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ARTIFICIAL INTELLIGENCE ADOPTION AND LABOUR MARKET OUTCOMES: A STUDY OF EMPLOYMENT PERCEPTIONS IN CENTRAL EUROPE

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Abstract

This research paper examines the relationship between artificial intelligence (AI) adoption in organizations and three critical labour market outcomes: overall employment rates, job creation in emerging sectors, and job displacement in traditional industries. Drawing on a cross-sectional survey of 160 working professionals across various industries in Hungary and Central Europe, the study employs Pearson correlation and multiple regression analyses to test three hypotheses. Results indicate statistically significant positive correlations between AI adoption and perceptions of employment rates (r = 0.311, p < 0.001), job creation (r = 0.498, p < 0.001), and job displacement (r = 0.459, p < 0.001). Notably, the relationship between AI adoption and job creation perceptions is stronger than that between AI adoption and job displacement perceptions, suggesting qualified optimism regarding AI's net employment effects within the Central European professional context. The study contributes individual worker-level perceptual evidence supporting the dual-effect model of AI and employment, extending the literature beyond macroeconomic analyses and beyond the traditional focus on Western economies. Policy implications for governments, educational institutions, and business leaders are discussed, emphasizing the critical role of institutional frameworks in determining whether AI adoption yields positive or negative employment outcomes.

Keywords: Artificial Intelligence, Employment, Job Creation, Job Displacement, Labour Market, Central Europe, Automation, Skills Development

1. Introduction

Artificial intelligence represents one of the most significant technological advancements of the twenty-first century, fundamentally transforming the nature of work and economic organization globally. Unlike previous waves of automation that primarily affected manual and physical labour, AI technologies now perform cognitive tasks: making decisions, analysing data, and executing processes that were once considered exclusively within the domain of human workers. This technological shift has generated intense debate among scholars, policymakers, and practitioners regarding the future of employment and the distribution of work in an AI-driven economy (Acemoglu & Restrepo, 2020; Briggs & Kodnani, 2023).

Recent projections highlight the scale of potential disruption. Goldman Sachs Research estimates that AI automation could displace approximately 300 million full-time jobs worldwide, with white-collar occupations in customer service, finance, and administration being particularly vulnerable (Briggs & Kodnani, 2023). However, research by Acemoglu and Restrepo (2020) presents a more nuanced picture, suggesting that AI creates two simultaneous effects: a displacement effect that eliminates certain jobs and a reinstatement effect that creates new employment opportunities. The net impact on employment depends on the relative strength of these effects, which is substantially influenced by institutional and policy contexts.

The World Economic Forum's Future of Jobs Report 2025 projects that by 2030, AI will displace 92 million jobs globally while creating 170 million new positions, resulting in a net gain of approximately 78 million jobs. However, these projections are contingent on societies investing in workforce reskilling, education programs, and transitional support mechanisms (World Economic Forum, 2025). This dependency on institutional responses underscores a central thesis: that the employment outcomes of AI adoption are not technologically determined but rather shaped by policy choices, educational investments, and organizational strategies.

Despite growing scholarly attention to AI's labour market implications, significant gaps remain in the existing literature. Most studies focus exclusively on either job creation or job displacement, rarely examining both simultaneously within a single research design. Furthermore, the majority of empirical investigations concentrate on the United States and Western Europe, with limited attention to Central European economies that exhibit intermediate levels of AI adoption and unique institutional characteristics (Kuhn, 2019). This paper addresses these gaps by investigating the perceptions of working professionals in Hungary and Central Europe regarding AI's impact on employment rates, job creation, and job displacement.

1.1 Research Questions

This study is guided by three research questions:

RQ1: What impact does the degree of AI adoption have on employment rates in various economic sectors?

RQ2: To what extent does increase AI adoption contribute to job creation in new and emerging AI-driven sectors?

RQ3: How do job displacement rates in conventional sectors relate to the degree of AI adoption?

1.2 Research Hypotheses

Based on the theoretical framework and empirical literature, three hypotheses are proposed:

H1: Professionals working in industries with higher AI adoption perceive more stable and positive employment conditions than professionals in less AI-intensive industries.

H2: Industries with higher rates of AI adoption are perceived by working professionals as experiencing greater emergence and growth of new job roles as a result of AI.

H3: Industries with higher AI adoption rates experience higher rates of job displacement, particularly in routine, repetitive, and codifiable occupations.

2. Literature Review

2.1 Theoretical Frameworks

Three theoretical frameworks dominate academic discourse on the relationship between technological advancement and employment. The first, skill-biased technological change theory, posits that technological progress benefits workers with higher education and technical skills while reducing demand for lower-skilled workers (Autor, 2015). This framework predicts increasing wage inequality and labour market polarization, with AI-intensive industries showing higher wage growth for skilled workers alongside declining employment in routine occupational categories.

The second framework, the task-based model proposed by Acemoglu and Restrepo (2020), conceptualizes jobs as bundles of tasks that can be performed by either humans or machines. AI automates certain tasks, creating a displacement effect, while simultaneously generating new tasks that require human input, creating a reinstatement effect. The net employment outcome depends on the balance between these effects, which is shaped by institutional conditions.

The third framework, Schumpeter's theory of creative destruction, suggests that technological advancement eliminates existing jobs while creating new employment opportunities in emerging industries. Historical evidence supports this theory, as each major technological transition has ultimately led to increased total employment (Bessen, 2019). However, the critical question remains whether the rate of job creation through AI is sufficient to offset the rate of job displacement.

2.2 AI Adoption and Overall Employment Rates

The relationship between AI adoption and employment rates is more complex than simplistic narratives of technological unemployment suggest. Research by Chole et al. (2024) demonstrates that organizations investing in both AI adoption and workforce development maintain stable or increasing employment rates, challenging the assumption of inherent conflict between AI adoption and employment growth.

Comparative analyses across nations provide compelling evidence that institutional contexts determine employment outcomes. Countries like Denmark and Sweden, which combine high AI adoption rates with robust social safety nets and active labour market policies, have maintained employment levels despite widespread automation (Georgieff & Hyee, 2022). Conversely, nations with weaker institutions have experienced more acute employment disruption. These observations support the argument that AI's employment impact is fundamentally a question of policy and governance rather than technological inevitability (Buntak, 2019; Chen, 2022).

The dimension of time is critical in understanding AI's employment effects. Brynjolfsson, Rock, and Syverson (2021) demonstrate that while AI adoption often leads to initial productivity and employment stagnation, productivity gains materialize only after a lag period of several years. Studies employing short timeframes inevitably produce pessimistic findings, whereas longer observation periods reveal AI's beneficial employment effects.

2.3 Job Creation in New Industries

Historical evidence supports qualified optimism regarding AI's capacity to create jobs. Each major technological advance of the past two centuries ultimately generated more employment than it destroyed (Bessen, 2019). Recent projections align with this historical pattern, with the World Economic Forum (2025) forecasting net job creation of 78 million positions globally by 2030.

AI-driven job creation spans multiple occupational categories, including machine learning engineers, AI ethics specialists, data governance officers, and digital transformation consultants (Aithal & Prabhu, 2024). These positions require new skills that did not previously exist in the labour market, creating challenges and opportunities for workforce development. Industries ranging from healthcare and finance to manufacturing are generating new roles requiring AI-related competencies.

Geographic concentration of AI-related jobs presents significant challenges for policymakers. AI companies tend to cluster in cities with developed digital infrastructure and technological ecosystems, creating regional disparities in employment benefits (Challoumis, 2024). While these clusters generate economic benefits for surrounding areas, regions lacking necessary infrastructure may experience employment losses relative to AI-intensive areas.

Access to learning and reskilling programs emerges as the single most important condition for individuals to benefit from AI-driven job creation. Workers with access to such programs are significantly more likely to secure new positions in AI-intensive sectors (Liang, 2024). However, educational institutions often struggle to maintain pace with rapidly evolving skill requirements, creating persistent skills gaps.

2.4 Job Displacement in Traditional Industries

The threat of job displacement in traditional industries remains a primary concern regarding AI adoption. Frey and Osborne's (2013) influential Oxford study estimated that approximately 47% of US jobs were at high risk of automation. However, Arntz, Gregory, and Zierahn (2016) offered a more conservative estimate of approximately 9% of OECD jobs at risk, emphasizing that most occupations contain both automatable and non-automatable tasks.

AI automation disproportionately affects workers in low- and middle-skill positions, particularly in clerical work, customer service, financial services, and manufacturing (Balakumar et al., 2024). These workers often have limited options for responding to displacement, creating significant economic and psychological consequences. Research by Braganza, Chen, Canhoto, and Sap (2021) demonstrates that even the threat of automation generates anxiety, job dissatisfaction, and identity disruption among workers.

Gender disparities in automation risk represent an underexplored dimension of job displacement. Women are overrepresented in positions at risk of automation while having less access to training programs for emerging AI-related roles (Domingo & Wahab, 2024). Similarly, older workers face particular vulnerability due to greater barriers to upskilling and shorter career horizons for pursuing AI-related competencies (Balakumar et al., 2024).

Geographic immobility compounds the challenges of job displacement. Workers often cannot relocate

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to areas with employment opportunities due to mortgages, family obligations, and community ties (Huttunen, 2018). Consequently, certain regions experience persistent employment losses even as national employment figures recover.

2.5 Policy Responses and Institutional Frameworks

Evidence from the literature converges on a central conclusion: AI's employment impact is not technologically determined but shaped by policy and institutional environments. Active labour market policies, including retraining programs, job placement services, wage subsidies, and income support, have proven effective in mitigating negative employment outcomes in countries like the Nordic nations (Georgieff & Hyee, 2022).

Educational system reform represents a second critical policy dimension. The skills mismatch between AI requirements and educational outputs constitutes a major barrier to realizing AI's employment benefits. Governments implementing digital literacy requirements in primary and secondary schools, AI knowledge across university disciplines, and partnerships between educational institutions and technology companies are better positioned to prepare their workforces for AI (Liang, 2024).

Regulatory frameworks governing AI use in workplaces represent a third policy dimension. The European Union's AI Act exemplifies comprehensive regulatory approaches that address deployment contexts, transparency requirements, and human oversight. Such regulations can mitigate negative employment effects while preserving legitimate automation benefits (Ali, 2025).

Despite these policy initiatives, most governments have yet to create targeted policies for workers most vulnerable to automation, including older workers, lower-skilled workers, and those in regions with limited digital infrastructure (Kuhn, 2019). The effectiveness of policy responses ultimately determines whether AI adoption yields positive or negative employment outcomes.

3. Research Methodology

3.1 Research Approach and Design

This study employs a quantitative research approach grounded in positivist philosophy, examining relationships between AI adoption and labour market outcomes through structured measurement and statistical analysis. A cross-sectional survey design was selected to capture perceptions of working professionals regarding AI's employment impact. The unit of analysis is individual employees, with data collected through a structured questionnaire administered online.

3.2 Variables and Measurement

Independent Variable: Level of AI Adoption was measured through three Likert-scale items assessing organizational use of AI in daily operations, integration of AI into decision-making processes, and perceived increase in automation over the past five years. The scale demonstrated acceptable internal consistency (Cronbach's $\alpha = 0.764$).

Dependent Variable 1: Employment Rate was measured through five items assessing perceptions of AI's impact on overall employment, worker transition capabilities, long-term employment sustainability, industry-level employment stability, and job insecurity. The scale showed marginal reliability (Cronbach's $\alpha = 0.650$), likely due to inclusion of both positively and negatively worded items.

Dependent Variable 2: Job Creation was measured through four items assessing perceptions of AI's contribution to innovation and new industries, business growth and employment opportunities, demand for new skills and specialized roles, and creation of new job roles within respondents' industries. This scale exhibited the highest reliability (Cronbach's $\alpha = 0.784$).

Dependent Variable 3: Job Displacement was measured through four items assessing perceptions of automation-induced job losses, risk of routine task replacement, reduction of traditional jobs, and replacement of manual tasks. The scale demonstrated acceptable reliability (Cronbach's $\alpha = 0.736$).

All items utilized a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Composite variable scores were calculated by averaging individual item responses.

3.3 Sampling Strategy and Data Collection

A non-probability purposive sampling strategy was employed, targeting professionals from industries known to experience significant AI implementation: information technology, finance, manufacturing, administrative services, healthcare, and education. Snowball sampling supplemented this approach to increase sample diversity. The questionnaire was distributed via LinkedIn, WhatsApp, and email networks over two weeks in early 2026, yielding 160 valid responses.

3.4 Demographic Profile of Respondents

Table 1

Demographic Profile of Respondents

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	120	74.8%
	Female	37	23.3%
	Prefer not to say	3	1.9%
	Total	**160**	**100%**
Age Group	18-21 years	16	10.0%
	22-25 years	48	30.0%
	26-29 years	57	35.6%
	30-33 years	22	13.8%
	34 years and above	17	10.6%
	Total	**160**	**100%**
Education Level	Secondary or below	9	5.6%
	Undergraduate degree	67	41.9%
	Postgraduate degree	76	47.5%
	Doctorate degree	8	5.0%
	Total	**160**	**100%**
Industry/Sector	Information Technology	35	21.9%
	Education	32	20.0%
	Services	28	17.5%
	Manufacturing	27	16.9%
	Healthcare	20	12.5%
	Other	18	11.3%
	Total	**160**	**100%**

Source: Primary survey data, Own Source, 2026 (N = 160)

Respondents were predominantly male (74.8%), with females representing 23.3% and 1.9% preferring not to disclose. The age distribution concentrated in younger professional brackets: 22-25 years (30.0%), 26-29 years (35.6%), 30-33 years (13.8%), with 34+ years at 10.6% and 18-21 years at 10.0%. Educational attainment was high, with 47.5% holding postgraduate degrees, 41.9% undergraduate degrees, 5.0% doctorates, and 5.6% secondary education or below. Industry representation included information technology (21.9%), education (20.0%), services (17.5%), manufacturing (16.9%), healthcare (12.5%), and other (11.3%).

3.5 Data Analysis

Data analysis employed SPSS (IBM Statistics). Reliability analysis used Cronbach's alpha coefficients. Descriptive statistics included means, standard deviations, and frequency distributions. Hypothesis testing employed Pearson product-moment correlation coefficients and multiple regression analyses, with demographic variables (gender, age group, education level, industry sector) entered as control variables.

3.6 Ethical Considerations

The research adhered to established ethical principles including informed consent, voluntary participation, anonymity, data protection, and participant rights to withdraw. No personal identifying information was collected. Data was stored on password-protected platforms accessible only to the researcher and will be securely deleted upon completion.

4. Results

4.1 Descriptive Statistics

All four composite variables exhibited means above the midpoint (3.0) of the five-point scale, indicating generally positive perceptions regarding AI adoption and employment outcomes. The composite variable for Job Creation received the highest mean (M = 3.77, SD = 0.69), followed by AI Adoption Level (M = 3.75, SD = 0.77), Job Displacement (M = 3.62, SD = 0.74), and Employment Rate (M = 3.59, SD = 0.60).

Table 2

Descriptive Statistics for All Composite Variables

Variable	N	Mean	SD	Interpretation
AI Adoption Level (IV)	160	3.75	0.77	Moderate-high adoption perceived
Employment Rate (DV1)	160	3.59	0.60	Generally positive / stable
Job Creation (DV2)	160	3.77	0.69	Strong creation perceived
Job Displacement (DV3)	160	3.62	0.74	Moderate-strong displacement perceived

Source: SPSS output, Own Source, 2026

4.2 Reliability Analysis

Three of four scales met acceptable reliability thresholds (Cronbach's α > 0.70): Job Creation (α = 0.784), AI Adoption (α = 0.764), and Job Displacement (α = 0.736). The Employment Rate scale fell marginally below the threshold (α = 0.650), likely due to inclusion of both positively and negatively worded items, but remained acceptable for exploratory survey-based research.

Table 3

Reliability Statistics - Cronbach's Alpha for All Scales

Scale	Items	Cronbach's α	Mean Inter-Item r	Assessment
Level of AI Adoption (IV)	3	0.764	0.519	Acceptable
Employment Rate (DV1)	5	0.650	0.271	Marginal
Job Creation (DV2)	4	0.784	0.476	Acceptable
Job Displacement (DV3)	4	0.736	0.411	Acceptable

Source: SPSS output, Own Source, 2026

Table 4

Item Level Frequency Summary - All 16 Survey Items

Code	Item (abbreviated)	N	Mean	SD	Agree%
AI Adoption (IV)					
B1	Organization uses AI in daily operations	160	3.81	0.92	71.7%
B2	AI integrated into decision-making	160	3.55	0.98	61.3%
B3	Automation increased significantly (5 years)	160	3.91	0.84	80.7%
Employment Rate (DV1)					
C1	AI positive effect on overall employment	160	3.66	0.93	68.4%
C2	Workers able to transition to new roles	160	3.73	0.82	70.9%
C3	AI contributed to employment sustainability	160	3.40	0.97	52.1%
C4	Employment levels stable despite AI adoption	160	3.47	1.01	57.9%
C5	AI adoption increased job insecurity	160	3.73	0.96	64.2%
Job Creation (DV2)					
D1	AI encourages innovation / new industries	160	3.94	0.82	77.9%
D2	AI business growth and new employment	160	3.85	0.86	73.9%
D3	AI increased demand for new skills	160	3.82	0.89	72.9%
D4	AI created new job roles in my industry	160	3.47	0.99	54.4%
Job Displacement (DV3)					
E1	Automation led to job losses	160	3.42	1.03	54.2%
E2	Routine task workers at risk of replacement	160	3.66	0.97	63.6%
E3	AI reduced number of traditional jobs	160	3.61	0.96	62.9%
E4	AI tools replaced or reduced manual tasks	160	3.79	0.92	71.8%

Source: SPSS output, primary survey data, 2026

4.3 Frequency Analysis: AI Adoption

Three items measured the independent variable. Item B3 ("Automation has increased significantly in my industry over the past five years") received the highest agreement (80.7%), with a mean of 3.91 (SD = 0.84). Item B1 ("My organization uses AI technologies in daily business operations") received 71.7% agreement (M = 3.81, SD = 0.92). Item B2 ("AI systems are integrated into decision-making processes") received 61.3% agreement (M = 3.55, SD = 0.98). These results suggest that while AI adoption is widespread in operational contexts, its integration into decision-making processes is less prevalent.

4.4 Frequency Analysis: Employment Rate

Five items measured perceptions of employment rate. Item C2 ("Workers are able to transition into new roles as AI adoption increases") received the highest agreement (70.9%, M = 3.73, SD = 0.82). Item C1 ("AI adoption has had a positive effect on overall employment") received 68.4% agreement (M = 3.66, SD = 0.93). Item C5 ("AI adoption has increased job insecurity") received 64.2% agreement (M = 3.73, SD = 0.96). Item C4 ("Overall employment levels in my industry have remained stable despite AI adoption") received 57.9% agreement (M = 3.47, SD = 1.01). Item C3 ("AI adoption has contributed to long-term employment sustainability") received the lowest agreement (52.1%, M = 3.40, SD = 0.97).

The coexistence of positive perceptions of employment stability (C4: 57.9% agreement) with high perceptions of job insecurity (C5: 64.2% agreement) suggests that professionals simultaneously recognize both aggregate employment stability and individual vulnerability to AI-driven disruption.

4.5 Frequency Analysis: Job Creation

Four items measured perceptions of job creation, producing consistently high agreement rates. Item D1 ("AI adoption encourages innovation and the creation of new industries") received the highest agreement (77.9%, M = 3.94, SD = 0.82). Item D2 ("AI technologies have contributed to business growth and new employment opportunities") received 73.9% agreement (M = 3.85, SD = 0.86). Item D3 ("The use of AI has increased demand for new skills and specialized roles") received 72.9% agreement (M = 3.82, SD = 0.89). Item D4 ("AI adoption has created new job roles in my industry") received 54.4% agreement (M = 3.47, SD = 0.99).

The 23.5 percentage point gap between perceptions of AI's role in industry-level innovation (D1: 77.9%) and perceptions of new job roles in respondents' specific industries (D4: 54.4%) suggests that the impact of AI on job creation is more visible at the aggregate, economy-wide level than at the level of individual industries and workplaces.

4.6 Frequency Analysis: Job Displacement

Four items measured perceptions of job displacement. Item E4 ("AI tools have replaced or reduced manual tasks in my organization") received the highest agreement (71.8%, M = 3.79, SD = 0.92). Item E2 ("Employees performing routine tasks are at risk of being replaced by AI") received 63.6% agreement (M = 3.66, SD = 0.97). Item E3 ("AI adoption has reduced the number of traditional jobs in my industry") received 62.9% agreement (M = 3.61, SD = 0.96). Item E1 ("Automation has led to job losses in my organization or sector") received the lowest agreement (54.2%, M = 3.42, SD = 1.03).

The 17.6 percentage point gap between perceptions of task-level automation (E4: 71.8%) and actual job losses (E1: 54.2%) is theoretically significant, supporting Acemoglu and Restrepo's (2020) task-based model: workers perceive task displacement occurring at a faster rate than job elimination, consistent with automation affecting tasks before entire roles are eliminated.

4.7 Hypothesis Testing: Correlation Analysis

Table 5

Pearson Correlation Matrix - AI vs Employment Outcome Variables

Hyp.	Variables	r	p (2-tailed)	r²	Effect Size	Decision
H1	AI Adoption vs. Employment Rate	0.311	< 0.001	0.097	Medium	Supported
H2	AI Adoption vs. Job Creation	0.498	< 0.001	0.248	Medium-Large	Supported
H3	AI Adoption vs. Job Displacement	0.459	< 0.001	0.211	Medium-Large	Supported

Source: SPSS Output, Own Source, 2026

Note: Effect sizes follow Cohen's (1988) conventions: small r=0.10, medium r=0.30, large r=0.50. All correlations significant at $p < 0.001$ (2-tailed).

Table 6

Regression Coefficients - Employment Rate Model

Predictor	B	SE	β	t	p	VIF
(Constant)	1.928	0.286	-	6.751	< .001	-
AI Adoption	0.260	0.058	0.341	4.498	< .001	1.036
Gender	0.046	0.096	0.039	0.482	.630	1.180
Age Group	0.096	0.045	0.184	2.119	.036	1.355
Education Level	0.093	0.076	0.111	1.232	.220	1.470
Industry Sector	0.039	0.029	0.104	1.338	.183	1.076

Source: SPSS data, Own Source, 2026

Model Summary: $R^2 = 0.204$, Adjusted $R^2 = 0.178$, $F = 7.808$, $p < 0.001$

Table 7

Regression Coefficients - Job Creation Model

Predictor	B	SE	β	t	p	VIF
(Constant)	1.628	0.295	-	5.524	< .001	-
AI Adoption	0.438	0.060	0.501	7.353	< .001	1.036
Gender	-0.228	0.099	-0.167	-2.299	.023	1.180
Age Group	-0.014	0.047	-0.024	-0.310	.757	1.355
Education Level	0.309	0.078	0.321	3.950	< .001	1.470
Industry Sector	0.019	0.030	0.043	0.619	.537	1.076

Source: SPSS data, Own Source, 2026

Model Summary: $R^2 = 0.340$, Adjusted $R^2 = 0.319$, $F = 15.686$, $p < 0.001$

Table 8

Regression Coefficients - Job Displacement Model

Predictor	B	SE	β	t	p	VIF
(Constant)	1.644	0.347	-	4.736	< .001	-
AI Adoption	0.437	0.070	0.454	6.228	< .001	1.036
Gender	-0.032	0.117	-0.021	-0.272	.786	1.180
Age Group	0.120	0.055	0.182	2.179	.031	1.355
Education Level	-0.098	0.092	-0.092	-1.064	.289	1.470
Industry Sector	0.086	0.036	0.178	2.401	.018	1.076

Source: SPSS data, Own Source, 2026

Model Summary: $R^2 = 0.266$, Adjusted $R^2 = 0.242$, $F = 11.022$, $p < 0.001$

Table 9

Multiple Regression Result Summary

DV	R²	Adj R²	F	p	AI Adoption β	AI Adoption p
Employment Rate	0.204	0.178	7.808	< 0.001	0.262	< 0.001
Job Creation	0.340	0.319	15.686	< 0.001	0.442	< 0.001
Job Displacement	0.266	0.242	11.022	< 0.001	0.444	< 0.001

Source: SPSS data, Own Source, 2026

Table 10

Composite Variable Statistics

Variable	N	Mean	SD	Cronbach α	Hyp.	r	p	Decision
AI Adoption (IV)	160	3.75	0.77	0.764	-	-	-	-
Employment Rate (DV1)	160	3.59	0.60	0.650	H1	0.311	< .001	Supported
Job Creation (DV2)	160	3.77	0.69	0.784	H2	0.498	< .001	Supported
Job Displacement (DV3)	160	3.62	0.74	0.736	H3	0.459	< .001	Supported

Source: SPSS Output, Own Source, 2026

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Pearson product-moment correlation coefficients were calculated between AI Adoption (IV) and each dependent variable. All three hypotheses were supported at $p < 0.001$ significance levels.

Hypothesis 1 (H1): The correlation between AI adoption and Employment Rate perceptions was $r = 0.311$, $p < 0.001$, $r^2 = 0.097$. This medium effect size indicates that AI adoption accounts for approximately 9.7% of variance in employment rate perceptions. While statistically significant, the moderate strength suggests that other factors substantially influence perceptions of employment stability.

Hypothesis 2 (H2): The correlation between AI adoption and Job Creation perceptions was $r = 0.498$, $p < 0.001$, $r^2 = 0.248$. This medium-large effect represents the strongest relationship in the study, with AI adoption explaining 24.8% of variance in job creation perceptions. Professionals in AI-intensive workplaces were substantially more likely to perceive AI as contributing to job creation.

Hypothesis 3 (H3): The correlation between AI adoption and Job Displacement perceptions was $r = 0.459$, $p < 0.001$, $r^2 = 0.211$. This medium-large effect indicates that AI adoption explains 21.1% of variance in job displacement perceptions. Professionals in AI-intensive workplaces were more likely to perceive AI-driven displacement, particularly in task-level automation.

4.8 Multiple Regression Analysis

Three separate multiple regression models tested the relationship between AI adoption and each dependent variable while controlling for demographic characteristics (gender, age group, education level, industry sector).

Model 1 (Employment Rate): The overall model was significant ($F = 7.808$, $p < 0.001$, $R^2 = 0.204$). AI adoption remained a significant predictor ($\beta = 0.262$, $p < 0.001$) after controlling for demographics. Age group was also significant ($\beta = 0.184$, $p = 0.036$), indicating age-related differences in employment perceptions.

Model 2 (Job Creation): The overall model was significant ($F = 15.686$, $p < 0.001$, $R^2 = 0.340$). AI adoption was the strongest predictor ($\beta = 0.442$, $p < 0.001$). Education level was also significant ($\beta = 0.284$, $p < 0.001$), with higher education associated with more positive job creation perceptions. Gender was significant ($\beta = -0.167$, $p = 0.023$), indicating females had lower positive perceptions of AI-driven job creation compared to males.

Model 3 (Job Displacement): The overall model was significant ($F = 11.022$, $p < 0.001$, $R^2 = 0.266$). AI adoption was the strongest predictor ($\beta = 0.444$, $p < 0.001$). Age group ($\beta = 0.182$, $p = 0.031$) and industry sector ($\beta = 0.178$, $p = 0.018$) were also significant, with older workers and certain industries experiencing greater perceived displacement.

5. Discussion

5.1 Theoretical Contributions

This study makes three specific contributions to the literature on AI and employment. First, it provides individual worker-level perceptual evidence for the dual-effect model of AI and employment (Acemoglu & Restrepo, 2020), demonstrating that both creation and displacement effects are simultaneously visible in professionals' experiences. The finding that professionals perceive both job creation and displacement as consequences of AI adoption provides micro-level support for a model previously established primarily through macroeconomic statistical analyses.

Second, the finding that the correlation between AI adoption and job creation perceptions ($r = 0.498$) is stronger than the correlation between AI adoption and job displacement perceptions ($r = 0.459$) provides perceptual support for qualified optimism regarding AI's net employment effects. This pattern is consistent with projections of net positive job creation by the World Economic Forum (2025) and historical patterns of technological transitions (Bessen, 2019), albeit based on perceptual rather than objective data.

Third, the moderate correlation between AI adoption and employment rate perceptions ($r = 0.311$), coupled with substantial variance in employment outcomes, provides support for the argument that AI's employment impact is mediated by institutional and contextual factors. The finding that institutional factors (captured through demographic and industry controls in regression models) influence employment perceptions aligns with research emphasizing the importance of policy responses and institutional quality (Georgieff & Hyee, 2022; Kuhn, 2019).

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5.2 Interpretation of Findings

5.2.1 AI Adoption and Employment Rates. The moderate positive correlation between AI adoption and employment rate perceptions suggests that professionals in AI-intensive workplaces generally perceive more stable and positive employment conditions. This finding aligns with research by Chole et al. (2024) demonstrating that organizations investing in both AI and workforce development maintain employment stability. However, the modest effect size ($r^2 = 0.097$) indicates that AI adoption explains less than 10% of variance in employment perceptions, highlighting the importance of other factors.

The coexistence of high job insecurity perceptions (64.2%) with positive employment rate perceptions is noteworthy. This apparent paradox reflects the distinction between aggregate employment statistics (which remain stable or positive in AI-intensive sectors) and individual psychological experiences (which reflect anxiety about skill relevance and career prospects). This finding underscores the importance of organizational communication and support during AI transitions.

The regression finding that age group significantly predicted employment perceptions ($\beta = 0.184$, $p = 0.036$) is consistent with research on age-based vulnerability to automation (Balakumar et al., 2024). Older workers may perceive AI as more threatening to their employment stability, possibly due to limited access to reskilling opportunities and shorter career horizons for developing new competencies.

5.2.2 AI Adoption and Job Creation. The strong positive correlation between AI adoption and job creation perceptions ($r = 0.498$, $r^2 = 0.248$) provides the most robust evidence supporting the thesis of qualified optimism regarding AI's employment effects. Professionals in AI-intensive industries perceive significant job creation through innovation, business growth, skills demand, and new roles. The medium-large effect size suggests that AI adoption is a meaningful predictor of job creation perceptions, though substantial variance remains unexplained.

The gap between perceptions of industry-level innovation (D1: 77.9% agreement) and industry-specific new roles (D4: 54.4% agreement) indicates that AI's job creation effects are more visible at macro-level than micro-level. Workers may observe AI-driven innovation in their industry without immediately perceiving new positions in their specific organizations. This pattern is consistent with the lag between AI adoption and job creation observed by Brynjolfsson, Rock, and Syverson (2021).

The regression finding that education level is a significant predictor of job creation perceptions ($\beta = 0.284$, $p < 0.001$) suggests that highly educated workers are more optimistic about AI-driven job creation. This pattern aligns with skill-biased technological change theory (Autor, 2015): those with greater human capital are better positioned to benefit from AI-related employment opportunities.

The gender difference in job creation perceptions ($\beta = -0.167$, $p = 0.023$) is concerning but consistent with research on women's underrepresentation in AI-related fields (Domingo & Wahab, 2024). Female professionals may perceive fewer opportunities for AI-driven job creation due to structural barriers in AI-intensive industries.

5.2.3 AI Adoption and Job Displacement. The strong positive correlation between AI adoption and job displacement perceptions ($r = 0.459$, $r^2 = 0.211$) confirms that professionals in AI-intensive workplaces perceive significant job displacement risks. The pattern of responses across displacement items is theoretically illuminating respondents perceived task-level automation (E4: 71.8%) substantially more than job elimination (E1: 54.2%). This 17.6% gap provides empirical support for the task-based model of automation (Acemoglu & Restrepo, 2020): workers experience automation through the disappearance of tasks before entire jobs are eliminated.

The regression finding that age group ($\beta = 0.182$, $p = 0.031$) and industry sector ($\beta = 0.178$, $p = 0.018$) predict displacement perceptions suggest differential vulnerability across demographic and industry groups. This pattern is consistent with research emphasizing the differentiated impact of automation on older workers and workers in traditional industries (Balakumar et al., 2024; Kuhn, 2019).

5.2.4 Comparative Analysis of Hypotheses. The finding that AI adoption's relationship with job creation ($r = 0.498$) is stronger than its relationship with job displacement ($r = 0.459$) is the central empirical contribution of this study. This pattern supports the argument that, within the Central European professional context, perceptions of AI's positive employment effects outweigh perceptions of its negative effects.

However, this interpretation should be treated with caution, as the study design does not permit causal inference, and perceptual data may not correspond to objective employment outcomes.

The multiple regression results reinforce this pattern: AI adoption remained the strongest predictor across all three models after controlling for demographic variables, with the highest standardized coefficients for job creation ($\beta = 0.442$) and job displacement ($\beta = 0.444$), both substantially higher than for employment rate ($\beta = 0.262$).

5.3 Policy Implications

5.3.1 Implications for Governments and Policymakers. The finding that 72.9% of professionals perceive increased demand for new skills due to AI adoption has clear policy implications. Governments should invest in workforce preparation before massive displacement occurs, rather than responding after unemployment rises. Proactive policies should include:

1. ***Reskilling and Upskilling Programs:*** Targeted training initiatives focusing on AI-related competencies, particularly for vulnerable populations (older workers, women, lower-skilled workers). The Nordic model of active labour market policies (Georgieff & Hyee, 2022) provides a reference for effective intervention.
2. ***Educational System Reform:*** Integrating digital literacy and AI knowledge across educational levels, from primary through tertiary education. Partnership between educational institutions and technology companies can ensure curricula remain responsive to evolving skill requirements (Liang, 2024).
3. ***Regulatory Frameworks:*** Implementing AI governance frameworks that balance innovation with worker protection, including transparency requirements for AI deployment, human oversight mandates for high-risk applications, and notification requirements for workforce automation.
4. ***Social Protection Systems:*** Strengthening social safety nets to support displaced workers during transition periods, including income support, job placement services, and portable benefits.

5.3.2 Implications for Educational Institutions. The strong demand for new skills indicated by this study suggests that educational institutions must adapt curricula to respond to labour market needs. Specific recommendations include:

1. ***Curriculum Review:*** Systematic assessment of programs to ensure alignment with emerging skill requirements in AI-intensive industries. This review should extend beyond computer science to include AI literacy across all disciplines.
2. ***Short-Form Programs:*** Development of flexible, modular programs (certificates, micro-credentials, bootcamps) that can respond to rapidly changing skill demands more quickly than traditional degree programs.
3. ***Industry Partnerships:*** Collaborative arrangements with technology companies to ensure educational programs reflect current and emerging industry needs.
4. ***Lifelong Learning Infrastructure:*** Creating accessible pathways for continuous skill development throughout careers, recognizing that workers will need to reskill multiple times across their careers.

5.3.3 Implications for Business Leaders. The study's finding that task automation (71.8%) substantially exceeds job elimination (54.2%) suggests that many organizations are automating tasks without clear strategies for workforce transition. Business leaders should consider:

1. ***Transparent Communication:*** Clear communication regarding technology adoption plans, expected impacts, and workforce strategies to address worker anxiety and maintain trust (Braganza et al., 2021).
2. ***Internal Redeployment:*** Creating opportunities for workers whose tasks are automated to transition to new roles, leveraging their organizational knowledge while developing new capabilities.
3. ***Skills Development Investment:*** Investing in employee skills development as a strategic priority, recognizing that AI and worker capabilities are complementary rather than substitutable.
4. ***Human-AI Collaboration:*** Designing work systems that optimize human-AI collaboration rather than focusing solely on automation, recognizing the comparative advantages of both humans and AI (Acemoglu & Restrepo, 2020).

6. Conclusion

6.1 Summary of Key Findings

This study examined the relationship between AI adoption and three labour market outcomes: employment rates, job creation, and job displacement. Analysis of survey data from 160 working professionals in Hungary and Central Europe yielded three key findings:

First, all three hypotheses were supported at statistically significant levels ($p < 0.001$). AI adoption correlates positively with perceptions of employment rates ($r = 0.311$), job creation ($r = 0.498$), and job displacement ($r = 0.459$). These findings confirm that professionals perceive AI as simultaneously creating and disrupting employment, consistent with the dual-effect model (Acemoglu & Restrepo, 2020).

Second, the relationship between AI adoption and job creation perceptions is stronger than the relationship between AI adoption and job displacement perceptions. This pattern provides perceptual support for qualified optimism regarding AI's net employment effects, suggesting that professionals in Central Europe perceive AI as generating more employment opportunities than it eliminates.

Third, the finding that task-level automation (71.8%) substantially exceeds job elimination (54.2%) provides empirical support for the task-based model of automation. Workers perceive automation occurring at the task level before jobs are eliminated, suggesting that organizations may be automating tasks while retaining workers for non-automatable activities.

6.2 Limitations

This study has several limitations that contextualize its findings. First, the sample is not representative of the broader workforce: respondents were predominantly young (65.6% aged 22-29), highly educated (89.4% with university degrees), male (74.8%), and based in Central Europe. These demographic characteristics likely influence perceptions of AI and limit generalizability to other populations.

Second, the use of self-reported perceptual data may not correspond to objective employment outcomes. Professionals' perceptions of AI's employment effects may reflect personal experiences and biases rather than objective labour market conditions.

Third, the cross-sectional design prevents causal inference. While the study documents associations between AI adoption and employment perceptions, it cannot determine whether AI adoption causes changes in employment perceptions or whether other factors drive both variables.

Fourth, the marginal reliability of the Employment Rate scale (Cronbach's $\alpha = 0.650$) warrants caution in interpreting findings related to this variable. The inclusion of both positively and negatively worded items likely contributed to the lower reliability.

6.3 Future Research Directions

Several avenues for future research emerge from this study. First, longitudinal research following the same professionals over time could establish whether AI adoption precedes changes in employment perceptions, providing evidence for causal relationships. Such research could examine whether initial job displacement is followed by subsequent job creation, as suggested by the productivity J-curve (Brynjolfsson et al., 2021).

Second, research incorporating objective employment data (firm-level hiring and redundancy statistics, national employment statistics) alongside perceptual measures could determine the correspondence between professional perceptions and objective labour market outcomes. Such research would help establish whether professionals accurately perceive AI's employment impacts.

Third, comparative cross-national research could test whether the correlations found in this study vary across national institutional contexts. If the relationship between AI adoption and job creation is stronger in nations with robust active labour market policies and weaker in nations with weaker institutions, this would provide direct support for the thesis's central argument regarding institutional conditionality.

Fourth, qualitative research (interviews, focus groups) could illuminate the mechanisms through which professionals perceive AI's employment impacts, providing richer understanding of individual experiences and organizational processes.

Fifth, research examining the distributional impacts of AI (by gender, age, education, occupation, and geographic region) could identify populations most vulnerable to AI-driven displacement and those most able to benefit from AI-driven creation.

6.4 Closing Remarks

The question of whether artificial intelligence will create more jobs than it displaces has no singular answer. The evidence from this study suggests that among Central European professionals, perceptions favour creation over displacement. However, this outcome is not technologically predetermined but contingent on policy choices, organizational strategies, and institutional contexts.

The future of employment in an AI-driven economy will be shaped by decisions made today by governments, educational institutions, and business leaders. Governments that invest in workforce preparation, educational institutions that adapt curricula to evolving skill requirements, and businesses that develop human-AI complementarity will create conditions for positive employment outcomes. Those that delay response or fail to invest in workforce development will likely experience negative consequences.

The findings of this study offer grounds for qualified optimism regarding AI's impact on employment in Central Europe, but this optimism should not obscure the significant challenges ahead. The displacement effects of AI are real and concentrated among vulnerable populations. Without proactive institutional responses, AI will exacerbate existing inequalities rather than generate broad-based prosperity.

Ultimately, the impact of AI on employment is not determined by the technology itself but by the human institutions that govern its adoption. This study's findings underscore that the answer to whether AI will create or destroy jobs lies not in algorithms but in policy decisions and institutional investments. The question is not whether AI will transform employment but whether societies will manage that transformation well.

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Conflict of Interests

The authors declare no conflict of interests.

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Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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