AI in the Workplace and Changing Competence Profiles: A Comparative Study in Poland

Paulina Rutecka-Cicha
Department of Informatics,
University of Economics in Katowice
Katowice, Poland *paulina.rutecka-cicha@uekat.pl*

Karina Rutecka-Cicha
Department of Communication Design and
Analysis, University of Economics in Katowice
Katowice, Poland *karina.rutecka-cicha@uekat.pl*

Abstract

The increasing use of artificial intelligence (AI) in the workplace raises questions about changes in employees' competence profiles and patterns of AI use. This study examines these changes using a comparative approach based on two waves of survey data collected in Poland at the turn of 2024/2025 (N = 288) and 2025/2026 (N = 308). The same research instrument was applied in both waves, providing direct comparison over time. The results show an increase in the use of AI tools in professional work, while limited differences in declared competence levels were observed between the two waves. Additional analyses reveal that the relationship between competencies and AI use varies across different areas, and that distinct user profiles can be identified based on the combination of competence levels and AI usage patterns. The findings suggest that changes related to AI adoption follow a gradual and adaptive pattern rather than a disruptive one. The study contributes by providing a short-term comparative perspective on competence development in AI-supported work environments.

Keywords: GenAI, digital literacy, competences, Human–AI complementarity, AI adoption trends

1. Introduction

The development of artificial intelligence (AI) is no longer seen as a temporary trend but as a defining feature of contemporary technological change. The observed changes are a natural consequence of the introduction of LLMs to the public in 2022. As continuous development is a feature of this technology, AI can be understood not only as an innovation but as a key technological driver shaping contemporary organizational practices.

In recent years, AI systems implemented across sectors have become major accelerator of digital transformation [21], understood as a process in which digital technologies reshape business models, organizational processes, and user experiences [38, 39]. AI-based technologies integrated into everyday work support tasks such as information processing, content creation, data analysis, and decision-making [17]. As a result, AI is treated as a key element of the digital infrastructure of modern workplaces [2, 8, 16]. At the same time, discussions on the future of work and the relationship between human skills and intelligent technologies intensify [7, 17, 19, 27].

Rather than replacing human labor, AI technologies reshape the structure of tasks and work processes. Research suggests that many contemporary applications of AI augment human capabilities instead of automating them [19, 33]. This leads to new forms of human–AI collaboration, where human cognitive skills and algorithmic capabilities support problem solving [15], and to the reconfiguration of work practices, including how tasks are

distributed and coordinated [20].

Digital technologies modify the composition of tasks within occupations rather than eliminating entire jobs [8]. The interaction between humans and AI can be characterized by its complementarity, where technological systems are to enhance human productivity and expand the scope of performed tasks [1].

As technological systems become more capable of performing routine tasks, the importance of certain human skills evolves. Previous studies indicate that increasing demand for cognitive, analytical, and creative capabilities, which enable the effective use of digital technologies [1, 2, 10]. Competencies related to analytical thinking, adaptability, continuous learning, and digital literacy are considered crucial in digitally mediated workplaces [41].

Market reports further emphasize ongoing changes in competence structures. For example, the World Economic Forum identifies analytical thinking, technological literacy, creativity, resilience, and lifelong learning as key competencies in AI-driven environments [42]. These competencies reflect the need for workers who can adapt to evolving technological systems.

Despite the growing body of research on AI and the future of work, relatively little attention has been devoted to short-term changes in employees' competence profiles associated with the increasing use of AI tools [2, 10].

This raises the question of whether competence profiles and patterns of AI use remain stable or evolve over time. To address this issue, this study compares the results of two survey waves conducted one year apart using the same research instrument, allowing for the identification of potential changes in declared competencies and AI usage patterns over time. Taking the above under consideration, the research questions for this paper were formed as follows:

RQ1: What is the trend in the declared levels of AI-related competencies among employees?

RQ2: What is the trend in AI tool usage patterns among employees?

RQ3: Is the relationship between competencies and AI tool usage stable over time?

The structure of this paper is as follows: Section 2, Theoretical Background, provides a review of the literature on technological acceleration, sociotechnical perspectives on work, the transformation of work processes, as well as competence development in AI-supported environments; Section 3, Materials and Methods, describes the research procedure; Section 4, Results, contains a detailed account of the study results. Finally, the paper concludes with Section 5, Conclusion and Discussion, which interprets the results in light of the theoretical framework, summarizes the main findings, and outlines their implications.

2. Literature Review

2.1. Technological Acceleration and the AI Diffusion

Technological development in contemporary societies can be characterized as an acceleration process. Advances in digital technologies have speeded up the pace of adoption of new tools. As a result, digitalization itself has become a mechanism of technological acceleration [35] visible in areas such as communication and product development.

The development of AI technologies further illustrates this phenomenon. The evolution of predictive, generative, and agentic AI systems has brought new possibilities in organizational contexts [11]. At the same time, the rapid growth of AI is associated with shorter innovation cycles and a faster pace of technological deployment [34].

Technological milestones reflect this acceleration. Breakthroughs in deep learning enabled the large-scale application of neural networks [22], while the transformer architecture created the foundation for LLMs [37]. More recently, publicly available generative AI systems, have accelerated blending AI in organizational and professional contexts [5, 9, 29].

These developments illustrate the pace of technological innovation and the growing role of digital technologies in organizational contexts. To understand their implications, it is necessary to examine how technologies interact with work practices and humans within organizational systems.

2.2. Technology and Work - Sociotechnical Perspective

Organizations can be viewed as systems composed of elements such as technologies, processes, and human resources that interact with their environment [40]. Taking that into consideration, one can observe that changes in technology influence not only the tools used in organizations but also the way work is organized. Sociotechnical systems theory emphasizes that effective work environment require alignment between the technical system and the social system of work [6, 14]. That is why technologies should not be analyzed separately from the people who use them and the work practices which they are involved in.

Later research have broaden this perspective by examining the relationship between digital technologies and organizational practices. Studies in sociomateriality show that technologies and work practices shape each other in organizational activities [24, 30]. This approach has also been applied to the analysis of modern digital systems and the development of technologies, including digital ones [3, 32]. This provides a useful starting point for analyzing how the growing use of AI technologies may affect the organization of work.

2.3. The Transformation of Work Processes

Digital technologies influence the way work processes are organized. Research indicates that technologies such as AI systems do not only provide new tools but also change how work is performed and coordinated [18]. By integrating algorithmic systems into everyday operations, such as decision-making or information flows, the organizations become mediated by technology, what may lead to a gradual transformation of existing work processes.

What is important, changes in work processes are linked to transformations in the structure of tasks which employees perform. Studies suggest that AI systems increasingly influence how tasks are assigned, evaluated, and sequenced [31]. For instance, technology applied in the organizational structure may automate certain routine activities. At the same time, the importance of tasks requiring human judgement, interpretation, and problem-solving will increase. However, those changes may alter the composition of work rather than eliminate entire jobs.

The implementation of such complex technical solutions leads to organizational digital transformation. It reshapes work practices by influencing how employees coordinate their activities, share knowledge, and organize their daily work routines [26, 36]. As a consequence, employees need to adjust their ways of working to new technological environments. Therefore, the value of digital technologies strictly their interaction with existing organizational practices, including knowledge sharing [28].

Above-mentioned developments suggest that technological change influence work at multiple levels. Understanding these transformations is particularly important in the context of the growing use of AI technologies, which increasingly interact with human activities in professional environments, as well as competencies humans need to perform their professional tasks properly.

2.4. Human–AI Complementarity and Competence Transformation

The presence of AI systems in organizational environments has broaden discussions on relations between human work and technologies. As already stated, rather than fully replacing human labor, many AI applications complement human capabilities and support employees in performing tasks [15, 19]. This is the automation–augmentation paradox, suggesting that on the one hand, AI automates certain activities while on the other enhances the effectiveness of human work [33]. This, in organizational practice, means that technology participates in work processes while humans remain responsible for interpretation, and decision-making.

The integration of technological systems into work environments has caused the evolution of the competencies required from employees. Research suggest that this type of change often occurs as an adaptive response to technological development rather than a direct consequence of existing technologies [25]. In the context of accelerating technology,

employees need to adjust their competencies and skills to new forms of collaboration with AI-supported systems.

The previously conducted studies have also tried to identify the competencies that may be important or even crucial in AI-supported work environments. Research indicates that both technical competencies, such as digital literacy, data analysis, and technological proficiency, and human-centered competencies, including critical thinking, creativity, and problem-solving, play a significant role in working with AI-supported systems [23]. Similar conclusions in an earlier study examining competencies related to the use of AI tools in professional work were presented [13]. That study referred to the competence areas highlighted in the World Economic Forum's "Future of Jobs" report, which identifies a set of competencies expected to become more and more important in the coming years. These include technological competencies such as AI and big data, networks and cybersecurity, and technological literacy, as well as human-oriented competencies such as analytical thinking, creativity, resilience, lifelong learning, leadership, and environmental awareness [42]. Together, these competencies reflect the increasing need to combine technological expertise with cognitive and social capabilities in technology-based work environments.

The reviewed literature indicates that technological acceleration and AI diffusion force a continuous adjustment of employee competencies. To explore these dynamics, this study examines how employees assess their shifting competence profiles and AI usage patterns over time.

3. Methods and Materials

The study was conducted using the CAWI (Computer-Assisted Web Interviewing) method on the dedicated platform of the Polish research panel SW Research. A questionnaire consisting of 57 questions was used. It was developed using a dedicated survey tool available on the SW Research platform. The study was conducted twice. The first wave was conducted between December 1, 2024, and January 15, 2025. The second wave was conducted between December 11, 2025, and February 26, 2026. Consequently, the research follows a repeated cross-sectional design (trend study) aimed at tracking shifts within the population of AI users over time, rather than monitoring a fixed panel of identical individuals. In both studies, only adult respondents were allowed to participate. Participation was voluntary and the survey could be discontinued at any moment.

A total of 701 respondents took part in the first study. However, 414 of them (58.97%) indicated that they had never consciously and intentionally used artificial intelligence solutions (AI, including language models such as ChatGPT) for professional or private purposes. In the second study, 471 respondents participated, of whom 161 (34.18%) declared that they had never used AI. As a result, two groups of adult AI users in Poland were obtained: respondents surveyed at the turn of 2024/2025 (288 respondents) and respondents surveyed at the turn of 2025/2026 (308 respondents).

In the survey, users were asked about their self-assessment of competencies and whether they used AI tools to support tasks requiring specific competencies. The study used ten key competencies identified by the World Economic Forum in the report "Future of Jobs 2025". The report indicates that these competencies will be the most important for employees in a rapidly changing labour market [42]. These competencies, presented in order of fastest growth, are: 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; Environmental Stewardship.

SPSS 29.0.2.0 software was used to analyze the collected data. For each of the ten competencies identified by the World Economic Forum (AT, CT, RFA, LLL, TS, LSI, TM, AIBD, NCS, ENV), two composite indicators were computed: self-assessed competence (Comp_) and AI-supported use (Use_). In the first step, reliability analysis was conducted by calculating Cronbach's alpha for the three items forming each Comp_ and Use_ variable.

Table 1. Cronbach's alpha values for the aggregate variables Comp_ and Use_

	Competence group name	Competence (Comp_)	AI Usage (Use_)
AT	Analytical Thinking	,858	,927
CT	Creative Thinking	,828	,913
RFA	Resilience, Flexibility and Agility	,819	,927
LLL	Curiosity and Lifelong Learning	,832	,889
TS	Technological Literacy	,835	,918
LSI	Leadership and Social Influence	,831	,929
TM	Talent Management	,810	,921
AIBD	Artificial Intelligence and Big Data	,824	,937
NCS	Networks and Cybersecurity	,807	,936
ENV	Environmental Stewardship	,825	,938

Tests of normality were statistically significant ($p < .001$), and Shapiro–Wilk statistics ranged between .915 and .981, indicating only minor deviations from normality. Because Likert scales were used in the study, the data were treated as ordinal and non-parametric tests were applied. First, the Mann–Whitney U test was used to compare differences between two independent groups, in this case between responses from respondents surveyed in 2024/2025 (hereafter referred to as "2025") and respondents surveyed in 2025/2026 (hereafter referred to as "2026").

In the next step, the composite variables Comp_ and Use_ were standardized, and the standardized values were saved as variables. These were then subjected to hierarchical cluster analysis in order to identify the most appropriate number of clusters. A four-cluster solution was selected. The number of clusters was determined based on the analysis of the dendrogram and the agglomeration schedule using Ward's method. Next, k-means cluster analysis was conducted. The distribution of observations across clusters can be considered acceptable. No cluster is extremely small, and the size of the smallest cluster (Cluster 4) exceeds 10% of the total sample [12]. Alternative solutions (3- and 5-cluster models) were also explored, but the four-cluster solution provided the most interpretable and theoretically meaningful structure.

4. Results

Based on the initial questions, the demographic profile of GenAI users was identified for both waves of the study (2025 and 2026). In the demographic section of the questionnaire, respondents were asked about their age, gender, level of education, and place of residence.

Table 2. Demographic characteristics of respondents in 2025 and 2026

	2025 (n = 288)	2026 (n = 308)	χ^2	Cramér's V	p
Age: 18-25	68	44	13,36	.15	0,004
Age: 26-35	68	67			
Age: 36-55	122	142			
Age: 56-75	30	55			
Education: Primary / Lower Secondary	19	26	1,24	.05	0,742
Education: Secondary / Vocational	142	154			
Education: Bachelor's degree	43	39			
Education: Master's degree and PhD	84	89			
Gender: Male	114	118	0,143	.02	0,931
Gender: Female	170	185			
Gender: Prefer not to answer	4	5			
Place of residence: Rural area	77	92	1,978	.06	0,577
Place of residence: Town ≤ 50,000 inhabitants	74	83			
Place of residence: Town ≤ 100,000 inhabitants	49	41			
Place of residence: City > 100,000 inhabitants	88	92			

χ^2 = Pearson chi-square test.

A chi-square test was conducted to determine whether statistically significant differences existed between respondents surveyed in 2025 (n = 288) and 2026 (n = 308). A significant difference was observed only for age distribution, $\chi^2(3) = 13.36$, $p = .004$. Cramér's V was calculated to assess the strength of association. Again, age was the only variable showing a

meaningful effect, although the magnitude of this association was small.
These findings suggest that the two cohorts were largely comparable in terms of demographic composition. At the same time, the results indicate that no substantial shifts occurred in the overall profile of AI users in Poland between 2025 and 2026. The 2026 sample was slightly older, with a higher proportion of respondents aged 36–55 and 56+ years.

Table 3. Comparison of purposes for using AI tools in 2025 and 2026

Purpose of AI Use	2025 (%)	2026 (%)	χ^2	p	Cramér's V
Text correction	36.1	39.3	0.64	.424	.03
Text generation	47.6	46.8	0.04	.842	.01
Translation	36.5	45.5	4.98	.026	.09
Text summarization	25.3	20.1	2.31	.128	.06
Information search	44.4	54.2	5.69	.017	.10
Information synthesis	9.4	16.6	6.75	.009	.11
Creating instructions	9.0	16.2	6.95	.008	.11
Problem solving	20.1	23.4	0.92	.339	.04
Code generation	4.9	7.8	2.14	.143	.06
Code correction	5.9	5.8	0.00	.976	.00
Image generation	16.7	26.0	7.65	.006	.11

χ^2 = Pearson chi-square test.

In the next step, we examined whether the way AI was used changed between 2025 and 2026. To this end, a series of chi-square tests was conducted to compare the general purposes for which AI tools were used. Statistically significant differences were observed for Translation, Information search, Information synthesis, Creating instructions, and Image generation. The largest Cramér's V effect sizes were observed for Information synthesis, Creating instructions, and Image generation; however, these effects were very small.

4.1. Cluster analysis

Standardized values were used in the analysis. Negative values indicate results below the mean, while positive values represent results above the mean. The further a value is from zero, the greater the deviation from the mean.

Table 4. Final Cluster Centers (Standardized Scores) for Competence and AI Use Variables

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Competence: Analytical Thinking (Comp_AT)	0,34	0,67	-0,27	-1,45
Competence: Creative Thinking (Comp_CT)	0,35	0,70	-0,24	-1,63
Competence: Resilience, Flexibility and Agility (Comp_RFA)	0,23	0,78	-0,29	-1,37
Competence: Curiosity and Lifelong Learning (Comp_LLL)	0,26	0,74	-0,23	-1,57
Competence: Technological Literacy (Comp_TS)	0,38	0,69	-0,31	-1,46
Competence: Leadership and Social Influence (Comp_LSI)	0,19	0,80	-0,25	-1,49
Competence: Talent Management (Comp_TM)	0,24	0,86	-0,32	-1,51
Competence: AI and Big Data (Comp_AIBD)	0,08	0,92	-0,25	-1,56
Competence: Networks and Cybersecurity (Comp_NCS)	-0,28	0,86	-0,09	-1,22
Competence: Environmental Stewardship (Comp_ENV)	-0,02	0,85	-0,18	-1,41
AI Use: Analytical Thinking (Use_AT)	-0,92	0,99	0,18	-1,07
AI Use: Creative Thinking (Use_CT)	-0,87	0,95	0,17	-1,04
AI Use: Resilience, Flexibility and Agility (Use_RFA)	-0,90	0,93	0,20	-1,04
AI Use: Curiosity and Lifelong Learning (Use_LLL)	-0,58	0,85	0,09	-1,17
AI Use: Technological Literacy (Use_TS)	-1,05	0,96	0,24	-0,94
AI Use: Leadership and Social Influence (Use_LSI)	-1,20	0,96	0,27	-0,72
AI Use: Talent Management (Use_TM)	-1,20	0,92	0,29	-0,69
AI Use: Artificial Intelligence and Big Data (Use_AIBD)	-1,16	0,99	0,21	-0,66
AI Use: Networks and Cybersecurity (Use_NCS)	-1,17	0,93	0,25	-0,62
AI Use: Environmental Stewardship (Use_ENV)	-1,20	0,95	0,23	-0,52
Number of cases in each Cluster	**142**	**158**	**233**	**63**

Cluster 1 (n = 142) includes respondents whose self-declared level of competencies is above the mean, but who use AI relatively rarely. This group may be interpreted as AI skeptics. Cluster 2 (n = 158) consists of individuals with high levels of competencies across all areas who are also intensive users of AI. Cluster 3 (n = 233) includes respondents whose competencies are

slightly below the mean but who use AI relatively frequently (above the mean). These individuals may compensate for lower competencies through the use of AI tools. Cluster 4 (n = 63) represents respondents with the lowest competency levels who also use AI the least often. This is the smallest cluster and appears clearly separated from the others.

Table 5. Distribution of Identified AI User Clusters by Survey Year (2025 vs. 2026)

	Cluster 1		**Cluster 2**		**Cluster 3**		**Cluster 4**		
Year	**n**	**% within**	**n**	**% within**	**n**	**% within**	**n**	**% within**	**Total**
2025	70	24,3%	69	24,0%	111	38,5%	38	13,2%	**288**
2026	72	23,4%	89	28,9%	122	39,6%	25	8,1%	**308**
Total	**142**	**23,8%**	**158**	**26,5%**	**233**	**39,1%**	**63**	**10,6%**	**596**

In the next step, cross-tabulation analysis was used to verify whether the cluster structure changed between 2025 and 2026. The results showed $\chi^2(3) = 5.096$, $p = .165$, Cramér's $V = .092$. No statistically significant difference was found in the cluster structure between 2025 and 2026, and the Cramér's V effect size was very small.

Table 6. Mann–Whitney U test results and effect sizes (r) for differences in competencies (Comp_) and AI-supported use (Use_) between 2025 and 2026

	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)	n	√N	r
Comp_AT	39021	80637	-2,546	**0,011**	596	24.42	**.10**
Comp_CT	42113	83729	-1,07	0,284			-
Comp_RFA	42121,5	89707,5	-1,066	0,287			-
Comp_LLL	43925,5	85541,5	-0,204	0,838			-
Comp_TS	43790	91376	-0,269	0,788			-
Comp_LSI	42750	84366	-0,766	0,444			-
Comp_TM	42638	84254	-0,82	0,412			-
Comp_AIBD	40483	82099	-1,85	0,064			-
Comp_NCS	44347	85963	-0,002	0,998			-
Comp_ENV	38317	79933	-2,884	**0,004**			**.12**
Use_AT	41730,5	83346,5	-1,252	0,211			-
Use_CT	42375,5	83991,5	-0,944	0,345			-
Use_RFA	35088	76704	-4,423	**<,001**			**.18**
Use_LLL	39919	81535	-2,119	**0,034**			**.09**
Use_TS	38804	80420	-2,65	**0,008**			**.11**
Use_LSI	42655	84271	-0,811	0,417			-
Use_TM	42069	83685	-1,093	0,275			-
Use_AIBD	44214,5	85830,5	-0,066	0,948			-
Use_NCS	41420,5	83036,5	-1,405	0,16			-
Use_ENV	43581,5	85197,5	-0,37	0,712			-

Next, Mann–Whitney U tests were conducted to compare the levels of competencies declared by AI users in 2025 (n = 288) and 2026 (n = 308). Effect sizes (r) were not calculated for competencies that did not reach statistical significance in the Mann–Whitney U test. The Mann–Whitney U tests revealed statistically significant differences between 2025 and 2026 in the use of AI in three competency areas: Resilience, Flexibility and Agility; Curiosity and Lifelong Learning; and Technological Literacy. In all cases, the effect sizes were small. No statistically significant differences were observed for the remaining competencies.

4.2. Sociodemographic differences in clusters

First, a cross-tabulation analysis was conducted to examine the relationship between clusters and the sectors declared by respondents (either their current employment sector or the field in which they study). Because respondents reported as many as 26 different industries, some of them were represented by only a small number of observations. To make the analysis more robust, these industries were grouped into eight broader categories: Technology & Digital (TE); Education & Research (ER); Business & Finance (BF); Public Sector (PS); Healthcare (HE); Industry & Manufacturing (IM); Infrastructure, Energy & Utilities (IEU); and Trade, Logistics & Services (TLS).

Respondents working or studying in the Technology & Digital (TE) area appear most often in Cluster 2 and Cluster 3, which means they tend to use AI more intensively. Most of them report competency levels slightly below the average (Cluster 3). The highest declared

competency levels can be observed among respondents from the Healthcare sector (37.3% in Cluster 2) and Education & Research (32.1% in Cluster 2). The lowest competency levels and the least frequent use of AI are reported by respondents from the Public Sector, where as many as 18.4% belong to Cluster 4. Cluster 1 most often includes respondents from Education & Research (30.2%). These individuals report competency levels above the mean but use AI relatively rarely.

Table 7. Cross-tabulation of respondent clusters and declared sectors

Industry Sector	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Total
Technology & Digital (TE)	19,6%	27,5%	45,1%	7,8%	51
Education & Research (ER)	30,2%	32,1%	32,1%	5,7%	53
Business & Finance (BF)	25,3%	21,7%	38,6%	14,5%	83
Public Sector (PS)	24,5%	24,5%	32,7%	18,4%	49
Healthcare (HE)	13,3%	37,3%	38,6%	10,8%	83
Industry & Manufacturing (IM)	28,9%	17,1%	42,1%	11,8%	76
Infrastructure, Energy & Utilities (IEU)	12,8%	23,1%	53,8%	10,3%	39
Trade, Logistics & Services (TLS)	27,8%	27,2%	37,0%	8,0%	162
Total	**23,8%**	**26,5%**	**39,1%**	**10,6%**	**596**

Cross-tabulation tables were also used to examine whether particular sociodemographic profiles dominated within specific clusters. First, cluster membership was analyzed across different age groups of respondents.

Table 8. Cross-tabulation of clusters and respondents' age groups

Age	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Total
	Count	% within	Count	% within	Count	% within	Count	% within	
18-25	16	14,3%	31	27,7%	55	49,1%	10	8,9%	112
26-35	38	28,1%	35	25,9%	50	37,0%	12	8,9%	135
36-55	69	26,1%	70	26,5%	95	36,0%	30	11,4%	264
56-75	19	22,4%	22	25,9%	33	38,8%	11	12,9%	85
Total	142	23,8%	158	26,5%	233	39,1%	63	10,6%	596

A chi-square test of independence was conducted to examine the association between age group and cluster membership. The relationship was not statistically significant, $\chi^2(9) = 11.02$, $p = .274$, Cramér's $V = .08$, indicating a negligible association. This suggests that the distribution of AI user profiles was relatively consistent across age groups.

Table 9. Cross-tabulation of clusters and respondents' gender groups

	Cluster 1		Cluster 2		Cluster 3		Cluster 4		
Gender	Count	% within	Count	% within	Count	% within	Count	% within	Count
Male	55	23,7%	57	24,6%	96	41,4%	24	10,3%	232
Female	87	24,5%	98	27,6%	131	36,9%	39	11,0%	355
Prefer not to answer	0	0,0%	3	33,3%	6	66,7%	0	0,0%	9
Total	**142**	**23,8%**	**158**	**26,5%**	**233**	**39,1%**	**63**	**10,6%**	**596**

Next, the analysis was conducted with respect to respondents' gender. In this case as well, no statistically significant differences were found, $\chi^2(3) = 6.38$, $p = .382$, Cramér's $V = .10$, indicating that AI user profiles were distributed similarly among male and female respondents.

Table 10. Cross-tabulation of clusters and respondents' education level groups

Education	Cluster 1		Cluster 2		Cluster 3		Cluster 4		n
	n	% within	n	% within	n	% within	n	% within	
Primary / Lower Secondary	6	13,3%	7	15,6%	22	48,9%	10	22,2%	45
Secondary / Vocational	46	15,5%	88	29,7%	132	44,6%	30	10,1%	296
Bachelor's degree	19	23,2%	20	24,4%	33	40,2%	10	12,2%	82
Master's degree and PhD	71	41,0%	43	24,9%	46	26,6%	13	7,5%	173
Total	**142**	**23,8%**	**158**	**26,5%**	**233**	**39,1%**	**63**	**10,6%**	**596**

Next, differences in education level across clusters were examined. A statistically significant association was found between education level and cluster membership, $\chi^2(9) = 53.56$, $p < .001$, Cramér's $V = .17$. Respondents with higher education (master's and doctoral

degrees) more often belonged to Cluster 1, whereas individuals with lower levels of education were more frequently represented in Cluster 3. The share of Cluster 4 decreased as the level of education increased. Respondents with primary or lower secondary education were strongly concentrated in Cluster 3.

Table 11. Cross-tabulation of clusters and respondents' place of residence groups

Place of residence	Cluster 1		Cluster 2		Cluster 3		Cluster 4		n
	n	% within	n	% within	n	% within	n	% within	
Rural area	41	24,30%	36	21,30%	74	43,80%	18	10,70%	169
Town ≤ 50,000 inhabitants	29	18,50%	46	29,30%	63	40,10%	19	12,10%	157
Town ≤ 100,000 inhabitants	26	28,90%	20	22,20%	34	37,80%	10	11,10%	90
City > 100,000 inhabitants	46	25,60%	56	31,10%	62	34,40%	16	8,90%	180
Total	142	23,80%	158	26,50%	233	39,10%	63	10,60%	596

No significant relationship was found between place of residence and cluster membership, $\chi^2(9) = 10.24$, $p = .332$, Cramér's $V = .08$. The distribution of AI user profiles was similar among respondents living in rural areas and in cities of different sizes.

5. Discussion and Conclusions

5.1. Discussion

The findings indicate gradual shifts in employees' competence profiles associated with AI use. However, the differences observed between the two waves of the survey suggest that noticed changes are not rapid or revolutionary but rather reflect a pattern of ongoing technological adaptation. This supports the assumption that competence development in technology-based work environments is, in fact, a continuous process shaped mostly by everyday practices not just a one-time adjustment. Comparable conclusions have been drawn in studies showing that the implementation of advanced technologies into organizations can start changes in job design, and competence requirements rather than immediate transformation [25, 31]. While these gradual trends align with existing theoretical assumptions, empirical and quantitative validation of these phenomena across sequential time periods contributes by converting qualitative expectations into statistical evidence,

The results also show an increase in the professional AI use, what suggests that AI is no longer in an experimentation stage, but is becoming part of regular and purposeful use in everyday tasks. This may reflect a broader process of technological normalization. This interpretation is consistent with recent studies indicating the GenAI diffusion in organizational contexts [4, 7].

Importantly, the relationship between competencies and the use of AI tools varies across different areas. While higher levels of certain competencies are associated with more frequent use of AI, this relationship is not equally strong in all cases. This suggests that AI does not simply replace existing competencies but interacts with them. In particular, the findings support the view that AI technologies are often complementary to human abilities. AI both automates certain tasks and supports human performance, with outcomes emerging from the interaction between human judgement and algorithmic capabilities [15, 33].

However, although AI implementation appears similar across sectors, some differences are still observed. This suggests that the impact of AI on work is not homogenous and its integration into everyday work practices depends on the specific organizational and task context. In digitally advanced environments, AI is a greater part of work processes, which may accelerate competence-related changes. This observation supports sociotechnical perspectives on work, which emphasize that the effects of technology depend on how it is integrated into existing systems of tasks, roles, and practices [18].The findings from both survey waves suggest that the growing use of AI contributes to a gradual reconfiguration of work. Yet, it cannot be said that this is a radical disruption. Changes can be observed at multiple levels, including the organization of work processes, the structure of tasks, and required competencies. However, these changes appear to follow an adaptive logic, in which employees adjust their skills and ways of working to evolving technological environments. This supports the view that AI should be understood as a complementary resource extending human capabilities, rather than as a substitutive technology, stealing people's jobs.

5.2. Conclusions

The study examined relations between employees' competence profiles and patterns of AI use, especially whether they have changed over time. The results indicate that some shifts in declared competencies can be observed, although their scale remains limited, which suggests an adaptive rather than disruptive pattern of change (RQ1). At the same time, a clear increase in professional AI use was identified, indicating a transition to more regular use (RQ2). The relationship between competencies and AI use remains present but varies across different areas, suggesting that AI interacts with, rather than replaces, human competencies (RQ3).

The findings show that changes related to AI adoption occur at multiple levels, and follow an adaptive logic, in which employees adjust their skills to evolving technological environments. This supports the view that AI should be understood as a complementary resource extending human capabilities.

5.3. Limitations and further research

This study has several limitations. First, the analysis is based on self-reported data, which may be subject to response bias and differences in individual interpretation of competence levels. This subjective self-assessment may introduce social desirability bias, potentially leading to an overestimation of actual skills. Furthermore, the utilization of the CAWI method could attract naturally more digitally literate respondents.

Second, although the study applies a repeated measurement design, the two waves do not follow the same individuals over time, which limits the ability to draw conclusions about individual-level changes. Third, the research was conducted within a single nation, which means the findings may not fully apply to other contexts. Future research could address these limitations. It would also be valuable to explore in more detail how specific organizational contexts influence the relationship between AI use and competence development. To further enhance objectivity, future studies should consider combining self-reported surveys with performance-based assessments.

5.4. Practical implications

The findings provide several practical implications for organizations using AI tools. First, the results suggest that higher AI availability does not mean higher competence levels. Organizations should actively support competence development alongside technology adoption, by, for instance, designing targeted training programs. Second, different user profiles indicate that employees use AI in various ways and on various competence levels. As a result, organizations should avoid uniform implementation strategies and instead adopt more tailored approaches, like, for example, support mechanisms depending on employee profiles. Finally, since some employees appear to compensate for lower competence levels through more intensive use of AI, organizations should pay attention to how AI is used in practice. This includes monitoring the quality of AI-supported work and ensuring that reliance on AI tools.

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