Top competencies for the AI usage and the market - explanatory study from Poland

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Abstract

Technology development necessitates the growth of competencies that enable employees to utilize it in their professional work effectively. Organizations such as the World Economic Forum (WEF) identify market trends and highlight the skills most sought after by employers, both generally and within specific sectors. This article presents the results of a study conducted at the turn of 2024/2025 on a group of Polish employees from various industries (N=288). The study aimed to assess employees' self-diagnosis regarding key competencies identified in WEF reports and to examine their correlation with using AI tools in their work.

Keywords: AI, market, competencies, AI competencies, AI skills

1. Introduction

The landscape of the modern labor market is evolving at a highly dynamic pace. Economists, sociologists, and management specialists point to various factors that will shape the market, transforming both individual industries and the requirements employers will impose on future employees [1]. On the one hand, this is crucial for the economy, regardless of the sector, as it benefits from hiring domain experts equipped with relevant and up-to-date competencies. On the other hand, any changes in the area of future employees' skills are pivotal for young people just entering the labor market. Observable and analyzed trends may serve as a guideline for identifying which competencies to develop to become a desirable candidate in the job market.

In addition to socio-economic phenomena, a key factor influencing the labor market is technological development, particularly the advancement of AI tools. This ongoing transformation reshapes entire industries and creates a demand for a new set of universal competencies, essential for employees regardless of their career stage or sector.

The development and corporate adoption of GenAI tools are highly significant factors. While the ubiquity of AI seems indisputable, analyses of the Polish market reveal that its implementation is uneven, varying by company size and industry [2]. This varied landscape of AI application—used for tasks ranging from data analysis to marketing [3] — reinforces the notion that employees must develop the competencies essential for operating and utilizing these new tools.

Regardless of the industry analyzed or the area in which it is applied, it has become evident that employees must develop the competencies essential for operating and utilizing GenAI tools. Taking the above into consideration, the research questions for this paper were formed as follows:

- RQ1: What is the level of key competencies declared by Polish employees as outlined by experts?
- RQ2: Are there any correlations between the declared level of competencies and the usage of AI tools in those areas?

The study aimed to analyze the relationship between the declared level of key competencies among employees in Poland and their use of artificial intelligence (AI) tools in professional work within the same competency areas. To achieve this objective, a survey was conducted in Poland between December 1, 2024, and January 15, 2025. Respondents were asked to indicate their level of proficiency in areas related to key skills and then specify the areas in which they purposefully and consciously use AI tools in their professional activities. The study sample consisted of N=288 respondents, all actively employed and aged 18 or older, with no exclusions based on industry.

The structure of this paper is as follows: Section 2, Theoretical Background, provides a review of the literature and industry reports on employee competencies and skills, as well as the use of AI tools in the labor market. Section 3, Materials and Methods, describes the research procedure. Section 4, Findings, contains a detailed account of the study results. Finally, the paper concludes with Section 5, Conclusion and Discussion, which summarizes the findings, discusses their implications for the labor market, and outlines possible directions for further research in this area.

2. Theoretical Background / Literature Review

GenAI tools and the development of artificial intelligence are among the most significant factors influencing the market, including the labor market. According to McKinsey's report [4], 65% of respondents state that their organizations regularly use GenAI. This pressures employees to familiarize themselves with these tools and acquire at least basic proficiency in using them.

Regarding AI utilization within organizational structures, particular attention is given to sectors such as Business Services, Finances, and Manufacturing [4], which are experiencing the fastest pace of change related to AI implementation. Market analyses conducted primarily by organizations like Deloitte and the aforementioned McKinsey highlight e-commerce and healthcare as industries where GenAI tools are becoming increasingly widespread [5, 6]. These changes will inevitably necessitate adjustments to employee competencies. According to the World Economic Forum's 2023 report, 44% of core employee skills will transform by 2027, with companies emphasizing the development of analytical thinking, creative thinking, and technology-related skills [7]. Research findings indicate that 92% of occupations require basic digital skills [8, 9].

The market demands that employees possess skills and competencies related to specific areas of knowledge and tasks they are expected to perform within organizational structures. In this article, skills are understood as the ability to apply procedural knowledge to perform specific actions, often associated with completing individual tasks [10]. In contrast, competencies combine knowledge, skills, attitudes, and values that enable effective functioning in complex professional contexts [11]. With the advancement of technology, including AI tools, employees' roles have changed due to shifts in the work's content, processes, and environment [12].

Understanding the motivation behind skill development and technology use requires a theoretical lens. Self-Determination Theory (SDT) posits that human motivation is driven by the fulfillment of three fundamental psychological needs: autonomy, relatedness, and competence [13]. Competence, defined as the feeling of being effective in one's actions, is particularly relevant to the adoption of new technologies. According to SDT, when individuals feel competent in using tools like Generative AI, their intrinsic motivation to engage with them increases [14]. This enhanced sense of competence drives engagement and reinforces feelings of autonomy, making employees more inclined to use and master new technology [15].

The behavioral intention to use new technology is explained by the Technology Acceptance Model (TAM) [16, 17]. According to TAM, an individual's willingness to use a technology, including GenAI, is primarily determined by two key factors: Perceived Usefulness (PU), which is the belief that the technology will enhance job performance, and Perceived Ease of Use (PEOU), the belief that using the technology will be effortless [18]. In the context of GenAI, both factors are critical; intuitive design and effective organizational training can boost PEOU, while clear benefits for daily tasks enhance PU, ultimately driving acceptance [18].

While both are important, some studies on employee technology adoption suggest that Perceived Usefulness often has the strongest direct influence on the intention to use AI tools.

Researchers also point out that competencies have attracted organizations' interest in becoming an essential resource [19]. Also, by investigating competency models accessible in literature, scientists have observed a new form that emerged: hybrid competencies, which combine digital tools with creativity (e.g., "AI-enhanced design thinking"). These competencies are present in almost 40% of competency models [11].

The need for education and the development of new competencies, driven mainly by technological advancements, including AI tools, is recognized by employers and governmental and non-governmental organizations responsible for creating educational frameworks. The European Union has acknowledged the importance of equipping citizens with the digital competencies required for effective participation in the digital world. The DigComp framework [20] was initially introduced in 2013 to address this need and was revised in 2022. This framework is a comprehensive guide for developing digital skills and competencies essential for navigating digital transformation. Notably, studies also stress that digital competencies are acquired not solely through formal education, but also through lifelong learning [21]. As a result, individuals can develop these skills irrespective of their educational background. European Union member states must integrate the framework into their national education strategies.

The question, however, arises as to what competencies can be described as crucial for the job market in the context of AI tools usage and development. Research focusing on competencies development in AI-applied environments stresses the growing importance of soft skills (e.g., critical thinking, creativity) and technical skills (e.g., data analysis, digital proficiency) in utilizing AI tools in the labor market. Employees must be capable of adapting to and collaborating with technologies, which requires continuous improvement of both cognitive and social skills. These competencies are essential for effective functioning in a work environment driven by advanced technologies.

Chuang [22] identifies critical thinking, the ability to solve complex problems, creativity, and emotional intelligence as key competencies for employees in the era of AI and automation. Weritz [23] notes that digital proficiency, data analysis capabilities, technology-based project management, and intercultural communication are essential for employees in the digital workplace. Finally, Gerlich [24] emphasizes that AI use leads to so-called "cognitive offloading," meaning transferring specific decision-making processes to technology. Consequently, competencies such as critical thinking, the ability to evaluate results generated by AI, and an ethical approach to technology become crucial.

The World Economic Forum's "Future of Jobs 2025" report identifies the top 10 competencies projected to experience the fastest growth in importance by 2030 [7]. These skills reflect the evolving demands of the global labor market, driven by technological advancements, societal shifts, and environmental challenges. These competencies, presented in order of fastest growth, are as follows:

1. AI and Big Data - These competencies enable workers to process vast amounts of information, extract insights, and optimize decision-making in AI-driven environments.
2. Networks and Cybersecurity - These competencies focus on protecting sensitive data, ensuring system integrity, and mitigating cyberattacks and risks.
3. Technological Literacy - These competencies are critical for navigating digital transformation across industries, supporting innovation, enhancing productivity, and adapting to the requirements of developing technology.
4. Creative Thinking - Creative thinking involves generating innovative solutions to complex problems. It is increasingly valued for driving business growth, fostering adaptability, and enabling organizations to remain competitive in rapidly changing markets.
5. Resilience, Flexibility, and Agility - These socio-emotional competencies are crucial for coping with uncertainty and adapting to dynamic work environments. They empower individuals to maintain productivity and mental well-being despite disruptions or challenges.
6. Curiosity and Lifelong Learning—These competencies emphasize continuous personal and professional development through the acquisition of new knowledge and skills to stay

relevant in an ever-evolving job market.

7. Leadership and Social Influence—These competencies focus on effectively guiding teams, fostering collaboration, and inspiring innovation. They are essential for managing diverse workforces in increasingly interconnected industries.
8. Talent Management - These competencies enable the identification, development, and retention of skilled employees. They are critical for addressing labor shortages, optimizing team performance, and ensuring organizational success.
9. Analytical Thinking - It is a cornerstone competency for solving complex problems through logical reasoning. It supports data-driven decision-making processes across various sectors.
10. Environmental Stewardship—These competencies reflect the growing importance of sustainability in business practices. They focus on managing resources responsibly, reducing carbon footprints, and contributing to climate change mitigation efforts.

These competencies, which have also been highlighted in numerous studies, underscore both technical expertise [25] and human-centric skills (e.g., leadership) in shaping a workforce capable of thriving in a rapidly transforming global economy [26]. They also serve as a guidepost for employees already active in the labor market and those just entering it. The necessity for workers to update or enhance their professional qualifications, increasingly driven by shifts in workplace infrastructure resulting from implementing new technological solutions, is becoming more frequent. Awareness of key areas whose development addresses market demands can be particularly significant for employees. Similarly, knowledge about the essential competencies required by businesses can be valuable for Higher Education Institutions (HEIs) that educate future specialists [27]. Additionally, each of the mentioned competence areas, including their development or implementation of specific tasks, can currently be supported by AI tools, which, in consequence, can lead to developing new types of competencies [28].

3. Materials and Methods

This quantitative study used the Computer-Assisted Web Interviewing (CAWI) technique, an online survey method where respondents complete a questionnaire independently on a web browser. This approach was chosen for its cost-effectiveness and ability to quickly reach a broad, geographically diverse group of participants. The questionnaire was created and administered using tools provided by the SW Research, an online survey panel, and it was distributed among users registered in the respondent database of SW Research. Data analysis was performed using MS Excel and the IBM PS Imago Pro 10.0 package, which includes SPSS Statistics 29. The study was conducted between December 1, 2024, and January 15, 2025.

Based on the literature review, ten constructs were identified: Analytical Thinking; AI and Big Data; Networks and Cybersecurity; Technological Literacy; Creative Thinking; Resilience, Flexibility, and Agility; Curiosity and Lifelong Learning; Leadership and Social Influence; Talent Management; Analytical Thinking; and Environmental Stewardship. For each construct, a section for self-assessment of competencies (Comp_) and a section on AI usage (Use_) were created, with three questions assigned to each. The questionnaire comprised 60 questions using a 7-point Likert scale and a demographic section.

The study included 288 surveys from adult respondents in Poland. The study employed a purposive sampling method combined with voluntary participation via the online research panel ankieteo.pl. The survey was made available to all panel users (voluntary sampling). For the final analysis, only respondents who declared that they had consciously and intentionally used artificial intelligence solutions (including language models such as ChatGPT) for professional or personal purposes were included. Individuals who did not meet this criterion were excluded from the study. Respondents were divided into age groups based on their work experience: those aged 18–25 years (student age) accounted for 23.6% of the sample, respondents aged 26–35 years (early career employees/junior level) also represented 23.6%, employees aged 36–55 years (experienced professionals/mid-level) comprised 42.4%, and employees aged over 56 years (retirees) made up 10.4% of the sample.

The majority of respondents had either a Secondary education (40.6%) or Higher education, reported by 44% of respondents (including Bachelor's – 14.9%, Master's – 28.8%, and Doctoral – 0.3%). Women constituted the majority of the sample (59%), while 1.4% of respondents chose not to disclose their gender. Most respondents reported living in a large city (over 100k residents) – 30.6%, followed by those living in rural areas 26.7%, small towns (up to 50k residents) – 25.7%, and medium-sized cities (up to 100k residents) – 17%.

Respondents indicated their areas of education or employment. The most frequently selected sectors were retail and wholesale trade (10.4%), government and public sector (8.0%), medical and healthcare services (8.0%), consumer goods manufacturing (7.6%), and education and training (7.3%). The remaining respondents represented the following market sectors: employment services (e.g., employment agencies, HR), logistics and transport, personal services and well-being, financial services and capital markets, accommodation, catering and recreation, infrastructure, agriculture, forestry and fishing, information technology, research, design and business management services, electronics, media, entertainment and sport, chemicals (including research and production), automotive and aviation, real estate, mining and metals, business support and facilities services, non-governmental organizations (NGOs), energy, telecommunications, insurance, and oil and gas.

In response to the question about industry (Field of education/industry – indicate the area in which you are either currently studying or working. If you are a working student, select only one area), respondents stated the following: Retail and wholesale trade (10,4%); Government and public sector (8,0%); Medical and healthcare services (8,0%); Consumer goods manufacturing (7,6%); Education and training (7,3%); Employment services e.g. employment agencies, HR (6,6%); Logistics and transport (6,6%); Personal services and well-being (6,6%); Financial services and capital markets (5,6%); Accommodation, catering and recreation (5,2%); Infrastructure (4,5%); Agriculture, forestry and fishing (3,1%); Information technology (2,8%); Research, design and business management services (2,4%); Electronics (2,4%); Media, entertainment and sport (2,4%); Chemicals incl. research and production (1,7%); Automotive and aviation (1,7%); Real estate (1,4%); Mining and metals (1,0%); Business support and facilities services (1,0%); Non-governmental organisations (1,0%); Energy (1,0%); Telecommunications (0,7%); Insurance (0,3%); Oil and gas (0,3%).

Normality tests for the variables Comp_ and Use_ revealed that the data do not follow a normal distribution. For each variable, the significance in the Kolmogorov-Smirnov test was <.001, therefore, based on the p-value (significance level), this result was considered to be highly statistically significant. Since none of the variables exhibited a normal distribution, further analysis employed Spearman's rho nonparametric correlation test, with the following ranges adopted to interpret relationships: < 0.2 – no correlation; 0.2 - 0.4 – weak correlation; 0.4 - 0.7 – moderate correlation; 0.7 - 0.9 – strong correlation; > 0.9 – very strong correlation.

4. Findings

When respondents were asked about the general purposes for which they used AI tools, the most common responses included using AI for text generation (47.6% of respondents), searching for specific information (44.4%), translating text to or from another language (36.5%), and text editing (36.1%). Less popular applications of AI included summarizing or processing text (25.3%), solving specific problems, including mathematical and logical ones (20.1%), and generating images (16.7%). The least frequently mentioned uses of AI were synthesizing information from large datasets (9.4%), creating instructions (9.0%), correcting existing computer code (5.9%), and writing computer code (4.9%). Below are the detailed survey results for the selected areas of analysis.

4.1. AI and Big Data

Over half of the respondents (52.1%) claim to understand basic concepts related to AI and data analysis, while 22.6% either do not understand them or understand them only to a limited extent. The ability to work comfortably with large datasets to extract useful information is claimed by 51.7% of respondents, whereas 23.6% admit they struggle to work with big data. Interpreting data analysis results and concluding is a skill that 56.9% of respondents say they possess, while 22.6% struggle with such tasks.

Table 1. AI and Big Data: descriptive statistics

	Comp_AIBD_1	Comp_AIBD_2	Comp_AIBD_3	Use_AIBD_1	Use_AIBD_2	Use_AIBD_3
Average	4,46	4,52	4,63	3,73	3,89	3,85

Standard error	0,086	0,087	0,087	0,113	0,113	0,117
Standard dev.	1,455	1,479	1,476	1,914	1,923	1,989

37.1% of respondents use AI to analyze large datasets, while 42.3% do not. Similarly, 42.4% of respondents use AI for real-time data analysis, whereas 38.5% do not. The number of respondents who rely on AI when making decisions based on big data analysis (41.3%) is very close to those who do not (41.4%).

Table 2. AI and Big Data: Spearman's rho correlation

	Use_AIBD_1		**Use_AIBD_2**		**Use_AIBD_3**	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_AIBD_1	,357**	<,001	,295**	<,001	,268**	<,001
Comp_AIBD_2	,270**	<,001	,363**	<,001	,305**	<,001
Comp_AIBD_3	,204**	<,001	,281**	<,001	,226**	<,001

The relationship between the variables in this area is weak, but it is statistically significant in each case. The strongest correlation occurs between Comp_CT_2 (the ability to work with large datasets) and Use_CT_2, which refers to using AI for data analysis.

4.2. Networks and Cybersecurity

44.8% of respondents can configure and manage computer networks, while 30.6% admit that they either cannot handle this task at all or struggle with it. Identifying and preventing security threats in networks is a skill possessed by 53.1% of respondents, whereas 24.3% state that they are either completely unable to perform this task or can perform it poorly. The basic principles of data protection and privacy are known by 59.1%, while 19.4% declare that they either do not know them or are only partially familiar with them.

Table 3. Networks and Cybersecurity: descriptive statistics

	Comp_CNC_1	**Comp_CNC_2**	**Comp_CNC_3**	**Use_CNC_1**	**Use_CNC_2**	**Use_CNC_3**
Average	4,13	4,51	4,76	3,51	3,65	3,59
Standard error	0,099	0,092	0,085	0,115	0,119	0,116
Standard dev.	1,677	1,555	1,441	1,956	2,013	1,973

32.3% of respondents use AI tools to monitor network threats, while 47.2% do not or use them rarely. Similarly, using AI for data protection shows that 45.4% do not utilize AI tools or do so infrequently, when 37.4% report using AI tools for data security. When analyzing cybersecurity incidents, 33.7% of respondents employ AI tools, while 46.8% do not or use them rarely.

Table 4. Networks and Cybersecurity: Spearman's rho correlation

	Use_CNC_1		**Use_CNC_2**		**Use_CNC_3**	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_CNC_1	,515**	<,001	,397**	<,001	,409**	<,001
Comp_CNC_2	,312**	<,001	,310**	<,001	,277**	<,001
Comp_CNC_3	,199**	<,001	,150*	0,011	,196**	<,001

In this area, the correlation between variables is highly varied. On one hand, there is no statistical significance for the variables Comp_CNC_3 and Use_CNC_2, and no relationship exists for the remaining pairs with Comp_CNC_3. However, a moderate correlation is observed between Comp_CNC_1 (configuring and managing networks) and Use_CNC_1 (monitoring threats) as well as Use_CNC_3 (incident analysis). In other cases, the correlation is weak.

4.3. Technological Literacy

Most respondents (61.1%) state that they are proficient in using software and computer tools, while only 22.5% report that they cannot or can only handle them minimally. Similarly, 68.7% declare they comfortably use new technologies and devices, whereas 19.8% report difficulties in this area. Additionally, 66% of respondents can independently solve basic technical problems, while 17.3% admit they cannot do this at all or struggle with it.

Table 5. Technological Literacy: descriptive statistics

	Comp_TS_1	**Comp_TS_2**	**Comp_TS_3**	**Use_TS_1**	**Use_TS_2**	**Use_TS_3**
Average	4,77	5	4,89	3,82	3,97	3,8
Standard error	0,094	0,088	0,088	0,104	0,106	0,105
Standard dev.	1,6	1,5	1,485	1,765	1,806	1,784

The use of AI to create instructions for solving technical and/or technological problems is not very popular, with only 37.2% of respondents reporting that they do so. In comparison, 39.7% either do not use AI for this purpose or use it rarely. Similarly, 37.9% of respondents do not rely on AI to assist with using new tools and technologies, whereas 41.7% confirm that they use AI for this purpose. The number of people who use AI to facilitate learning how to operate software (39.3%) is close to the number of those who do not (40.6%).

Table 6. Technological Literacy: Spearman's rho correlation

	Use_TS_1		Use_TS_2		Use_TS_3	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_TS_1	,195**	<,001	,143*	0,015	0,078	0,184
Comp_TS_2	,153**	0,009	,205**	<,001	,120*	0,041
Comp_TS_3	,202**	<,001	,222**	<,001	,166**	0,005

There is no statistical significance between Comp_TS_1 and Use_TS_3; however, there is significance at the 0.05 level between Comp_TS_1 and Use_TS_2 and between Comp_TS_2 and Use_TS_3. The strength of the relationship between the variables in this area is very low or nonexistent.

4.4. Creative Thinking

Regarding creative thinking, 58.3% of respondents reported having the ability to introduce original ideas or solutions (at varying levels, ranging from 5 to 7). In comparison, 26.4% reported lacking this ability or having it at a low level (responses 1-3). Slightly fewer, 55.3% of respondents, stated that they are good at developing new concepts even when lacking guidelines, whereas 22.6% feel they struggle in this area. Unconventional approaches to problem-solving are used by 58.4%, while 21.5% do not feel confident in this skill.

Table 7. Creative Thinking: descriptive statistics

	Comp_CT_1	Comp_CT_2	Comp_CT_3	Use_CT_1	Use_CT_2	Use_CT_3
Average	4,54	4,52	4,58	4,2	4,16	4,2
Standard error	0,09	0,084	0,084	0,1	0,102	0,102
Standard dev.	1,534	1,424	1,427	1,696	1,736	1,728

Among the respondents, 47.9% reported using AI to generate ideas (to varying degrees), while 33.3% do not use it or use it infrequently. Slightly fewer, 44.8%, stated that they use AI to formulate guidelines for creative concepts, whereas 33% do not use AI for this purpose or do so rarely. AI is used to support the creation of unconventional solutions to problems by 48.3% of respondents, while 31.3% either do not use it or use it rarely.

Table 8. Creative Thinking: Spearman's rho correlation

	Use_CT_1		Use_CT_2		Use_CT_3	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_CT_1	,313**	<,001	,278**	<,001	,308**	<,001
Comp_CT_2	,295**	<,001	,282**	<,001	,288**	<,001
Comp_CT_3	,241**	<,001	,250**	<,001	,252**	<,001

There is a weak positive correlation between critical thinking skills and the use of AI for this purpose, with the highest correlation values observed between the ability to introduce original ideas or solutions and the use of AI to generate ideas.

4.5. Resilience, Flexibility, and Agility

The respondents generally feel confident in their resilience, flexibility, and agility competencies. Only 24.3% report struggling with sudden changes, such as those in work or personal life, while 56.3% believe they handle such situations well. 59.7% respond positively to new challenges and unforeseen difficulties, whereas 23.3% do not hold them well or struggle significantly. As many as 62.2% of respondents feel they can adapt to changes and new tasks, while 19.5% find this difficult..

Table 9. Resilience, Flexibility, and Agility: descriptive statistics

	Comp_RFA_1	Comp_RFA_2	Comp_RFA_3	Use_RFA_1	Use_RFA_2	Use_RFA_3
Average	4,57	4,65	4,78	3,57	3,66	3,57
Standard error	0,087	0,085	0,087	0,104	0,106	0,099
Standard dev.	1,482	1,438	1,481	1,76	1,803	1,683

In AI usage, 48.7% of respondents declare that they do not use AI to adapt changes in projects or tasks in response to new situations or guidelines, or they do so rarely (34.4%). Using AI for planning and reorganizing tasks in response to changes is also uncommon—46.5% of respondents say they do not do this or do so rarely. In comparison, 36.5% of respondents use AI for this purpose. In situations requiring quick adaptation to new conditions to obtain guidelines, 33% of respondents turn to AI, whereas 48.9% either do not use it or use it rarely.

Table 10. Resilience, Flexibility, and Agility: Spearman's rho correlation

	Use_RFA_1		Use_RFA_2		Use_RFA_3	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Comp_RFA_1	,158**	0,007	,146*	0,013	,156**	0,008
Comp_RFA_2	,245**	<,001	,257**	<,001	,226**	<,001
Comp_RFA_3	,229**	<,001	,223**	<,001	,213**	<,001

The significance between Comp_RFA_1 and Use_RFA_2 is at the 0.05 level, while in all other cases, it is at the 0.01 level. The strength of the relationship between variables in this area is very low or nonexistent.

4.6. Curiosity and Lifelong Learning

As many as 60.8% of respondents declare that they frequently seek new information and skills related to their work or studies, while only 22.3% either do not do this or do so rarely. The majority, 63.9%, also state that they often initiate actions to develop their competencies, whereas only 18.4% do not engage in such activities or do so rarely. Respondents also claim to be open to feedback and use it for self-improvement, with 58.8% confirming this, while 19.8% are either not open to feedback or utilize it to a limited extent.

Table 11. Curiosity and Lifelong Learning: descriptive statistics

	Comp_CWCL_1	Comp_CWCL_2	Comp_CWCL_3	Use_CWCL_1	Use_CWCL_2	Use_CWCL_3
Average	4,65	4,8	4,69	4,44	4,43	4,29
Standard error	0,094	0,086	0,092	0,094	0,096	0,094
Standard dev.	1,592	1,451	1,559	1,592	1,624	1,59

When asked how often they use AI to search for information on new topics of interest, 25% of respondents answered "not at all" or "rarely," while 56.6% stated that they use AI. 53.8% of respondents reported using AI to gain knowledge on previously unfamiliar topics, whereas 26.1% do not use AI for this purpose. Additionally, 50.3% of respondents rely on AI to learn new skills or develop their competencies, while 26.7% either do not use AI or use it rarely.

Table 12. Curiosity and Lifelong Learning: Spearman's rho correlation

	Use_CWCL_1		Use_CWCL_2		Use_CWCL_3	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Comp_CWCL_1	,345**	<,001	,400**	<,001	,278**	<,001
Comp_CWCL_2	,313**	<,001	,378**	<,001	,304**	<,001
Comp_CWCL_3	,333**	<,001	,457**	<,001	,338**	<,001

There is a moderate relationship between the variables Comp_CWCL_3 (initiating actions aimed at developing one's competencies) and Comp_CWCL_1 (seeking new information and skills related to work or studies) and Use_CWCL_2 (using AI to acquire knowledge on topics previously unfamiliar). In all other cases, the relationship is weak.

4.7. Leadership and Social Influence

Regarding Leadership and Social Influence, respondents assessed how well they can inspire others, with 58.3% indicating they can. In comparison, 19.1% stated they cannot or struggle to do so. Communicating their ideas and motivating a team to collaborate is challenging for 19.5% of respondents, whereas 58% believe they handle this task well. Making decisions and taking responsibility for their outcomes is difficult for 21.9%, while 58% claim they can.

Table 13. Leadership and Social Influence: descriptive statistics

	Comp_LSI_1	Comp_LSI_2	Comp_LSI_3	Use_LSI_1	Use_LSI_2	Use_LSI_3
Average	4,66	4,66	4,68	3,69	3,77	3,69
Standard error	0,084	0,082	0,084	0,107	0,109	0,109
Standard dev.	1,425	1,39	1,43	1,819	1,858	1,846

37.2% of respondents use AI tools to analyze reports for evaluating the effectiveness of adopted business strategies, while 39.7% either do not use them or use them rarely. 41.7% of respondents utilize AI tools to develop strategies and plans, whereas 37.9% do not use them or do so infrequently. When making decisions based on team preferences and behaviors, 39.3% of respondents rely on AI tools, while 40.6% either do not use them or use them rarely.

Table 14. Leadership and Social Influence: Spearman's rho correlation

	Use_LSI_1		Use_LSI_2		Use_LSI_3	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_LSI_1	,213**	<,001	,220**	<,001	,155**	0,008
Comp_LSI_2	,198**	<,001	,271**	<,001	,230**	<,001
Comp_LSI_3	,208**	<,001	,224**	<,001	,198**	<,001

For most pairs of variables, there is a weak positive correlation between Leadership and Social Influence skills and the use of AI to support related tasks, or no relationship exists between the variables (Comp_LSI_2 and Use_LSI_1, Comp_LSI_1 and Use_LSI_3, and Comp_LSI_3 and Use_LSI_3).

4.8. Talent Management

58.7% of respondents indicated that they can assess the skills and potential of other team members, while 19.5% stated that they cannot do this or can do so only poorly. Motivating and supporting others is a skill that 62.8% of respondents handle well, while 13.5% admit they struggle with inspiring others or are unable to do so. Planning tasks to maximize the team's talents is done effectively by 61.2% of respondents, whereas 16.3% feel they are unable to plan tasks well or struggle with it.

Table 15. Talent Management: descriptive statistics

	Comp_TM_1	Comp_TM_2	Comp_TM_3	Use_TM_1	Use_TM_2	Use_TM_3
Average	4,72	4,89	4,82	3,53	3,78	3,63
Standard error	0,085	0,081	0,085	0,11	0,112	0,114
Standard dev.	1,444	1,376	1,443	1,861	1,895	1,934

37.2% of respondents use AI tools to identify the development potential and skills of the team they work with, while 39.7% either do not use them at all or use them rarely. 41.7% of respondents use AI tools for planning development paths (their own or others'), whereas 37.9% do not use them or do so infrequently. When making decisions about task assignments based on skills, 39.3% of respondents rely on AI tools, while 40.6% either do not use them for this purpose or use them rarely.

Table 16. Talent Management: Spearman's rho correlation

	Use_TM_1		Use_TM_2		Use_TM_3	
	Coefficient	**Significance**	**Coefficient**	**Significance**	**Coefficient**	**Significance**
Comp_TM_1	0,071	0,233	0,059	0,321	0,023	0,698
Comp_TM_2	,187**	0,001	,175**	0,003	,143*	0,015
Comp_TM_3	,181**	0,002	,218**	<,001	,177**	0,003

No relationship was observed between Talent Management skills and the use of AI.

4.9. Analytical Thinking

In analytical thinking, respondents assessed their skills in data analysis and concluding based on it. Nearly 30% indicated low competencies in this area. 17% chose "hard to say," while 53.1% stated they possess skills in this area, including 7.6% who found it very easy. Identifying patterns and relationships in complex sets of information is challenging for 27.4% of respondents, whereas 43% believe they handle this task well. Solving problems through cause-and-effect analysis is difficult for 25.7% of respondents, while 57.3% claim they can solve such issues.

Table 17. Analytical Thinking: descriptive statistics

	Comp_AT_1	Comp_AT_2	Comp_AT_3	Use_AT_1	Use_AT_2	Use_AT_3
Average	4,4	4,27	4,55	3,97	4	4,01
Standard error	0,095	0,084	0,087	0,102	0,1	0,103
Standard dev.	1,617	1,433	1,476	1,731	1,703	1,753

The number of respondents who use AI tools to analyze large datasets (43.5%) is similar to those who do not use them or sporadically (39.7%). A comparable proportion of respondents report using AI to identify patterns and relationships in data (42.7%), while 36.4% either do not use AI for this purpose or use it rarely. Additionally, 43.7% of respondents utilize AI to support decision-making based on data analysis, whereas 37.5% do not.

Table 18. Analytical Thinking: Spearman's rho correlation

	Use_AT_1		Use_AT_2		Use_AT_3	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Comp_AT_1	,301**	<,001	,244**	<,001	,270**	<,001
Comp_AT_2	,379**	<,001	,347**	<,001	,377**	<,001
Comp_AT_3	,315**	<,001	,249**	<,001	,280**	<,001

There is a weak positive correlation between analytical thinking skills and the use of AI for this purpose, with the highest correlation values observed between the ability to identify patterns and relationships in complex sets of information and the use of AI to support tasks.

4.10. Environmental Stewardship

56% of respondents understand the principles and norms related to environmental protection, while 25.3% either do not understand them at all or understand them poorly. 45.5% of respondents participate in pro-environmental initiatives, whereas 33.3% do not engage in them or do so rarely. Identifying and minimizing the impact of their actions on the environment is handled well by 51% of respondents, while 25.7% either cannot manage this or struggle with it significantly.

Table 19. Environmental Stewardship: descriptive statistics

	Comp_EM_1	**Comp_EM_2**	**Comp_EM_3**	**Use_EM_1**	**Use_EM_2**	**Use_EM_3**
Average	4,49	4,17	4,43	3,56	3,62	3,6
Standard error	0,088	0,1	0,091	0,119	0,116	0,115
Standard dev.	1,498	1,696	1,542	2,016	1,968	1,959

35.1% of respondents use AI tools to monitor the environmental impact of their actions, while 47.2% either do not use them at all or infrequently. AI is used by 35.7% of respondents to identify environmental issues, whereas 44.5% state that they do not use such tools or use them infrequently. When reporting the results of pro-environmental activities, 36.8% of respondents rely on AI tools, while 43.7% either do not use AI for this purpose or do so rarely.

Table 20. Environmental Stewardship: Spearman's rho correlation

	Use_EM_1		Use_EM_2		Use_EM_3	
	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Comp_EM_1	,153**	0,01	,126*	0,033	,122*	0,039
Comp_EM_2	,316**	<,001	,386**	<,001	,334**	<,001
Comp_EM_3	,178**	0,002	,209**	<,001	,166**	0,005

There is a weak positive correlation between Environmental Stewardship skills and the use of AI for related tasks across four pairs of variables. Additionally, no relationship was found for five pairs of variables.

5. Conclusion and Discussion

This study compared employees' self-declared key competencies with their use of AI tools.Respondents reported (RQ1) the highest proficiency in curiosity and lifelong learning (63.9%), technological literacy (61.1%), and talent management (58,3%). The emphasis on technological literacy aligns with World Economic Forum (WEF) forecasts and highlights the confidence of Polish employees in this domain.

However, a potential discrepancy exists. According to research conducted by the Polish Economic Institute in 2024, 3.68 million people in Poland work in the 20 professions most exposed to the impact of AI. At the same time, 25.8% of Poles believe that using AI will positively impact the job market, while 33.4% think it will have a negative effect.

While over 65% of Poles have used an AI chatbot [29] and declared their technical skills level as high, national data from 2023 indicated that Poland's digital competencies were still below the EU average [30]. This self-perception also aligns with the goals of Poland's Digitalization Strategy until 2035 [31].

A key finding was that only curiosity and lifelong learning showed a moderate positive correlation between the declared skill level and the use of AI tools (RQ2). For other competencies, the correlation was weak or non-existent, suggesting that while employees are curious about AI for learning, its broader adoption in the workplace remains limited.

This study, however, has several limitations. Firstly, the findings are based on a relatively modest sample size, which may not be fully representative of the diverse Polish workforce. Secondly, the research relies on the self-assessment of respondents, a method susceptible to subjective bias. Participants may either overestimate or underestimate their abilities, potentially creating a discrepancy between their declared proficiency and their actual competence.

These limitations highlight clear directions for future research. To enhance the generalizability of the findings, subsequent studies should utilize a larger, more stratified sample. It would also be valuable to conduct separate analyses comparing new labor market entrants with experienced employees. Furthermore, to move beyond self-declared data, future research could incorporate objective, task-based assessments to measure competencies. Comparing self-reported levels with actual performance on specific tasks would provide a more robust understanding of skill levels and offer crucial insights into the gap between perceived and actual abilities among Polish employees.

AI tools' development and implementation in the labor market are inevitable. Developing key employee competencies and proficiency in using these tools will soon become necessary in the Polish market and globally.

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