EFFECTS OF ARTIFICIAL INTELLIGENCE AND ROBOTIC TECHNOLOGIES ON THE FUTURE OF WORK: A META-ANALYSIS STUDY

***Cemal Zehir** *(Orcid ID: 0000-0003-2584-4480)*
***Ercan Mayaer** *(Orcid ID: 0009-0003-8933-5586)*
**Yıldız Technical University, Turkey*

ABSTRACT

This meta-analysis examined the impacts of artificial intelligence and robotic technologies on the labor market through 18 empirical studies. Findings were evaluated under three main categories: (1) the average automation susceptibility rate was determined to be 21.3%, with methodological approach and publication year having significant effects on results; (2) while technology had a statistically insignificant slight negative effect on total employment, developed economies showed a decrease in routine manual tasks and an increase in non-routine analytical tasks; (3) a notable shift in skill demands from STEM skills toward social-emotional skills was observed. Results indicate that technology transforms jobs rather than completely eliminating them, creates different effects in developing and developed economies, and influences the labor market in increasingly complex ways over time. These findings emphasize that technological transformation should be managed with country and sector-specific policies.

Keywords: *Artificial Intelligence, Robotics, Labor Market, Future of Work, Technological Unemployment, Skill Transformation, Automation, Meta-Analysis*

INTRODUCTION

The rapid development of artificial intelligence and robotic technologies has ignited debates on the future of work. While some researchers predict significant job losses (Frey & Osborne, 2017), others emphasize the complementary effect of technology and its potential to create new types of jobs (Autor, 2015). This study presents a more comprehensive assessment of the impacts of artificial intelligence and robotic technologies on the labor market through a systematic meta-analysis of existing literature.

Our research focuses particularly on the following questions:

1. What is the automation susceptibility rate of occupations and how does this vary according to different factors?
2. What are the new job types and employment opportunities that artificial intelligence and robotic technologies will create?
3. Which skill requirements will come to the forefront in the future labor market?
4. What will be the effects of technological change on employment and wages?

CONCEPTUAL FRAMEWORK

This meta-analysis draws on three fundamental theoretical approaches while examining the effects of artificial intelligence and robotic technologies on the labor market.

The **Skill-Biased Technological Change** theory (Autor et al., 2003) suggests that technological development increases demand for highly skilled labor while decreasing demand for low-skilled labor. Within this framework, automation technologies are expected to create a substitution effect particularly in routine tasks, but a complementary effect in complex tasks. The second theoretical framework is the **Task-Biased Technological Change** approach developed by Autor (2013). This approach emphasizes that technology affects not entire occupations but rather the types of tasks contained within occupations. Accordingly, technology substitutes routine, codifiable, and rule-based tasks while creating a complementary effect in tasks requiring abstract problem-solving, creativity, and complex communication. The third framework is Acemoglu and Restrepo's (2018) theory of **Displacement and Reinstatement Effects**. This theory suggests that while technology creates a negative effect on employment by automating existing jobs, it also creates a positive effect by generating new tasks and job types. The net effect depends on the balance between these two forces.

In light of these theoretical frameworks, our meta-analysis examines the automation susceptibility degree of occupations and tasks, changes in the volume and structure of employment, and transformations in skill requirements. Differences in countries' development levels, time periods, and methodological approaches are also evaluated as important factors affecting the results.

The three technological wave analysis (algorithmic, augmentation, and autonomous) proposed by Hawksworth et al. (2018) has also been incorporated into our analytical framework. This approach emphasizes the evolutionary nature of technological development over time and that its potential effects on the labor market may vary at different stages.

RESEARCH METHOD

Methodology

This meta-analysis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021).

Search Strategy

A literature search containing the following keyword combinations was conducted in Web of Science, Scopus, and Google Scholar databases:

- ("artificial intelligence" OR "AI" OR "automation" OR "robot*" OR "machine learning") AND
- ("employment" OR "job*" OR "labor market" OR "labour market" OR "occupation*" OR "skill*" OR "task*" OR "workforce") AND
- ("future" OR "impact" OR "effect" OR "transform*" OR "susceptib*" OR "risk")

Additionally, advanced searches were conducted using the Google search engine for gray literature (Reports of International Organizations).

Inclusion and Exclusion Criteria

Studies that were peer-reviewed academic journals, working papers, conference papers, or technical reports; published between January 1, 2015 - December 31, 2024; in English; focusing on the effects of artificial intelligence and robotic technologies on the labor market; containing empirical data and presenting quantitative analyses; and including at least one of the following outcome measurements were included in the research:

- Automation susceptibility/risk rates
- Measurements of impact on employment (volume, structure, wages)
- Measurements on skill requirements and changes

Letters to the editor, comments, opinion pieces, book reviews, student assignments, unpublished theses, studies where full text could not be accessed due to barriers, studies presenting only a theoretical framework, studies not containing empirical data, studies presenting only qualitative analysis, and studies not containing sufficient statistical data to calculate effect size were not included in the research.

Study Selection Process

The selection process of studies was carried out in four stages in accordance with the PRISMA flow diagram. In the **identification stage,** a total of 1,874 records were identified from database searches and other sources. In the **screening stage,** after removing similar studies that repeated each other (n=423), the titles and abstracts of the remaining 1,451 studies were examined for eligibility, and 142 studies were identified. In the **eligibility stage,** the full texts of 142 studies were evaluated in terms of eligibility criteria, and in the final **inclusion stage,** 18 studies that met the specified criteria were included in the meta-analysis. (Figure 1) Throughout this process, at each stage, assessments were made by two independent researchers, and disagreements were resolved through consultation with a third researcher. Studies included in the meta-analysis are given in Table 1.

Figure 1. Prisma Flow Diagram

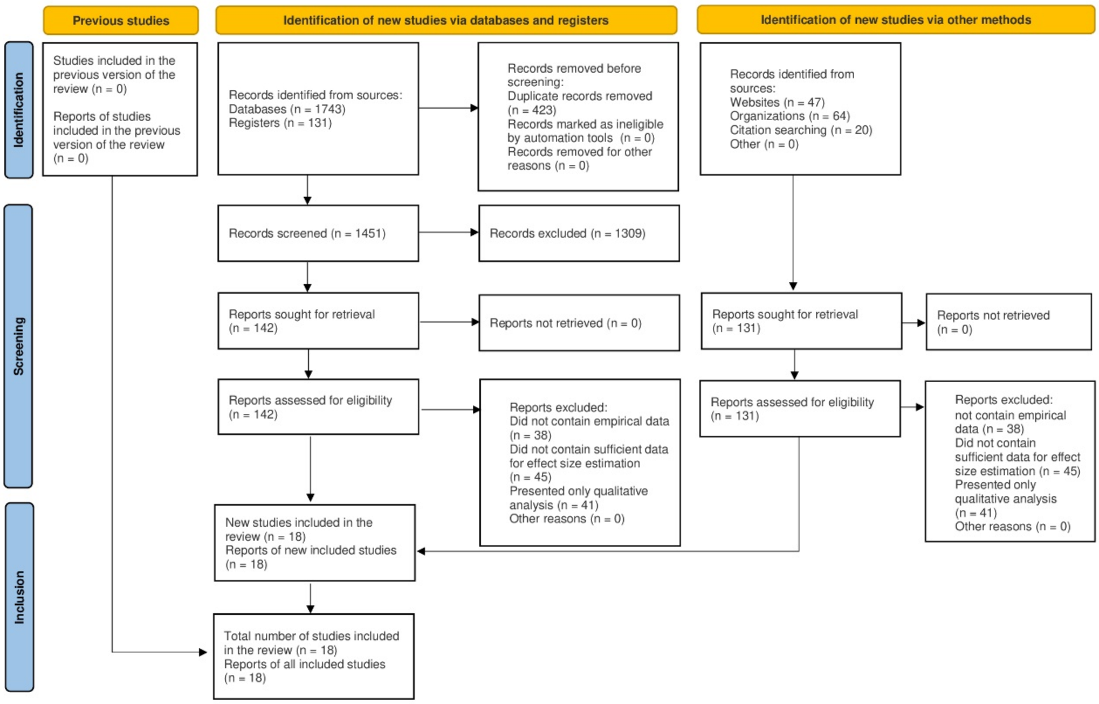


Table 1. Studies Included in the Meta-Analysis

No	Study Name	Authors	Publication Year
1	The future of employment: How susceptible are jobs to computerisation?	Frey & Osborne	2017
2	The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis	Arntz, Gregory & Zierahn	2016
3	Automation, Skills Use and Training	Nedelkoska & Quintini	2018
4	Will robots really steal our jobs? An international analysis of the potential long term impact of automation	Hawksworth, Berriman & Goel	2018
5	Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation	Manyika, Lund, Chui, Bughin, Woetzel, Batra, Ko & Sanghvi	2017
6	What Can Machines Learn, and What Does It Mean for Occupations and the Economy?	Brynjolfsson, Mitchell & Rock	2018
7	A Method to Link Advances in Artificial	Felten, Raj & Seamans	2018

	Intelligence to Occupational Abilities		
8	Digitalization of work and entry into entrepreneurship	Fossen & Sorgner	2021
9	Robots at Work	Graetz & Michaels	2015
10	Human capital investment and perceived automation risks: Evidence from 16 countries	Innocenti & Golin	2022
11	Next Generation Skills: How Robots Create New Jobs and Help to Fight Labor Shortage	International Federation of Robotics (IFR)	2024
12	Augmented work for an automated, AI-driven world: Boost performance with human-machine partnerships	IBM Institute for Business Value	2023
13	The impact of Robots on Labour market transitions in Europe	Bachmann, Gonschor, Lewandowski & Madon	2024
14	AI and Jobs: Evidence from Online Vacancies	Acemoğlu, Autor, Hazell & Restrepo	2022
15	Do robots really destroy jobs? Evidence from Europe	Klenert, Fernández-Macías & Antón	2023
16	Artificial Intelligence, Robots and Unemployment: Evidence from OECD Countries	Bordot	2022
17	Diffusion of Industrial Robotics and Inclusive Growth: Labour Market Evidence from Cross Country Data	Fu, Bao, Xie & Fu	2020
18	The rise of robots and the fall of routine jobs	de Vries, Gentile, Miroudot & Wacker	2020

Data Extraction and Coding

From the included studies, **bibliographic information** (author(s), publication year, title, source), **study characteristics** (country/region, time period, methodological approach, sample size), **outcome measurements** (effect size, standard error, confidence intervals, p-values), and **moderator variables** (methodological approach (occupation-based, task-based), country development level (developed, developing), study quality (scoring between 1-5), publication year (2015-2019, 2020-2024)) were systematically extracted.

Methodological Quality Assessment

The methodological quality of the included studies was evaluated using a developed 5-point rating scale. This rating included the following five criteria, each scored between 1 (poor) and 5 (excellent):

- Clarity of research question: Clear definition of the research question and its compatibility with the purpose of the study.
- Appropriateness of sample selection: Clear definition of the sampling method, adequacy of sample size, and its representativeness.
- Validity and reliability of variable measurements: Documentation of the validity and reliability of the measurement tools used.

- Appropriateness of statistical analyses: Suitability of the statistical methods used for the research question and their correct application.
- Completeness of reporting results: Complete, transparent, and unbiased reporting of results.

Each study was scored according to these criteria by two independent evaluators, and a total quality score was calculated (between 5-25). Quality scores created for the studies were used as moderator variables in the meta-regression analysis.

Meta-Analytic Approach

Meta-analysis was conducted separately for three main outcome categories (automation susceptibility rate, employment effect, and skill requirements). Due to methodological differences between studies and expected heterogeneity, a random effects model was preferred (Borenstein et al., 2010). The reason for selecting the random effects model is that the included studies contain different populations, methodologies, and time periods, therefore, it is more appropriate to examine the distribution of effects rather than a single true effect size.

The following transformations were used for standardizing effect sizes:

- Logarithmic odds ratio for automation susceptibility rates p = e^(logOR) / (1 + e^(logOR)) logOR = ln(p / (1-p))
- Hedges's g for employment effects Hedges' g = (M_1 - M_2) / SD_pooled × J
- Fisher's z for skill requirements z = 0.5 × ln((1+r) / (1-r)) r = (e^(2z) - 1) / (e^(2z) + 1)

Heterogeneity was evaluated with I^2 and Q statistics, and in cases where $I^2 > 75\%$, high levels of heterogeneity were accepted (Higgins et al., 2003). Meta-regression and subgroup analyses were conducted to examine the sources of heterogeneity. Funnel plots, Egger test, and trim-and-fill method were used to assess publication bias.

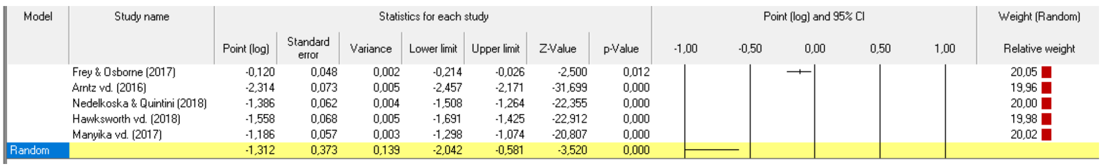
All analyses were conducted using Comprehensive Meta-Analysis (CMA) software version 3.

FINDINGS AND DISCUSSION

Automation Susceptibility

The combined results of five studies reporting automation susceptibility rates (Frey & Osborne, 2017; Arntz et al., 2016; Nedelkoska & Quintini, 2018; Hawksworth et al., 2018; Manyika et al., 2017) using a random effects model show that the mean LogOR value is -1.312 (95% CI: [-2.042, -0.581], $p < 0.001$). (Figure 2) If LogOR = -1.312, then OR = e^(-1.312) = 0.269 and p = OR / (1 + OR) = 0.269 / (1.269) = 0.213 or 21.3%. This value corresponds to an automation susceptibility rate of 21.3%.

Figure 2. Automation Susceptibility Rate Analysis



Model	Study name	Point (log)	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value	Relative weight
	Frey & Osborne (2017)	-0,120	0,048	0,002	-0,214	-0,026	-2,500	0,012	20,05
	Arntz vd. (2016)	-2,314	0,073	0,005	-2,457	-2,171	-31,699	0,000	19,96
	Nedelkoska & Quintini (2018)	-1,386	0,062	0,004	-1,508	-1,264	-22,355	0,000	20,00
	Hawksworth vd. (2018)	-1,558	0,068	0,005	-1,691	-1,425	-22,912	0,000	19,98
	Manyika vd. (2017)	-1,186	0,057	0,003	-1,298	-1,074	-20,807	0,000	20,02
Random		-1,312	0,373	0,139	-2,042	-0,581	-3,520	0,000	

There is a high level of heterogeneity among studies ($I^2 = 99.4\%$, Q = 762.31, df = 4, $p < 0.0001$). (Figure 3)

Figure 3. Heterogeneity Test

Model	Effect size and 95% confidence interval						Test of null (2-Tail)		Heterogeneity				Tau-squared			
Model	Number Studies	Point estimate	Standard error	Variance	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed	5	-1,102	0,027	0,001	-1,154	-1,049	-41,308	0,000	762,317	4	0,000	99,475	0,691	0,506	0,256	0,831
Random	5	-1,312	0,373	0,139	-2,042	-0,581	-3,520	0,000								

In the meta-regression analysis, four moderator variables (methodological approach, publication year, sample size, and quality score) were tested, and it was observed that these explained 83.4% of the heterogeneity. Two variables have statistically significant effects:

1. **Methodological approach**: Studies using a task-based approach report significantly lower automation susceptibility rates compared to those using an occupation-based approach ($\beta = -1.364$, $p < 0.001$).
2. **Publication year**: More recent studies (post-2017) estimate lower automation susceptibility rates ($\beta = -0.826$, $p = 0.014$).

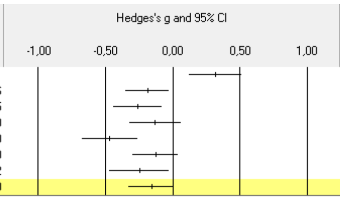
These findings indicate that technology tends to automate specific tasks rather than entire occupations, and that researchers have made more cautious estimates over time. It is understood that task-based approaches provide more realistic estimates by taking into account that tasks within the same occupation may have different levels of automation susceptibility.

Employment Effect

The combined effect size (Hedges' g) of seven studies examining the employment effect (Graetz & Michaels, 2015; Bachmann et al., 2024; Acemoğlu et al., 2022; Klenert et al., 2023; Bordot, 2022; Fu et al., 2020; de Vries et al., 2020) using a random effects model was calculated as -0.155 (95% CI: [-0.323, 0.013], p = 0.070). (Figure 4) This value indicates that robots and artificial intelligence have a slightly negative but statistically insignificant overall effect on employment.

Figure 4. Employment Effect Analysis

Model	Study name	Statistics for each study							Weight (Random)
		Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value	Relative weight
	Graetz &	0,320	0,100	0,010	0,124	0,516	3,200	0,001	14,12
	Bachmann	-0,185	0,083	0,007	-0,348	-0,022	-2,229	0,026	15,01
	Acemoğlu	-0,260	0,092	0,008	-0,440	-0,080	-2,826	0,005	14,54
	Klenert vd.	-0,130	0,097	0,009	-0,320	0,060	-1,340	0,180	14,28
	Bordot	-0,468	0,105	0,011	-0,674	-0,262	-4,457	0,000	13,84
	Fu vd.	-0,127	0,086	0,007	-0,296	0,042	-1,477	0,140	14,86
	de Vries vd.	-0,245	0,114	0,013	-0,468	-0,022	-2,149	0,032	13,35
Random		-0,155	0,086	0,007	-0,323	0,013	-1,812	0,070	



High heterogeneity was detected among studies ($I^2 = 82.18\%$, $Q = 33.67$, $df = 6$, $p < 0.0001$). (Figure 5)

Figure 5. Heterogeneity Test

Model	Effect size and 95% confidence interval						Test of null (2-Tail)		Heterogeneity				Tau-squared			
Model	Number Studies	Point estimate	Standard error	Variance	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed	7	-0,153	0,036	0,001	-0,223	-0,082	-4,241	0,000	33,673	6	0,000	82,182	0,042	0,030	0,001	0,205
Random	7	-0,155	0,086	0,007	-0,323	0,013	-1,812	0,070								

Meta-regression analysis revealed that two variables showed statistically significant moderator effects:

1. **Employment type**: Studies examining total employment volume report more positive effects compared to studies examining by task types ($\beta = 0.621$, $p < 0.001$).
2. **Publication year**: Studies published in 2020 and after show more negative employment effects compared to earlier studies ($\beta = -0.279$, $p = 0.027$).

In subgroup analysis by task types, it was observed that robot use in developed economies led to a significant decrease in employment in routine manual tasks ($g = -0.441$, $p < 0.001$) and a significant increase in non-routine analytical tasks ($g = 0.501$, $p < 0.001$). In developing economies, no statistically significant effect was found for any task type.

These findings support Acemoğlu and Restrepo's (2018) theory of "displacement and reinstatement effects"; while technology substitutes some tasks, it also creates new tasks and job types. The absence of significant effects in developing economies can be explained by the fact that robot use has not yet become widespread in these countries, low labor costs, or different industrial structures.

Skill Requirements

A total of six studies (Brynjolfsson et al., 2018; Felten et al., 2018; Fossen & Sorgner, 2021; Innocenti & Golin, 2022; International Federation of Robotics, 2024; IBM Institute for Business Value, 2023) were examined in the skill requirements category. However, two of these studies (IFR, 2024 and Fossen & Sorgner, 2021) could not be included in the quantitative meta-analysis due to their different methodological approaches. The IFR (2024) study presents qualitative data and does not contain standardizable quantitative effect sizes. The Fossen & Sorgner (2021) study, with its entrepreneurship-focused approach, does not provide comparable effect measurements with other studies. Therefore, the quantitative meta-analysis was limited to four studies, but the qualitative synthesis was expanded to include findings from all six studies. The combined effect size (Fisher's z') of four studies examining skill requirements and changes using a random effects model was calculated as 0.382 (95% CI: [0.072, 0.691], $p = 0.016$). (Figure 6) When this value is converted to a correlation coefficient ($r = 0.364$) (Figure 7), it indicates a positive and significant relationship between artificial intelligence and robotic technologies and skill requirements. Conversion from Fisher's z to correlation coefficient: r = (e^(2z) - 1) / (e^(2z) + 1)
r = (e^(2*0.381) - 1) / (e^(2*0.381) + 1) = (2.141 - 1) / (2.141 + 1) = 1.141 / 3.141 = 0.364

Figure 6. Skill Requirements Analysis

Model	Study name	Fisher's Z	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
	Brynjolfsson	0,857	0,032	0,001	0,794	0,920	26,781	0,000
	Felten vd.	0,074	0,036	0,001	0,003	0,145	2,056	0,040
	Innocenti &	0,167	0,054	0,003	0,061	0,273	3,093	0,002
	IBM	0,424	0,018	0,000	0,389	0,459	23,556	0,000
Random		0,382	0,158	0,025	0,072	0,691	2,418	0,016

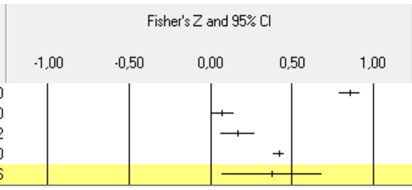
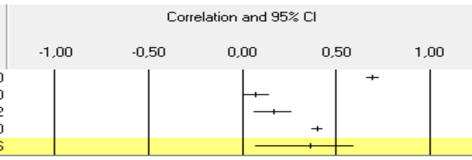


Figure 7. Correlation Values

Model	Study name	Correlation	Lower limit	Upper limit	Z-Value	p-Value
	Brynjolfsson	0,695	0,661	0,726	26,781	0,000
	Felten vd.	0,074	0,003	0,144	2,056	0,040
	Innocenti &	0,165	0,061	0,266	3,093	0,002
	IBM	0,400	0,370	0,429	23,556	0,000
Random		0,364	0,072	0,599	2,418	0,016



A very high level of heterogeneity was observed among studies ($I^2 = 98.9\%$, $Q = 299.45$, $df = 3$, $p < 0.0001$). (Figure 8)

Figure 8. Heterogeneity Test

Model	Effect size and 95% confidence interval						Test of null (2-Tail)		Heterogeneity				Tau-squared			
Model	Number Studies	Point estimate	Standard error	Variance	Lower limit	Upper limit	Z-value	P-value	Q-value	df (Q)	P-value	I-squared	Tau Squared	Standard Error	Variance	Tau
Fixed	4	0,436	0,014	0,000	0,409	0,464	31,407	0,000	299,459	3	0,000	98,998	0,098	0,092	0,009	0,314
Random	4	0,382	0,158	0,025	0,072	0,691	2,418	0,016								

In the meta-regression analysis, effect type was found to be a significant moderator: Studies measuring direct skill effects reported significantly higher correlation values compared to studies measuring indirect effects ($\beta = 0.640$, $p = 0.001$).

When examining the change in skill priorities over time, looking at IBM (2023) and IFR (2024) reports, while the priority ranking of STEM skills dropped from 1st place in 2016 to 12th place in 2023, human skills such as communication, teamwork, and time management rose from 10th place to 1st place. This dramatic change shows that technological development makes not only technical skills but also human-specific skills valuable. Additionally, according to the IBM (2023) study, 40% of the workforce will need to reskill within the next three years due to artificial intelligence and automation. This situation emphasizes the importance of education and skill development programs.

Publication Bias

Publication bias tests were applied for all three analysis categories. Although funnel plots (Figures 9, 12, 15) showed slight asymmetry, Egger regression tests (Figures 10, 13, 16) and trim and fill tests (Figures 11, 14, 17) did not detect any statistically significant bias in any category ($p > 0.05$).

Figure 9. Employment Susceptibility Rate Funnel Plot

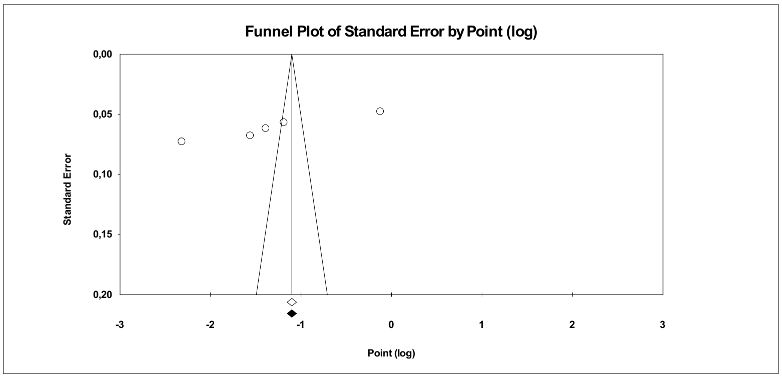


Figure 10. Employment Susceptibility Rate Egger Test

Egger's regression intercept

Intercept	-80,89718
Standard error	10,97820
95% lower limit (2-tailed)	-115,83476
95% upper limit (2-tailed)	-45,95960
t-value	7,36889
df	3,00000
P-value (1-tailed)	0,00258
P-value (2-tailed)	0,00517

Figure 11. Employment Susceptibility Rate Trim and Fill Test

Duval and Tweedie's trim and fill

		Fixed Effects			Random Effects			Q Value
	Studies Trimmed	Point Estimate	Lower Limit	Upper Limit	Point Estimate	Lower Limit	Upper Limit	
Observed values		-1,10170	-1,15397	-1,04942	-1,31177	-2,04223	-0,58130	762,31715
Adjusted values	0	-1,10170	-1,15397	-1,04942	-1,31177	-2,04223	-0,58130	762,31715

Figure 12. Employment Effect Funnel Plot

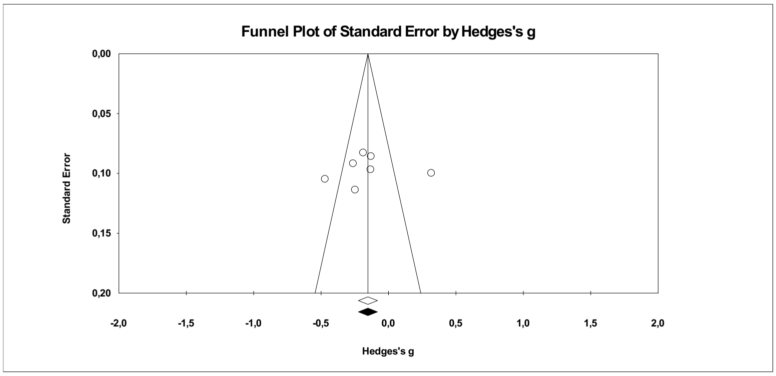


Figure 13. Employment Effect Egger Test

Egger's regression intercept

Intercept	-1,60701
Standard error	9,60306
95% lower limit (2-tailed)	-26,29245
95% upper limit (2-tailed)	23,07843
t-value	0,16734
df	5,00000
P-value (1-tailed)	0,43683
P-value (2-tailed)	0,87366

Figure 14. Employment Effect Trim and Fill Test

Duval and Tweedie's trim and fill

		Fixed Effects			Random Effects			Q Value
	Studies Trimmed	Point Estimate	Lower Limit	Upper Limit	Point Estimate	Lower Limit	Upper Limit	
Observed values		-0,15258	-0,22310	-0,08206	-0,15534	-0,32340	0,01272	33,67298
Adjusted values	0	-0,15258	-0,22310	-0,08206	-0,15534	-0,32340	0,01272	33,67298

Figure 15. Skill Requirements Funnel Plot

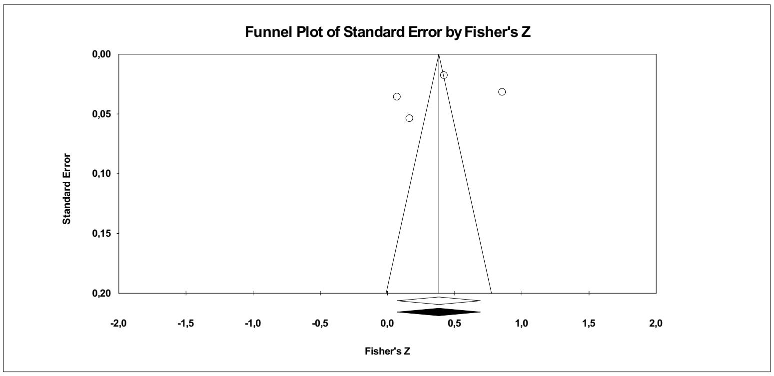


Figure 16. Skill Requirements Egger Test

Egger's regression intercept

Intercept	-4,51759
Standard error	15,77100
95% lower limit (2-tailed)	-72,37471
95% upper limit (2-tailed)	63,33953
t-value	0,28645
df	2,00000
P-value (1-tailed)	0,40074
P-value (2-tailed)	0,80148

Figure 17. Skill Requirements Trim and Fill Test

Duval and Tweedie's trim and fill

		Fixed Effects			Random Effects			Q Value
	Studies Trimmed	Point Estimate	Lower Limit	Upper Limit	Point Estimate	Lower Limit	Upper Limit	
Observed values		0,43649	0,40925	0,46373	0,38179	0,07237	0,69120	299,45948
Adjusted values	0	0,43649	0,40925	0,46373	0,38179	0,07237	0,69120	299,45948

Holistic Assessment

When we combine our findings in three main categories, it is seen that the impact of artificial intelligence and robotic technologies on the labor market is not one-dimensional but multi-dimensional. The average automation susceptibility rate (21.3%), while pointing to a significant workforce transformation potential, indicates that the scenario of "robots taking our jobs" is exaggerated. Employment effect analyses show that technology changes the structure of employment rather than the total employment volume, creating a decrease in routine manual tasks and an increase in non-routine analytical tasks. Skill requirements analyses show a shift from STEM skills to human skills. This situation suggests that as artificial intelligence technologies can undertake routine cognitive tasks, human-specific social-emotional skills become more valuable.

The fact that the time factor is a significant moderator in all analysis categories indicates that our understanding and expectations regarding the effects of technology on the labor market have evolved over time. Considering the three technological waves (algorithmic, augmentation, and autonomous) predicted by Hawksworth et al. (2018), it can be said that we are probably currently in the augmentation wave. At this stage, technology supports people to make them more efficient rather than completely eliminating jobs.

CONCLUSION AND RECOMMENDATIONS

This meta-analysis shows that the effects of artificial intelligence and robotic technologies on the labor market are complex and multi-dimensional. The average automation risk is lower than emphasized in previous public discussions, but still has significant potential for workforce transformation. Our study demonstrates that robots change the structure of work rather than completely eliminating employment, reducing routine manual tasks but increasing non-routine analytical tasks. It also identifies increased demand for social-emotional and technical skills.

The findings suggest avoiding overly optimistic or pessimistic perspectives when assessing the impact of artificial intelligence and robotics on the labor market. Therefore, future policy discussions should focus on how these technologies can complement human labor and how this transformation can be managed for a more inclusive labor market.

In light of our meta-analysis findings, we present the following policy recommendations:

1. Country-specific strategies: The differentiation of automation effects by country indicates that uniform policy approaches will be inadequate. Differentiated strategies are required for developed and developing countries.

2. Skill transformation programs: Given that a significant portion of the workforce will need skill transformation, investment should be made in training programs that develop both technical and social-emotional skills.
3. Support for new types of jobs: The potential of technological transformation to create new types of jobs should be strengthened with policies that support entrepreneurship ecosystems and new industries.
4. Gradual transition management: Considering the three technological waves (algorithmic, augmentation, and autonomous) mentioned by Hawksworth et al. (2018), workforce transitions should be managed with a long-term perspective.

This meta-analysis has some limitations. First, there are methodological differences among the included studies, which makes comparison difficult. Second, the data is not sufficient to evaluate the long-term impact of recent shocks such as the COVID-19 pandemic. Third, the potential effects of the newest technologies such as generative artificial intelligence have not been sufficiently examined in the existing literature.

Future research could focus on the following areas:

- More comprehensive examination of the effects of artificial intelligence and robotic technologies in developing countries
- Empirical analysis of the effects of generative artificial intelligence technologies on the labor market
- More detailed assessment of sector-specific impacts
- Examination of the differentiated effects of technological change on gender and age groups

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