourney)
Techniques	machine learning, deep learning, signal processing	generative models such as GAN (Generative Adversarial Networks) or Transformers

Note: the table above is a simplification to illustrate to the viewer the most important differences between classical and generative AI

Source: Prepared by PEI.

Predictions of the changes that generative artificial intelligence can bring to the economy and society are motivating technology companies in a race to try to gain a competitive advantage by introducing newer and improved models (Rahaman et al., 2023). There are more and more papers showing how models from different companies can pass the bar exam (Katz et al., 2024), the USMLE - US medical exam (Gilson et al., 2023), or the LEK - Medical Final Examination in Poland (Korgul et al., 2023).

These days, cost is a major barrier to implementing new solutions. Even among occupations with theoretically high exposure to AI in the US, companies are holding back from immediately adopting the new technology (Svanberg et al., 2024). Specialised generative AI models may gain more traction if data processing costs fall and methodological improvements are made (Leffer, 2023), while even a rapid decrease in costs would only translate into gradual adoption of the new technology rather than sudden implementation (Svanberg et al., 2024). **Studies conducted for developing countries suggest that the largest differences in GenAI exposure are between gender, employment status and sector**. Higher exposure was found for those with higher education and income and those employed in urban areas. In particular, higher exposure of women and full-time employees in banking, finance, insurance services and public administration has been noted (Gmyrek, Winkler-Seales, Garganta, 2024). As with classical artificial intelligence, it is also pointed out that GenAI is likely to increase the inequalities that exist between the returns to labour and capital, and it has been suggested that it will lead to greater income inequalities between demographic groups (Acemoglu, 2024).

Research on automation in Poland

In Poland, research on the impact of automation on the labour market has been conducted, among others, by the Institute for Structural Research, primarily in terms of industrial robots (Albinowski, Lewandowski, 2022; Bachmann et al., 2022; Doorley et al. 2023; Lewandowski, Szymczak, 2024). The research shows that while the impact of robotisation on the number of jobs is not clear (Bachmann et al., 2022) and the impact on employment levels of the increased use of robots e.g. in Poland is positive, the research of Doorley et al. (2023) points to a negative impact in some occupational groups, insofar as the quality of these jobs is changing. Robotic and digital technologies may increase the share of atypical employment (e.g. involuntary part-time work (Lewandowski, Szymczak, 2024)). The impact also varies between sociodemographic groups: the effect may be positive for women aged 20-49 and negative for those over 60. Younger men doing routine manual work are also at a disadvantage (Albinowski, Lewandowski, 2022). **The results of our study also indicate a heterogeneous impact of artificial intelligence depending on gender or education levels**.

In a recent report, analysts from IBS and Puls Biznesu (IBS, Impact, Puls Biznesu, 2024), using a method also used in this report (Felten, Raj, Seamans, 2021), show how AI can mitigate future shortages in the Polish labour market. The correlation between exposure to AI and projected staff shortages suggests that the greatest use of AI will be in precisely those groups of occupations where shortages will be greatest in a decade or so. In this sense, AI may be an opportunity for the Polish labour market, if, of course, a number of conditions enabling its use are met.

Research method

One of the most widely used approaches to studying the impact of artificial intelligence on the labour market is that developed by Felten, Raj and Seamans (2021), based on assessing the exposure of individual occupations to artificial intelligence (e.g. Cazzaniga et al, 2024; Department for Education, 2023; IBS, Spot Data, Business Pulse, 2024).

For each of the occupations included in the US O*NET classification, the authors assess the impact of artificial intelligence according to the activities required for the occupation (AI occupational exposure, AIOE). Each occupation was described using combinations from a set of 52 skills. An assessment was also made of how relevant each skill is to the occupation.

In the next step, the authors identified the 10 most important uses of AI, such as recognising images or answering chat questions. The next step was to determine to what extent each of the 10 AI applications is related to each of the 52 skills. Finally, using assessments made by those working on the Mechanical Turk platform, an assessment was made of how suitable each of the AI applications is for each of the 52 activities - in other words, how much AI can be used to perform such an activity. These activities made it possible to assess the impact of AI on each of the occupations from the O*NET database.

It seems crucial that the method adopted in this way allows only a relative comparison of individual professions (i.e. from those on which AI will have the least impact to those on which it will have the greatest impact). It also does not resolve whether a given activity will be replaced or supported by AI - the results obtained in this way cannot be interpreted in terms of AI replacing activities or professions. It can only be inferred that in occupations with a higher AIOE factor, the role of AI will be greater - so workers there will face greater changes.

Table 2. 10 AI application on which the AIOE indicator is based

AI Application	Definition
Strategy games	the ability to play at high-level abstract games sometimes requiring complex strategy and reasoning, such as chess, go or checkers
Real-time video games	the ability to play a variety of real-time, high-level video games of increasing complexity
Image recognition	the ability to identify which objects are in a still image
Responding to visual questions	the ability to recognize events, relationships and context from a still image
Image generation	creation of complex images
Ability to read with comprehension	the ability to answer simple questions that require understanding of the text
Language modelling	the ability to model, predict or imitate human language
Translation	translation of words or text from one language into another
Speech recognition	translating spoken language into text
Recognition of instrumental works	identification of instrumental musical works

Source: Prepared by PEI based on Felten, Raj, Seamans (2021).

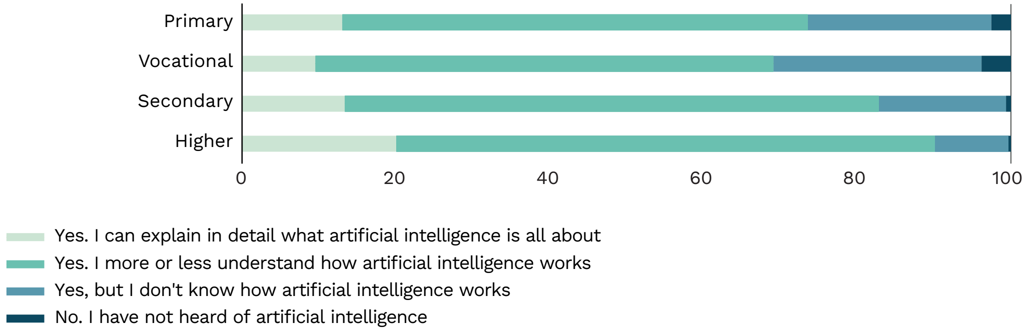
What is presented above is not an exhaustive list of AI applications, it is a simplification indicating its basic applications, which include the most likely and most common uses of AI that could impact the workforce. While we cannot say whether high exposure will lead to higher or lower employment, we accept that it is likely to mean major disruption to the content and organisation of work, and along with it major uncertainty in the affected demographic groups..

Chapter 2. Artificial intelligence in the Polish labour market

Poles' awareness of AI

According to a 2024 survey by the Polish Economic Institute, Poles have varying knowledge of artificial intelligence. Most respondents have heard of AI, but their declared level of understanding of how artificial intelligence works depends on their age, gender and level of education (Łukasik, Korgul, 2024). 14.5 % of respondents claim to be able to explain in detail what artificial intelligence is all about, while 67.4 % have a general knowledge of it. A further 16.9 % admit that they have heard of AI but do not know how it works, while only 1.2 % have never heard of it. Education plays a key role in the level of knowledge about AI - the higher the level, the greater the belief in understanding artificial intelligence. An exception is the group of respondents with primary education; however, in this group, individuals from the youngest age groups are overrepresented, which may positively influence the declared familiarity with AI. (Łukasik, Korgul, 2024).

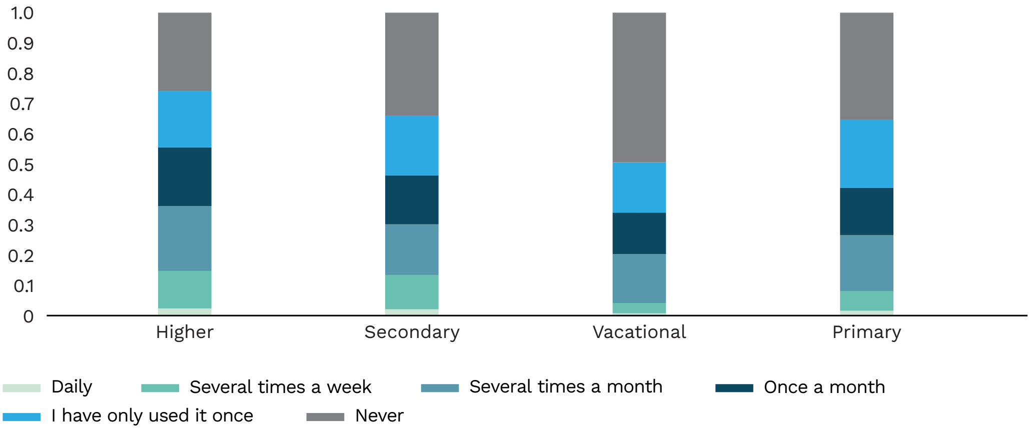
Figure 2. Respondents' answers to the question 'Have you heard of artificial intelligence?' by education (%)



Source: Prepared by PEI.

The use of AI chatbots, such as Gemini or ChatGPT, is increasingly common in Poland (Kucharczyk, 2023). The frequency of use of these tools varies according to the age, gender and education of the users (Łukasik, Korgul, 2024). **More than 65 % of respondents said they had used an AI chatbot at least once, and almost 2 % claimed they use one daily**. 14 % of those with tertiary education say they use an AI chatbot at least a few times a week, while in the case of those with vocational education and primary education these figures are 3% and 8%, respectively. In contrast, half of those with vocational education and 36 % with primary education have never used a chatbot. Among those with secondary education, the figure is 34 % and for those with higher education it is 26%.

Figure 3. Share of responses to the question 'In the last 3 months, how often have you used an AI-based chatbot (e.g. ChatGPT, Gemini, Copilot)?' by education (%)

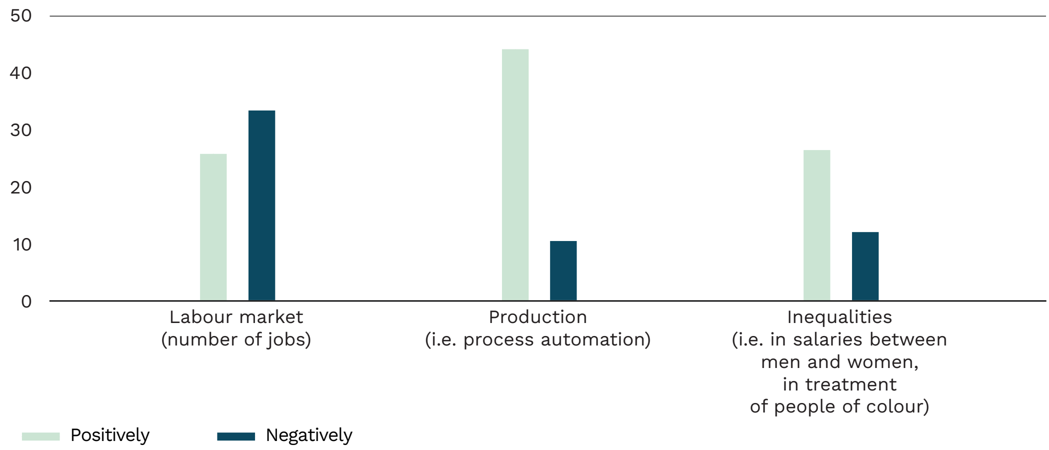


Source: Prepared by PEI.

Poles' opinions on the impact of AI on the labour market

According to the April 2024 PEI's survey, 25.8 % of respondents believed that the use of AI would positively impact the number of jobs, while 33.4 % indicated that it would have a negative impact. At the same time the majority of respondents expect a positive impact of AI on production processes and a reduction in inequalities (Figure 4). In another question one in five respondents (20.5 % of women and 19.5 % of men) were concerned that the automation of tasks using AI could lead to job cuts in the public sector, raising questions about the future of employment and social security for workers.

Figure 4. Percentage of responses to the question ‘How do you think the use of artificial intelligence will affect the following areas?’



Source: Prepared by PEI.

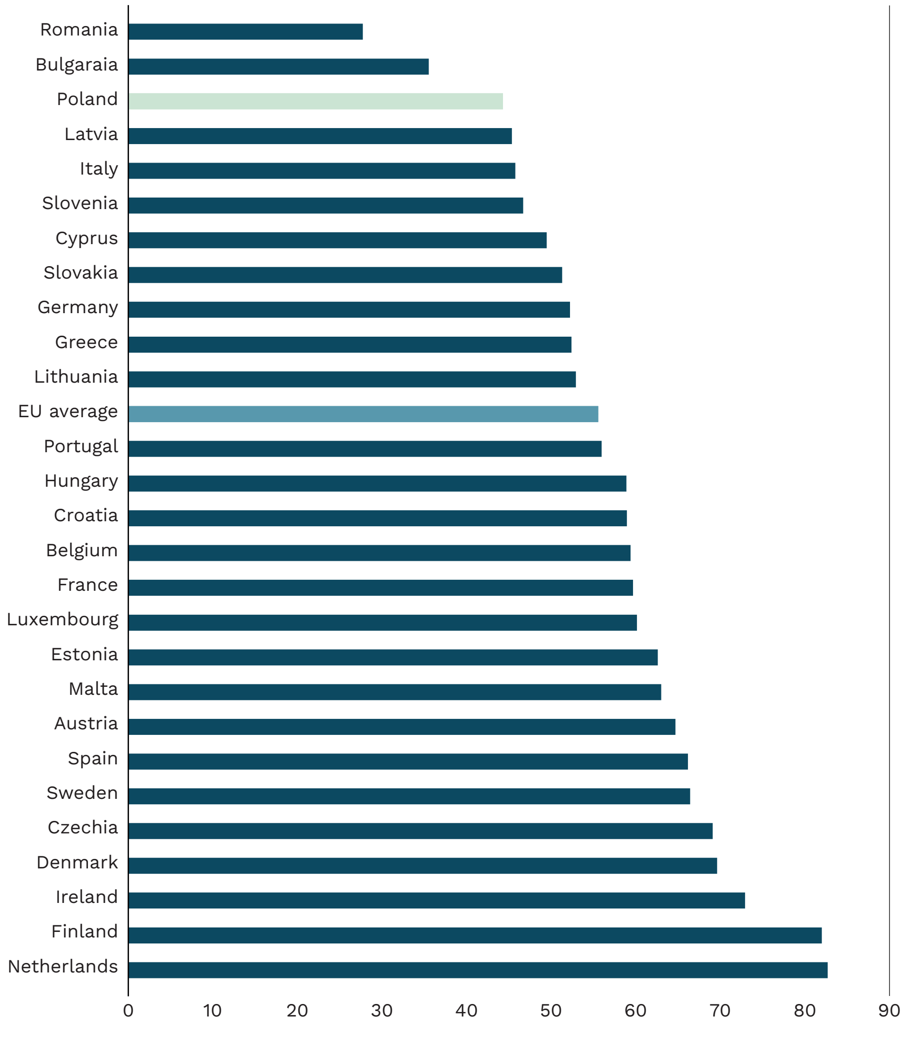
The Digital Poland (2024) survey also reveals mixed feelings among the Polish public about the impact of artificial intelligence on the labour market. According to it, as many as 42 % of respondents believe that AI will eliminate more jobs than it will create. Those with higher education (43 %) are more likely to express this concern than those with primary education (31 %). Only 18 % of Poles believe that AI will create new jobs, and this group is dominated by young people (26 %), residents of large cities (21 %) and those who are more knowledgeable about AI (22 %).

Digital competences of Poles

Digital skills are one of the key factors for the use of artificial intelligence with positive effects on the labour market. Poland is one of the countries with a low use of ICT technologies and a low level of digital skills, and in this respect ranks third from last in the European Union.

The overall assessment of digital literacy levels is made up of data from several areas. Poles are better at using information and data (e.g. verifying information available online) and solving problems in the digital environment (e.g. e-banking or changing application settings). Our weaker areas are creation of content (texts, spreadsheets, editing files), using content responsibly (including, for example, managing personal data) and communicating in the digital environment. **Despite this, Poles significantly underperform the EU average in each of these categories. Such a situation may lead to a number of unfavorable consequences**. In the economic sphere, it could mean a slower adoption of new digital solutions, and thus a loss of competitiveness for Polish enterprises. In the social sphere, it may result in susceptibility to the negative effects of technological development.

Figure 5. Percentage of people with basic or above-basic overall digital skills in 2023 in the EU27



Source: Prepared by PEI based on data from CEDEFOP.

Chapter 3. Investigating the impact of AI on the Polish labour market

Creating an AI impact study for Poland

In this report, a methodology based on the calculations of Felten, Raj and Seamans (2021) is used. Above all, it is one of the most widely used methodologies by international institutions and individual countries evaluating similar assumptions (Department for Education, 2024) to analyse occupational exposure to AI on a national scale. In doing so, it allows not only for the analysis of general exposure to AI, but to specific models for generating images and text (large language models), which are particularly changing the labour market in recent times. The methodology also gives relative results (i.e. it ranks groups of occupations in terms of exposure to artificial intelligence) - without indicating a specific number of workers affected in one way or another - which we believe is a more appropriate approach when technology such as artificial intelligence is changing so rapidly.

It is worth noting that our approach is based on data from the U.S. labour market. This primarily concerns the assignment of tasks to specific occupations (and thus the assessment of the degree of exposure to AI, which depends on these tasks). The scope of tasks performed in particular occupations may differ in Poland compared to the U.S. Additionally, to aggregate occupations into larger groups, we used employment data from the U.S. market. This makes the calculations for the Polish market, conducted on these occupational groups, less precise. As a result, the findings we obtained may not fully reflect the specific conditions of the Polish market and should be interpreted with caution.The analysis used data for 938 occupations (O*NET classification), which were aggregated to 121 groups of occupations in line with the classification of occupations and specialities (KZIS). The transition between databases used a database created by the Institute for Structural Research (IBS, 2016), and data on the number of workers in each occupation group came from the LFS for 2022. Twelve occupations from the original list were not included due to a lack of equivalents in the KZIS database.

Three AIOE measures were used for the analysis - an original measure that considers AI based on the 10 tasks identified earlier (AIOE), a measure that considers the impact of large language models (LLM), and a measure that refers to image generation (GenIm), extracted from the original database repository (www1). The original AIOE measure is used to assess the overall impact of AI on different professions, allowing to analyse to what extent tasks in these professions can be automated or assisted by AI. **The AIOE measure is also treated by us as the primary indicator of the exposure of various occupations to AI, while the other two serve as supplementary measures**. The AIOE LLM focuses on the impact of large language models on text processing and generation tasks, such as writing or data analysis. AIOE GenIm, on the other hand, is used to measure the impact of image-generating technologies. Each of these measures takes into account the specific capabilities of the relevant AI technologies and their potential impact on the labour market. It is important to note that the AIOE standards were created to reflect the realities, and skill sets specific to US occupations. Due to the different level of technical sophistication, digitisation or automation in comparable occupations between the US O*NET and the Polish KZIS, it is possible that the results of the survey conducted using this method in Poland may be partially distorted.

Results – the impact of AI on the Polish labour market

There are currently around 3.68 M people in Poland working in 20 occupations that will be most affected by artificial intelligence (measured by the broadest AIOE measure). This represents about 22 percent of all employed individuals covered by the study (approximately 16.5 million). A list of these professions is presented in Table 3. The professions most exposed to artificial intelligence include, in particular, those requiring higher qualifications and specialists - financiers, lawyers, programmers. Mathematicians, some civil servants, secretaries, as well as academics and some business executives are also classified in this group. **As predicted by other studies, these are largely workers doing non-routine and cognitive work, which distinguishes this wave of automation from previous ones**.

In contrast, the occupations most exposed to the use of large-scale language models (LLM) or image generation technologies have 3.45 M and 3.43 M employees, respectively. These occupations mostly overlap with those listed as most vulnerable to change due to the use of artificial intelligence, but there are five new groups of workers for LLM and six for image generation.

Occupations that have a high exposure to LLM but did not appear on the list of professions most exposed to the effects of artificial intelligence according to the AIOE measure are secondary school teachers; administrative staff and specialist secretaries; sales agents and brokers; other teaching and educational professionals and customer information staff. For image generation, they are architects, surveyors and designers; physicists, chemists and earth science specialists; managers in mining, industry, construction and distribution; specialists in biological sciences and related fields; technicians in physical, chemical and technical sciences; and managers for other types of services.

Table 3. Jobs that are most exposed to AI

	AIOE			AIOE LLM			AIOE GenIm		
Rank	**Group of occupations**	**Number of employees in Poland (K)**	**Score**	**Group of occupations**	**Number of employees in Poland (K)**	**Score**	**Group of occupations**	**Number of employees in Poland (K)**	**Score**
1	financial specialists	293.7	1.45	legal specialists	137.2	1.46	architects, surveyors and planners	146.2	1.86
2	mathematicians, actuaries and statisticians	9.7*	1.42	academics	101.4	1.41	computer systems analysts and programmers	359.3	1.64
3	legal specialists	137.2	1.34	administration and management specialists	467.2	1.29	engineers (excluding electrical engineering)	256.9	1.64
4	public servants for supervision	206.1	1.32	sales, marketing and public relations specialists	294.7	1.28	mathematicians, actuaries and statisticians	9.7*	1.51
5	administration and management specialists	467.2	1.25	specialists in social and religious fields	117.5	1.26	database and network specialists	55.5	1.47
6	computer systems analysts and programmers	359.3	1.22	secretaries (general)	51.6	1.25	electrotechnology engineers	75.7	1.40
7	secretaries (general)	51.6	1.19	teachers of lower and upper secondary schools (except vocational education teachers)	109.4	1.25	financial specialists	293.7	1.38
8	sales, marketing and development managers	98.6	1.18	writers, journalists and philologists	66.5	1.25	information and communications technology managers	26.1	1.28
9	financial and statistical staff	66.3	1.14	financial specialists	293.7	1.24	sales, marketing and development managers	98.6	1.26

10	academics	101.4	1.13	mathematicians, actuaries and statisticians	9.7*	1.23	sales, marketing and public relations specialists	294.7	1.15
11	engineers (excluding electrotechnology)	256.9	1.11	sales, marketing and development managers	98.6	1.17	physicists, chemists and earth scientists	26.3	1.14
12	writers, journalists and philologists	66.5	1.11	administrative staff and specialised secretaries	98.7	1.17	managers in mining, industry, construction and distribution	228.3	1.13
13	business and management service managers	223.6	1.11	agents and brokers	323.2	1.17	specialists in biological sciences and related fields	60.2	1.12
14	information and communications technology managers	26.1	1.06	other teaching and educational professionals	173.5	1.12	librarians, archivists and museum professionals	25.3	1.05
15	sales, marketing and public relations specialists	294.7	1.04	customer information officers	94.9	1.07	business and management service managers	223.6	1.04
16	specialists in social and religious fields	117.5	1.04	business and management service managers	223.6	1.07	legal specialists	137,.	1.02
17	intermediate financial staff	337.6	1.02	intermediate financial staff	337.6	1.03	writers, journalists and philologists	66.5	1.00
18	database and network specialists	55.5	1.02	computer systems analysts and programmers	359.3	0.98	Physical, chemical and engineering science technicians	419.6	0.98
19	librarians, archivists and museum professionals	25.3	1.01	financial and statistical staff	66.3	0.98	managers for other types of services	160.6	0.96
20	office support staff	488.3	1.00	librarians, archivists and museum professionals	25.3	0.95	administration and management specialists	467.2	0.94

Warning: *Due to the representative method of surveying, it is necessary to be cautious in the use of data in those cases where more detailed breakdowns have been used and there are low-order numbers of less than 20,000. Data for which the values after generalisation of the sample results are below 10,000 should not be included in the analysis due to the very high random sampling error, and have therefore been indicated as a form closer to signalling their position than to a specific number of employees.

Source: Prepared by PEI.

The number of those working in the 20 occupations least exposed to AI is more than twice as low as in the most exposed occupations (about 1.66M, 10 percent of the employed). In Table 4, we present a list of 20 such occupations. The jobs least exposed to AI are those that require manual labour - labourers in simple jobs in various industries, as well as jobs related to agriculture or livestock. There is more overlap between the indicated occupations than the most exposed group in terms of AI. In the case of general AI, only middle and high school teachers do not appear in the least exposed group for LLM or image generation, in the case of LLM it is government supervisory officials and operators of wood and paper processing machinery and equipment. There are more such occupational groups in the case of image generation: here only waiters and bartenders; personal care workers in health care and related occupations; street and market vendors; dieticians and nutritionists, athletes, trainers and related occupations and veterinary technicians occur exclusively in this category.. Approximately 2.07 M people work in the occupations least affected by the use of LLM models, and approximately 1.59 M work in image generation.

Table 4. Jobs that are least exposed to AI

	AIOE			AIOE LLM			AIOE GenIm		
Rank	Group of occupations	Number of employees in Poland (K)	Score	Group of occupations	Number of employees in Poland (K)	Score	Group of occupations	Number of employees in Poland (K)	Score
1	agricultural, forestry and fishing blue-collar workers	46.0	-1.68	agricultural, forestry and fishing blue-collar workers	46.0	-1.53	waiters and bartenders	80.6	-1.83
2	simple transport and storage workers	39.0	-1.65	simple transport and storage workers	39.0	-1.46	domestic, office and hotel cleaners and helpers	311.9	-1.83
3	elementary industrial workers	125.3	-1.63	subsistence fishermen and gatherers	0.9*	-1.44	employees carrying out simple tasks related to food preparation	74.9	-1.78
4	labourers performing simple work in mining and construction	36.8	-1.59	elementary industrial workers	125.3	-1.43	elementary industrial workers	125.3	-1.75
5	domestic, office and hotel cleaners and helpers	311.9	-1.47	labourers performing simple work in mining and construction	36.8	-1.41	simple transport and storage workers	39.0	-1.72
6	vehicle washers, window washers, launderers and other cleaners	22.6	-1.47	painters, building structure cleaners and related workers	87.9	-1.35	vehicle washers, window washers, launderers and other cleaners	22.6	-1.70

7	Subsistence crop and livestock farmers	1.2*	-1.47	Subsistence crop and livestock farmers	1.2*	-1.34	facility managers	120.7	-1.68
8	painters, building structure clean-ers and related workers	87.9	-1.44	Foundry moulders, welders, tinsmiths, metal fitters and related workers	195.6	-1.28	labourers per-forming simple work in mining and construction	36.8	-1.64
9	subsistence fisher-men and gatherers	0.9*	-1.41	seafarers and relat-ed persons	5.7*	-1.26	agricultural, forestry and fish-ing blue-collar workers	46.0	-1.58
10	other workers in simple jobs	78.5	-1.31	woodworkers, furniture joiners and related trades workers	154.2	-1.24	Subsistence crop and livestock farmers	1.2*	-1.40
11	facility managers	120.7	-1.29	operators of machinery and equipment for metal production, processing and finishing	33.8	-1.23	other workers in simple jobs	78.5	-1.27
12	employees carrying out simple tasks related to food preparation	74.9	-1.26	other workers in simple jobs	78.5	-1.21	painters, building structure clean-ers and related workers	87.9	-1.24
13	Foundry moulders, welders, tinsmiths, metal fitters and related workers	195.6	-1.22	vehicle washers, window washers, launderers and other cleaners	22.6	-1.17	personal care workers in health care and related fields	114.5	-1.23
14	teachers of lower and upper second-ary schools (except vocational educa-tion teachers)	109.4	-1.17	mining and related machine and plant operators	79.1	-1.13	street and bazaar vendors	19.3*	-1.16
15	seafarers and related persons	5.7*	-1.12	rubber, plastic and paper product ma-chine operators	92.4	-1.12	nutritionists and dieticians	8.5*	-1.05
16	operators of machinery and equipment for metal production, processing and finishing	33.8	-1.12	domestic, office and hotel cleaners and helpers	311.9	-1.12	woodworkers, furniture join-ers and related trades workers	154.2	-1.00
17	woodworkers, furniture joiners and related trades workers	154.2	-1.08	textile, fur and leather goods ma-chine operators	40.1	-1.08	athletes, coaches and related professions	31.6	-0.98
18	textile, fur and leather goods ma-chine operators	40.1	-1.05	public servants for supervision	206.1	-1.06	veterinary technicians	5.5*	-0.98

19	rubber, plastic and paper product machine operators	92.4	-1.03	operators of woodworking and papermaking machinery and equipment	55.7	-1.05	textile, fur and leather goods machine operators	40.1	-0.90
20	mining and related machine and plant operators	79.1	-1.03	lorry and bus drivers	459.7	-1.04	Foundry moulders, welders, tinsmiths, metal fitters and related workers	195.6	-0.90

Warning: *because of the representative method of surveying, caution is needed in the use of data in those cases where more detailed breakdowns have been used and there are low-order numbers of less than 20,000. Data for which the values after generalisation of the sample results are less than 10,000 should not be included in the analysis due to the very high random sampling error, and have therefore been indicated as a form closer to signalling their position than a specific number of employees.

Source: Prepared by PEI.

The AIOE index is scaled so that, while maintaining a relative form, its scores have the same weight. In our case, 57 of the occupational groups analysed show higher levels of exposure to AI in relation to the skills that are relevant and frequent to them. In contrast, 69 jobs are less exposed to AI than the average. **In terms of the number of employees, there are slightly more employed in occupations with a higher exposure to AI than the average (8.4 M compared to 8.1 M)**.

Box 1. Demographic changes in the Polish labor market, automation, and AI.

The progressing aging of society is a challenge for the Polish labor market. Already in 2023, 25 percent of the working population (aged 18-64) consisted of individuals aged 50 or older. **According to an analysis by PIE, by 2035, the Polish labor market will shrink by 2.1 million workers, which represents 12.6 percent of the current workforce**. The most significant impact of demographic changes will affect the education sector (with a reduction in the workforce of up to 29 percent) and the healthcare sector (a reduction of up to 23 percent). Industrial sectors (sections B-E) could lose as many as 400,000 workers by 2035 (an 11 percent decline).

One potential solution to mitigate the negative effects of labor supply decline is the use of modern technologies. **Automation, the use of industrial robots, RPA (Robotic Process Automation) systems, and artificial intelligence can support human work, increase efficiency, or even fully replace it**. Such solutions can automate some of the tasks performed in regular jobs, which may reduce the demand for human labor, particularly in sectors currently or potentially facing labor shortages.

Currently, the low level of adoption of new technologies in companies in Poland and low digital skills levels, is a barrier to pursuing such solutions. However, it can be assumed that the shrinking labor supply, rising labor costs, and challenges in maintaining or growing production levels will drive the need for automation investment in Polish enterprises. There is still significant potential for automation in Polish industry, as indicated by the very low robot density (59 robots per 10,000 industrial workers)—one of the lowest in Europe.

In this context, artificial intelligence should be seen as a technology with great potential to take over some tasks from humans, thus increasing work efficiency. With appropriate labor market policies and a developed system encouraging lifelong learning, this can help mitigate the negative effects of demographic changes without the risk of increasing unemployment.

Source: Own study based on Kukołowicz, Leszczyński, Lubasiński (2024), Leśniewicz (2024).

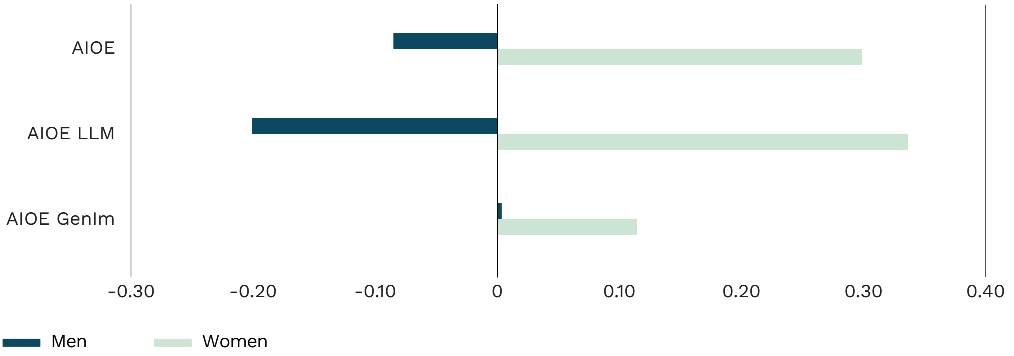
AI and the sociodemographic characteristics of Poles

In order to analyse the impact of AI by sociodemographic background in Poland, we used LFS data for gender, education and provincial data.

In all groups of occupations, women in Poland are more exposed to AI-induced disruptions in the workplace than men, as presented in Figure 6. Of the 121 analysed occupations in Poland, women are more likely to perform those jobs that are at risk of being exposed to AI. The results of the AIOE index are higher for women in all three of its variants, particularly in its basic scope and those related to the impact of large language models on the work environment. The gender difference in AIOE GenIm impact does occur, yet it is smaller.

As many as 28 % of all working women and 17 % of men are employed in the group of 20 occupations most likely to be affected by the introduction of AI. Despite the higher overall number of working men than women, **women also lead the group of the 20 most AI-exposed occupations in terms of numbers - 2.16 M compared to 1.53 M**. This is probably because women are less likely to take on manual jobs and are more likely to be better educated than men - so they work in occupations more strongly exposed to the use of AI.

Figure 6. Exposure to AI by gender, based on occupational exposure of each group (weighted average of AI exposure, taking into account the number of employed women and men in a given occupation)



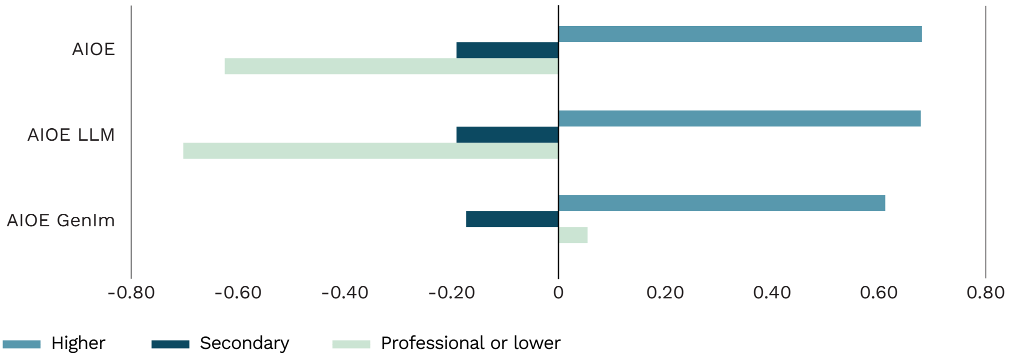
Source: Prepared by PEI, using BAEL data.

Employees with a university degree are the most exposed to the impact of AI. Exposure to the impact of AI in the workplace increases as the level of education increases. This is the case for both the impact of classical AIOE, language models and image generation. The only exception to this is the exposure of workers with vocational or lower qualifications to image generation, where the exposure is higher than that of workers with secondary education, but still not as high as those with higher education.

As many as 44 % of all employees with a university degree work in Poland in the 20 occupational groups that are most exposed to AI. They make up as much as 82 % of the group of all people working in such occupations - and therefore the most exposed to change. This compares to 10 % for workers with secondary education, and less than 1 % for workers with vocational or lower education. In contrast, the order is reversed in the 20 occupational groups with the lowest exposure to AI, with only 3 % of all workers with university education, 11 % with secondary education and 20 % with vocational or lower education.

In Map 1, we present an analysis of the scale of exposure to various aspects of AI by voivodeships in Poland, taking into account AIOE, AIOE_LLLM and AIOE_GenIm. The analysis shows that e**mployees in the Masovian voivodeship are (on average) most exposed to AI**, which is due to the concentration of specialised professions - requiring higher salaries, related to cognitive work - in and around Warsaw. Those employed in the 20 occupational groups most strongly exposed to AI account for as much as 31 % of workers in this voivodship, while those employed in the 20 least exposed account for only 6 %.

Figure 7. Exposure to AI by level of education

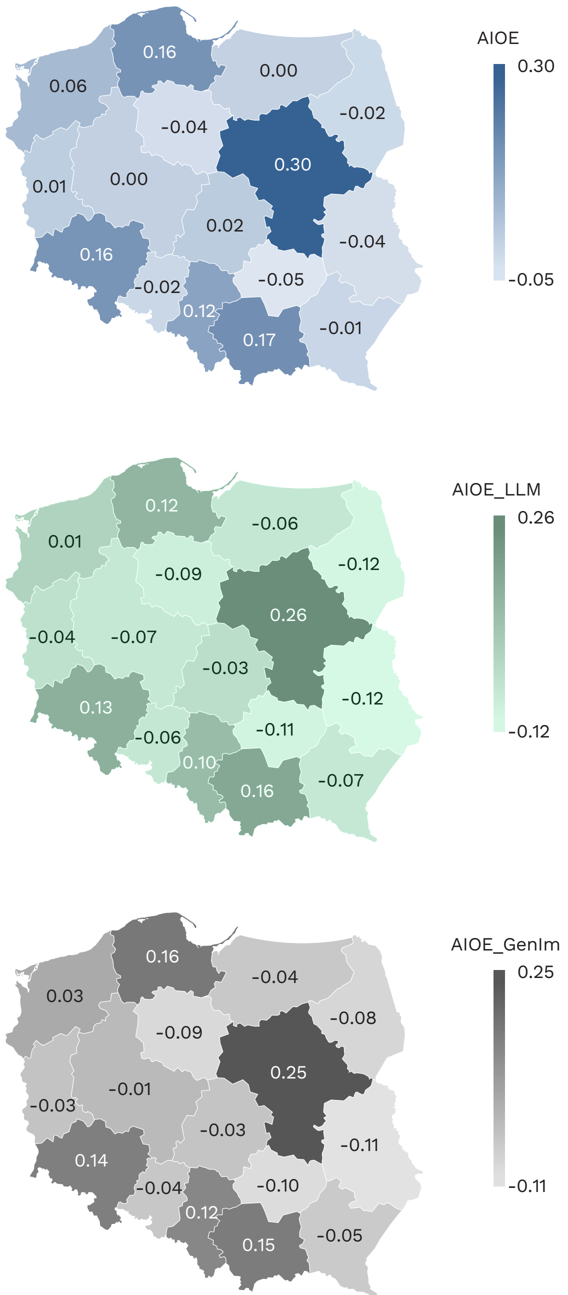


Source: Prepared by PEI.

Lesser Poland, Lower Silesia, Pomerania and Silesia also show high average exposure scores in all three categories. This suggests **a stronger impact of artificial intelligence in the voivodeships containing large urban agglomerations, which concentrate the activities of companies and institutions using advanced technologies**, which further increases exposure to artificial intelligence. In contrast, Świętokrzyskie, Lublin, Kuyavian-Pomeranian and Podlaskie voivodeships have the lowest indicators in Poland.

In terms of the percentage of employees in the 20 occupations most strongly exposed to AI, the Lower Silesian (26 %), Lesser Poland (25 %) and Pomeranian (24 %) voivodeships follow the Masovian Voivodeship. The list is closed by Świętokrzyskie (14 %) and Lublin (15 %). On the other hand, in the 20 professions least exposed to AI, the largest percentage of people work in the Lubuskie and Subcarpathian Voivodeships (12 % each). In this classification, the differences between voivodeships is much smaller, with the lowest values recorded in the Masovian (6.4%) and Podlaskie (8%) Voivodeships.

Map 1. Average exposure to AI by voivodship, calculated based on employment in each occupational group in the voivodship



Source: Prepared by PEI.

Impact of AI on economic sectors in Poland

To determine to what extent individual economic sectors are exposed to AI, we again used data prepared for the US market, following the methodology developed by Felten and his team (2021). The AIIE (Artificial Intelligence Industry Exposure) indicator was prepared for the US NAICS classification of economic activities has been converted to the Polish PKD.[1] The use of US data, means that the results for Poland may be subject to error, which arises from differences between the structure of employment and the level of sophistication in individual sectors. The results obtained should therefore be viewed with caution. This indicator, like those discussed in the previous section, is relative. This means that if it takes a value higher than 0 for a given section of the economy, that section is more exposed to AI than the average for the economy as a whole. Similarly, taking negative values indicates lower exposure. This indicator does not speak about absolute values - in particular, negative values do not mean that a given section is not exposed to the effects of AI.

Analysis of the rates of exposure to AI across economic sectors shows significant variation in the adaptation and use of these technologies, which is consistent with the conclusions of the analyses of occupations. **The agriculture, forestry, hunting and fishing sector records the lowest exposure to AI, suggesting that it is the least affected by the development of these technologies. Similarly, low levels of exposure can be seen in catering and accommodation activities and construction**.

The financial and insurance activities sector, on the other hand, exhibits the highest exposure to AI, indicating the potential for extensive use of these technologies in process automation, data analysis, and information management. High exposure is also observed in the professional, technical, and education sectors. It is worth noting that the IT sector ranks only fourth, although the situation changes when considering exposure to language models, where this sector rises to third place.

Other sectors, namely **wholesale and retail and arts, entertainment and leisure activities, show large differences in exposure to AI, depending on whether we examine general exposure to AI (AIOE) or profiled for LLM or image generation**. This may indicate narrow applications of AI technology in these industries, affecting only certain activities or processes. Healthcare and social care have moderate exposure, with more emphasis on the use of AI in data analytics than in image generation technology.

The analysis shows that sectors related to finance, technology and communication are leading the way in AI adoption, which may be related to their greater reliance on advanced technological tools. On the other hand,

[1] To do this, we combined the six-level NAICS codes with the number of individuals employed in that area in the US and the corresponding AIIE, and then, creating weighted averages, moved to the top-level NAICS classifications and determined the corresponding PAC codes.

sectors that are traditional and more associated with manual labour, such as agriculture or construction, remain less affected by AI, which may be due to the different nature of work in these areas, at least currently.

Table 5. Results of indicators for sectors by PKD classification

PKD (Sections)	AIIE	AIIE LLM	AIIE GenIm
A – Agriculture, forestry, hunting and fishing	-2.00	-1.85	-1.94
B – Mining and quarrying	-0.68	-0.85	-0.13
C – Manufacturing	-0.40	-0.51	-0.06
D – Generation and supply of electricity, gas, steam and hot water	0.20	0.05	0.65
F – Construction	-1.10	-1.11	-0.70
G – Wholesale and retail trade	0.03	0.19	-0.55
H – Transport and storage	-1.02	-1.09	-0.64
I – Accommodation and food service activities	-1.12	-0.73	-2.07
J – Information and communication	1.20	1.13	1.38
K – Financial and insurance activities	2.05	1.97	1.60
L – Real estate activities	0.36	0.34	0.37
M – Professional, scientific and technical activities	1.71	1.56	1.93
N – Administrative and support service activities	-0.61	-0.47	-0.85
O – Public administration and defence; compulsory social security	0.39	0.39	0.33
P – Education	1.34	1.49	0.90
Q – Health care and social assistance	0.62	0.74	0.10
R – Arts, entertainment and recreational activities	-0.60	-0.24	-1.40
S – Other service activities	-0.25	-0.16	-0.38

Source: Prepared by PEI.

Discussion

At this stage of the implementation of AI-based solutions in the economy, we do not know whether it will prove to be more complementary to the skills of the workforce, or whether its implementation will lead to more automation of current tasks and a reduction in employment in certain occupations. In contrast, both the literature and our own study suggest that highly skilled occupational groups will be the most affected by AI.

Barriers to AI implementation

A barrier to the wider implementation of artificial intelligence is still the relatively low labour costs, compared to European conditions, which do not motivate executives to take steps towards automation. Then there is the lack of trust in AI-based service providers by some business representatives. **The processing of sensitive data, on external servers, required to support advanced AI means that new solutions may raise fears of leaks and be incompatible with corporate compliance**. Nor are they motivated by fears of inadequate results generated by large language models, sometimes described as hallucinatory. All this is reinforced by the low level of digital literacy in Polish society, which means that many employees are simply not ready to implement and effectively use new tools. These factors will inhibit the implementation of solutions based on artificial intelligence, thus postponing potential changes and allowing time for preparation.

The conclusions of the discussion on the impact of artificial intelligence on the Polish labour market are thus the same as in the discussions on accelerating digital transformation, the motivations of entrepreneurs and breaking down barriers to other modern technologies.

As Poland moves up European and global value chains, labour costs rise and the overall size of the workforce declines, the proportion of workers encountering the impact of artificial intelligence in their workplace is likely to increase. In the face of this, action is needed to increase the resilience of exposed workers to the rapid changes taking place in their workplace and to create the right conditions to enable them to adopt the changes resulting from the adaptation of new technology favourably.

Education and qualification

Increasing the universality of lifelong learning, promoting re-skilling and up-skilling, as well as appropriately recommending pathways for upgrading competences and evolving career paths are crucial for workers to be able to adapt to changes in the labour market, whether caused by the impact of artificial intelligence or other factors. Currently, Poland ranks sixth from the bottom (8.7 %) in the European Union in terms of educational efforts made by adults to increase their knowledge, competences or acquisition of skills. In this aspect, it is worth looking at the experience of other countries and the new solutions they are introducing - an example is Individual Training Accounts in France (www2). Employees accumulate funds from employers in individual accounts, which they can then use for self-selected skills courses. Another interesting solution is training leave in Sweden, which allow employees to undertake training on a part- or full-time basis (Święcicki, Witczak, 2023). Such leaves are unpaid, while workers can receive a grant to compensate for up to 80 % of their lost income and apply for preferential loans. A significant challenge, however, is the design of development paths, the individualisation of support and the foresight of the skills needed in the future. **The pace of change and the heterogeneous impact of AI are a major challenge for labour market policies and institutions supporting workers in adapting to change** and are forcing far-reaching changes in this area.

Developing digital skills remains one of the key challenges for Poland in the ongoing digital transformation process, part of which is the implementation of AI-based solutions. Today, only 44.3 % of Poles have at least basic digital skills, which places us 11.2 pp below the EU average, but is also just over half the score of the Netherlands, the current EU leader. A digitally literate society is crucial for increasing the digital resilience of the workforce and is one of the pillars of the EU's digital policy. Given Poland's declared target of 80 % of the population having at least basic digital skills by 2030, efforts in this direction should be significantly intensified (www3).

Developing AI proficiency is also important. Due to the rapid development of generative AI and the possibility for people without specialist qualifications to use it relatively cheaply and easily, its popularity will continue to grow. However, the frequency of use of AI-based solutions does not translate into proficiency in using it (Department for Education, 2024). The focus should be on disseminating the skills to enable the wider community to use these solutions safely and effectively. Possibilities include teaching methods for using generative AI in education and promoting training in the use of these solutions for adults.

Regulation and monitoring

With the Artificial Intelligence Act, the European Union is a forerunner and leader in regulating and safeguarding against the negative effects of AI. The new **European regulations emphasise risk mitigation and the central role of humans**. Although only 3.7 % of companies in Poland declare the use of AI, placing our country third from last in the EU, national public policies supporting the implementation of AI should encourage the implementation of the technology in a way that is safe for the labour market and that takes into account local conditions.

It is also crucial that artificial intelligence is used legally and without harm to society. **Setting formal and informal ethical standards, codes of conduct or recommendations** for the responsible use of artificial intelligence in the workplace can help achieve this goal. Given the importance of data and data security, copyright or competition law, various national authorities, including UODO, UOKiK or UKE, as well as relevant ministries, industry organisations (including collecting societies, media associations) and non-governmental organisations (NGOs) should be involved in this process.

Monitoring progress and ongoing analysis of its impact on businesses, the labour market and the employees themselves is also necessary to effectively exploit the opportunities offered by the implementation of artificial intelligence. Collecting data and controlling changes will translate into a more accurate understanding of the processes taking place, and thus into a more effective response to new needs and emerging issues.

Reorganisation of the labour market

The current ratios between labour and corporate taxation may contribute to disadvantageous effects for workers in the future, in the form of excessive job losses to the automation of work by AI (Brollo et al., 2024). Increasing CIT rates can help to offset the inequalities that arise and provide funding for education, which, as we suggested above, is crucial to ensure resilience to AI-driven change. In addition, state revenue from taxing labour due to reductions or changes in the nature of employment can be offset by new revenue from corporate entities that will benefit from automation.

Ultimately, an important approach to address changes in the labour market and in the demand for specific skills is to **redesign existing jobs** (Nurski, Ruer, 2024). Companies should consider in advance which skills in their processes are being or will be replaced by AI in the foreseeable future. Identifying skills that are losing relevance and those that will increase productivity in the new realities will generate benefits for both employees and employers. With such knowledge, companies will be able to focus on hiring staff complementary to automation and on internal training provided (in good time) for staff to acquire the required skills.

International aspect

Despite the strong media presence and numerous discussions about the future of AI in the labor market and its use in various economic sectors, actual implementations are still at an early stage. Many companies are just experimenting with AI applications, and the solutions available on the market are evolving rapidly and may still be far from their final form. **Nevertheless, it is important to note that delays in adopting AI could lead to a loss of competitiveness—technological changes are happening so quickly that excessive fear of risk could result in greater losses in the long run than in previous waves of technological change**.

At the same time, attention should be given to the specific characteristics of the Polish economy. The strong presence of companies with foreign capital may lead to polarization in the market—that is, companies where development and investment decisions are made abroad may implement AI-based solutions more quickly and on a larger scale, thereby gaining market share at the expense of domestic firms that are less inclined to take such steps (perhaps facing greater barriers to accessing capital).

Business services sector

Finally, **it is also worth taking note of the impact AI can have on the business services sector, which employs over 450,000 people in Poland, mostly with higher education**, and is concentrated in the largest urban areas. This sector has traditionally been an important entry point into the labor market for university graduates. However, with the development of AI applications, it will undergo significant transformation. According to industry report authors (ABSL, 2024), jobs will be "displaced by AI, transformed by AI, supported by AI, enhanced by AI, or integrated with AI" (p. 17). **This means that "some jobs will be eliminated" but it is also likely that opportunities for new entrants into this sector will decrease**. The consequences of this accelerating process—the ABSL (2024) report authors themselves acknowledge that changes are happening faster than they anticipated just a year ago—could be felt across the Polish economy, as this sector employs approximately 7 percent of all workers in Poland's enterprise sector.

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