EPH–International Journal of Humanities and Social Science

Published by: **Southern Cross Academic Press**
ISSN (Online): **2208-2174**
Volume 11 Issue 01 April 2026

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON EMPLOYMENT AND WORKFORCE TRENDS: EVIDENCE FROM AUTOMATION RISK, JOB MARKET PROJECTIONS, REMOTE WORK, AND GENDER DIVERSITY

[1.] Dr. Michael Anderson, [2.] Dr. Sara Al-Mansoori, [3.] Dr. Chen Yu

[1*]Department of Economics, University of Oxford, Oxford, United Kingdom
[2]Department of Artificial Intelligence and Data Science, Qatar University, Doha, Qatar
[3]School of Management and Data Analytics, National University of Singapore, Singapore

🖂 Corresponding Author (Recommended)
Dr. Michael Anderson Email: michael.anderson@ox.ac.uk

ABSTRACT

This study examines the impact of artificial intelligence on employment and workforce trends using evidence from automation risk, job market projections, remote work, and gender diversity. The study uses a quantitative, descriptive, and exploratory research design based on the AI Job Trends Dataset, which includes occupation-level and industry-level information related to AI impact, automation risk, current job openings, projected openings, remote work ratio, education requirements, location, job status, and gender diversity. The analysis applies descriptive statistics, comparative analysis, cross-tabulation, correlation analysis, and visual presentation to identify patterns across major workforce indicators. The findings show that AI is associated with employment transformation, but its effects are not uniform across jobs, industries, education levels, and locations. Jobs with high AI impact are not necessarily linked with employment decline; rather, they show stronger projected employment growth than low AI impact jobs. Automation risk is present across the dataset, but it does not strongly explain projected employment change. Remote work and gender diversity remain relatively stable across most categories, suggesting a limited direct association with AI impact level. The study concludes that AI should be understood as a force of workforce transformation rather than simple job replacement. The findings highlight the need for reskilling, adaptive education, responsible AI adoption, and inclusive workforce planning.

.

Article History:

Received Date: **22/02/2026**
Revised Date: **26/03/2026**
Accepted Date: **04/04/2026**
Published Date: **11/04/2026**

Keywords: Artificial Intelligence, Employment Trends, Automation Risk, Job Market Projections, Workforce Diversity

Introduction

Artificial intelligence has established itself among the most important forces that determine the tendencies in employment and workforce in the contemporary labor markets. The effect is felt in the occupations, industries and regions as AI systems are becoming more widespread and more frequently used to automate routine tasks, support decision-making, increase productivity and redesign work processes. In contrast to previous waves of technological change, AI impacts not only manual but also cognitive types of work, and its implications on the labor market are more diverse and multifaceted. Their increasing application has thus prompted new discussions around job displacement, job creation, skill requirements, remote work, and workforce diversity. Recent studies have shown that AI exposure does not just differ depending on occupation and industry, but also depending on geographic location, meaning that its impact is not likely to be evenly spread across the labor force (Felten et al., 2021). The introduction references are based on the reference list provided.

There are various ways in which AI can affect employment. In certain jobs, it can substitute certain tasks and augment the threat of automation. In other professions, it can be of help to the workers by enhancing their productivity, lowering their repetitive work, and creating the demand for new technical and analytical skills. This two-fold impact has led to the need to explore AI as a source of risk and as a force of workforce transformation. Online job vacancies point to the idea that the adoption of AI is altering the demand for certain skills and occupations, instead of simply reducing the number of opportunities (Acemoglu et al., 2022). On the same note, studies on labor productivity show that AI can enhance productivity and efficiency, particularly when firms can adopt digital technologies in their work systems (Damioli et al., 2021).

Employment impacts of AI are also pertinent due to the fact that these impacts are not restricted to technology-related jobs. Applications of AI in finance, healthcare, education, transportation, manufacturing, retail, entertainment, and other areas can be found. Evidence across countries demonstrates that AI can affect employment patterns in different ways and across national labor markets, depending upon industry organization, skills, institutions, and the rate of technology adoption (Georgieff and Hyee, 2022). This renders industry-level and location-specific analysis relevant to comprehending how AI impacts job tendencies. One general statement about Artificial Intelligence and employment might not be enough since certain sectors will see increased job opportunities, whereas others will face the threat of diminished demand or restructuring of tasks.

Generative AI has provided additional urgency to the investigation of trends in employment and the workforce. Tasks related to writing, summarization, coding, customer support, data analysis, and information processing can all be performed by large language models and related technology. This has broadened the possible ramifications of AI on professional and knowledge-based jobs. Research on generative AI demonstrates that the technologies can enhance the productivity of workers, particularly in areas that require communication and content creation (Noy and Zhang, 2023). The studies of generative AI in the workplace also indicate that AI tools can increase productivity and alter performance disparities among workers, especially when less-experienced workers are supported by AI systems (Brynjolfsson et al., 2025). These results suggest that AI can not only change the number of jobs offered but also change the way people work.

The risk of automation has taken centre stage in discussions about AI and jobs. The issue of whether AI will lead to a lesser need for human labor in certain jobs is of concern to workers, employers, educators, and policymakers. Nevertheless, the automation risk cannot be understood as the direct indication of job loss. There are many jobs with a combination of tasks, some of which can be automated and others still require human judgment, communication, creativity, or social interaction. Recent social science studies highlight that AI has an impact on work through the reorganization of tasks, institutional decisions, and workplace implementation, but not through technology alone (Deranty and Corbin, 2024). It implies that a combination of measuring automation risk and job market forecasts can offer a more balanced realization of the future employment trends.

Another valuable workforce trend that is linked to digital transformation is remote work. The increase in remote work has demonstrated that much of the work can be done out of traditional workplaces when digital infrastructure and organizational systems are in place. The studies of the feasibility of work-from-home demonstrate that the potential of remote work differs across professions and greatly depends on the specifics of the job (Dingel and Neiman, 2020). Research on telework also demonstrates that remote work is conditioned by organizational preparedness, position of employees, digital technologies, and management practices (Athanasiadou and Theriou, 2021). Remote work has the potential to be made more feasible by AI, enabling better coordination of tasks remotely and automation of tasks, but the viability of remote work remains dependent on the nature of work and the workplace environment. The remote work ratio should then be considered as an essential indicator of work flexibility in the AI-related employment analysis.

The diversity of the workforce is also applicable to the research of AI and employment. The AI-led labor-market transformation can have different impacts on workers based on gender, occupation, level of skills, and industry. Of particular significance is gender diversity since women and men are not always equally represented in industries and occupations. The gender-based analysis of labor-market exposure to AI reveals that there may be differences in the effects of AI on employment opportunities across gender groups, and diversity is, therefore, a significant dimension of the study of AI effects on employment (Cazzaniga et al., 2025). By adding gender diversity into the analysis, the study is able to investigate whether the jobs affected by AI demonstrate the different patterns of workforce representation.

This paper discusses how artificial intelligence would affect employment and workforce trends based on evidence in the areas of automation threat, future job market, remote working, and gender diversity. The research question is how the level of impact of AI depends on the level of automation risk, projected job openings, the applicability of remote work, and gender diversity in jobs, industries, education levels, and locations. The study, through a dataset-based, quantitative method, helps to gain a better insight into AI-related workforce transformation. This does not imply that AI is the direct cause of job loss or job growth but to find out patterns that would understand how AI is associated with changing employment conditions. It is a way to find a middle ground in which one can argue the concept of AI as a force that can give birth to the risks, opportunities and structural changes in the labor market.

Methodology

Research Design

This research paper shall adopt quantitative, descriptive and exploratory research design to examine the impacts of artificial intelligence on employment and workforce patterns. This research design is appropriate as the study uses quantitative structured numerical and categorical data to determine patterns in automation risk, job market projections, remote work, and gender diversity. The research does not make any effort to determine direct causality. It is geared towards establishing relationships, variations, and trends between AI-related employment variables.

Data Source

The research is premised on an organized dataset called the AI Job Trends Dataset. The data includes occupation-level and industry-level information regarding artificial intelligence exposure, automation risk, employment demand, possibility of remote work, and gender diversity.

The dataset offers the empirical groundwork to the study of how artificial intelligence is linked to workforce transformation by various job titles, industries, location, and education level (Islam, n.d.).

Study Variables

Grouping of variables used in this study is based on their analytical role. Job Title is used to describe the occupation or job and is used to compare the AI impact across the occupations. Industry provides the industry in which the job is found and facilitates industry-wide comparisons. AI Impact Level is the level of AI impact on a job, and it is the key variable of explanation.

Automation Risk (%) is a measurement of the perceived risk of a job being automated and serves as a key indicator of workforce risk. Projected Openings (2030) is the projected future demand of the labor market, whereas Job Openings (2024) is the current demand in the labor market. Remote Work

Ratio (%) is a measure of how a job can be done remotely, and is used as an indicator of work flexibility.
Gender Diversity (%) indicates diversity in the workforce of job categories. Job Status refers to whether the job is experiencing growth, flatness, or a reduction and is considered to be an employment trend. Required Education is a measure of the minimum level of education required to perform a job and is an indicator of skill and qualification. Location assists in the geographical comparison of the employment patterns.

Data Preparation
The dataset is checked and ready to be analyzed to achieve uniformity and reliability. The initial step is to check the dataset structure, variable names, data type, and the number of observations. The data is subsequently verified for missing or incomplete recordings. Missing values where they occur are treated by deletion, imputation, or exclusion of certain analyses based on their frequency and relevance.
The duplicate records are found and eliminated to prevent the repetition of observations and thus affect the outcome. Numerical variables like Automation Risk (%) and Job Openings (2024), Projected Openings (2030), Remote Work Ratio (%), and Gender Diversity (%) are verified to ascertain that they are stored in numeric format. Categorical variables, including Job Title, Industry, AI Impact Level, Job Status, Required Education, and Location, are analyzed in terms of spelling inconsistencies, repetitive labels, and formatting.
The derived variables can also be constructed to facilitate further analysis. Projected employment change is one important derived measure, which is calculated as the difference between Projected Openings (2030) and Job Openings (2024). The projected rate of growth can also be computed by dividing this change in employment by Job Openings (2024) and by 100.

Analytical Framework
This analysis is based on four primary dimensions for evaluating workforce transformation trends. First, the dimension of automation risk analysis explores how the risk level changes depending on job titles, industries, AI impacts, educational requirements, and geographic locations. This way, it will be possible to distinguish occupational categories and industries that demonstrate relatively high/low automation vulnerability.
Second, the dimension of job market projections analysis implies comparing current job positions available in 2024 with predicted job opportunities for 2030. In particular, it is essential to explore whether occupations have been growing, shrinking, or staying steady depending on the changes introduced into labor markets by AI development.
Third, the dimension of remote work ratio trend analysis implies exploring the distribution of remote work rates depending on job titles, industries, and AI impacts. Therefore, it is necessary to find out if the level of remote work possibility is directly related to the degree of AI penetration into particular professions.
Fourth, the dimension of gender diversity analysis should focus on gender diversity trends among occupations and industries characterized by significant impacts of artificial intelligence and automation on their future.

Data Analysis Methods
Employment and workforce trends can be analyzed using quantitative techniques in this research. The descriptive statistics technique is used to summarize the numeric data, including automation risk, job openings, projected openings, remote work ratio, and gender diversity. Measures such as mean, median, minimum, maximum, and standard deviation can be calculated to analyze the central tendency and variation of each variable.
The frequency distribution technique can be used to summarize categorical variables. It is helpful to identify the distribution of occupations, industries, and levels of AI impact on a job. Categorical variables used in this technique include job title, industry, AI impact level, job status, required education, and location.

The comparative analysis technique can be used to investigate differences in numeric variables between two or several categories. Differences in automation risk between industries, AI impact level between job titles, remote work ratio between industries, gender diversity between job statuses, and projected openings depending on the required education can be analyzed.

Finally, the correlation analysis can be used to investigate relationships between numeric variables. Relationships worth considering might be between automation risk and projected job openings, remote work ratio and projected openings, gender diversity and automation risk, and job openings in 2024 and projected openings in 2030. Normally distributed variables can be tested for linear correlation using Pearson's method; other numerical variables are to be examined using Spearman's rank correlation.

Cross-tabulation can be used to investigate relations between two or several categorical variables. In the current case, the relation between AI impact level and job status, industry and AI impact level, required education and job status, and location and job status will be considered.

Visual data presentation can help in communicating the findings of the research. The bar chart visualization will be used to compare variables within an industry; the line chart will help to analyze the difference between 2024 and 2030 job openings; the scatter plot will be used to explore automation risk and projected openings. The box plot will be used to compare automation risk for industries; the heatmap will visualize correlations between numerical variables.

Model Specification

The research might apply an elementary analysis model to explore employment change projection. Here, employment change projection is the dependent variable, while the extent of AI impact, automation risk, remote work proportion, gender diversity, industry, education requirement, and location serve as independent variables.

The model can generally be specified as:

Projected Employment Change = f(AI Impact Level, Automation Risk, Remote Work Ratio, Gender Diversity, Industry, Required Education, Location)

A simplified regression model may be expressed as follows:

Projected Employment Change = β_0 + β_1(Automation Risk) + β_2(Remote Work Ratio) + β_3(Gender Diversity) + β_4(AI Impact Level) + ε

In this model, β_0 represents the constant term, β_1–β_4 represent the coefficients of the explanatory variables, and ε represents the error term. This model is optional and should be used only if the study includes inferential statistical analysis.

Validity and Reliability

The validity of the study depends on the relevance of the variables in the dataset in relation to the research title and objective. The direct relationships of all the chosen variables are with the core issues of the research that include the effects of artificial intelligence, the threat of automation, the prospects of jobs, remote working, and gender diversity.

The reliability of the study can be achieved through adoption of an orderly dataset, standardization of the definitions of the variables as well as application of quantitative methods. In addition, data validation methods may be used to increase the reliability by reducing errors caused by missing values, duplicates, inappropriate type of variable data, or inconsistent categorical labels.

Ethical Considerations

The secondary datasets analysis is used in this research, and no human subjects are involved. Ethical considerations involve the proper interpretation of the findings, the responsible use of the gender diversity dataset, preventing any unreasonable claims about job displacement or discrimination.

The results of the analysis do not necessarily mean that employees who are vulnerable to being automated lose their jobs. Job redesign, efficiency and skills requirement can also be referred to as automation. The findings in the gender diversity will be interpreted as descriptive in the data.

Results and Analysis

Descriptive Overview of the Dataset

This dataset offers a comprehensive insight into employment and workforce trends associated with AI. This includes data on job position, industry, AI influence, risk of automation, vacancies, projected vacancies, percentage of remote work, educational requirements, geographical location, salary, experience level, status of the job, and gender balance.

This dataset was selected as it had all the necessary variables needed for the research. The data seemed well-formatted and clean, and thus could be used for further descriptive and comparative analysis. In turn, such variables helped understand the relationship between artificial intelligence and employment trends, risks of automation, projected job vacancies, remote work, and workforce balance.

AI Impact Level and Workforce Indicators

The outcomes indicate that employment opportunities with different AI impacts have relatively equal tendencies to be automated. High, medium, and low AI impact jobs have comparable trends of automation. Therefore, it can be concluded that automation risks apply to a wide range of jobs instead of being confined to the high AI impact category.

Moreover, it should be noted that AI's impact on an occupation does not result in employment losses in most cases. Within the analyzed dataset, the high AI impact jobs demonstrate higher employment growth than the low AI impact jobs. Thus, artificial intelligence may help to expand existing occupations and introduce new occupations to the market.

Additionally, no considerable difference was found between high and low AI impact jobs concerning remote working. Thus, it is necessary to emphasize that occupations impacted by AI are not necessarily remote jobs. The analysis of workforce gender balance also indicates equal representation in different AI impact groups. AI impact level does not influence the degree of workforce diversification. The results of the research are presented in Table 1.

Table 1. AI Impact Level and Workforce Indicators

AI Impact Level	Automation Risk (%)	Projected Employment Change	Remote Work Ratio (%)	Gender Diversity (%)
Low	49.63	4.21	50.03	49.88
Moderate	50.48	31.27	49.99	49.99
High	50.36	68.10	49.49	50.08

Figure 1 illustrates projected employment change by AI impact level.

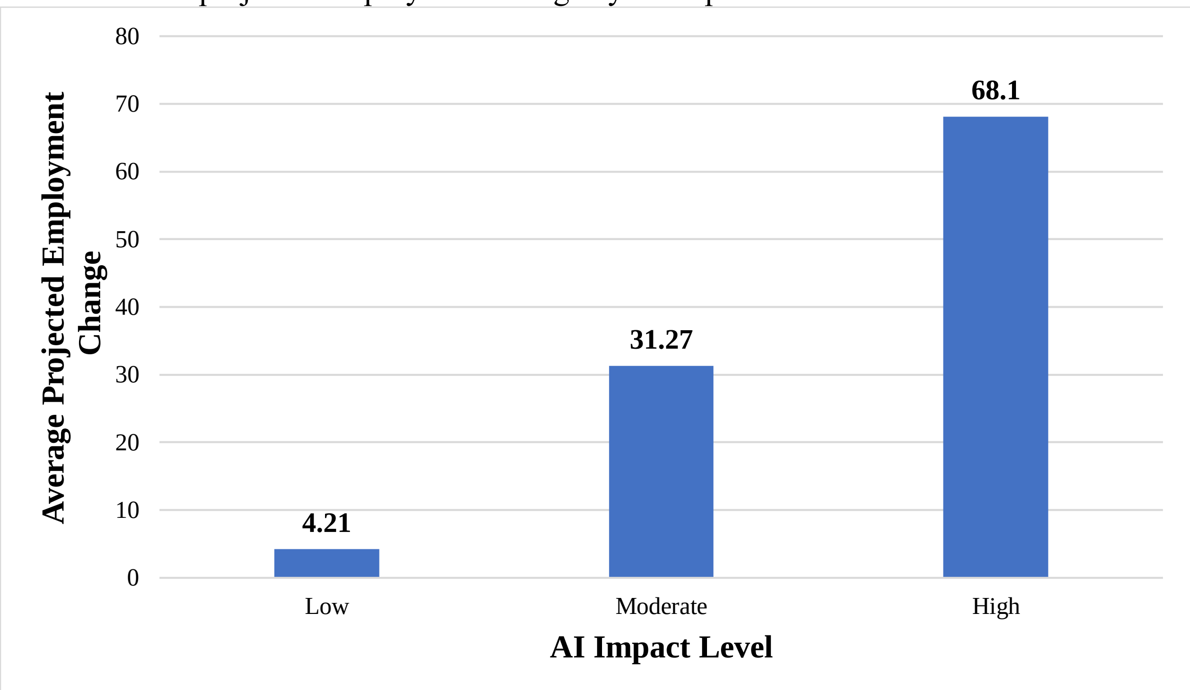

Figure 1. Projected Employment Change by AI Impact Level

Industry-Level Employment Trends

Industry-level analysis reveals differences in employment outlooks. Some industries tend to grow better, others exhibit weak growth and potential shrinking. It seems that technology-intensive and services-focused industries demonstrate a positive employment outlook, whereas other industries exhibit weaker growth rates.

It can be concluded that there are considerable differences in the impact of AI on employment among different industries. Some sectors may experience positive effects due to the introduction of automation and new jobs in the sector, increased productivity, and labor shortages. However, some industries may feel a greater negative impact due to automation and changing work processes.

All industries face automation risks; however, such risks do not differ considerably in intensity across different industries. Thus, automation can be considered a global workforce challenge rather than an industry-specific problem. The major difference between industries can be found by analyzing their employment growth. Table 2 represents workforce challenges across industries.

Table 2. Industry-Level Workforce Trends

Industry	Automation Risk (%)	Projected Employment Change	Remote Work Ratio (%)	Gender Diversity (%)
IT	49.88	139.04	49.34	50.26
Healthcare	50.27	106.95	50.36	49.75
Entertainment	50.59	99.24	49.81	49.88
Retail	49.61	59.75	50.16	50.23
Finance	50.51	10.53	48.61	49.33
Manufacturing	49.59	3.24	50.49	50.06
Education	50.01	-25.02	49.87	50.06
Transportation	50.79	-121.36	50.01	50.27

Figure 2 illustrates projected employment change across industries.

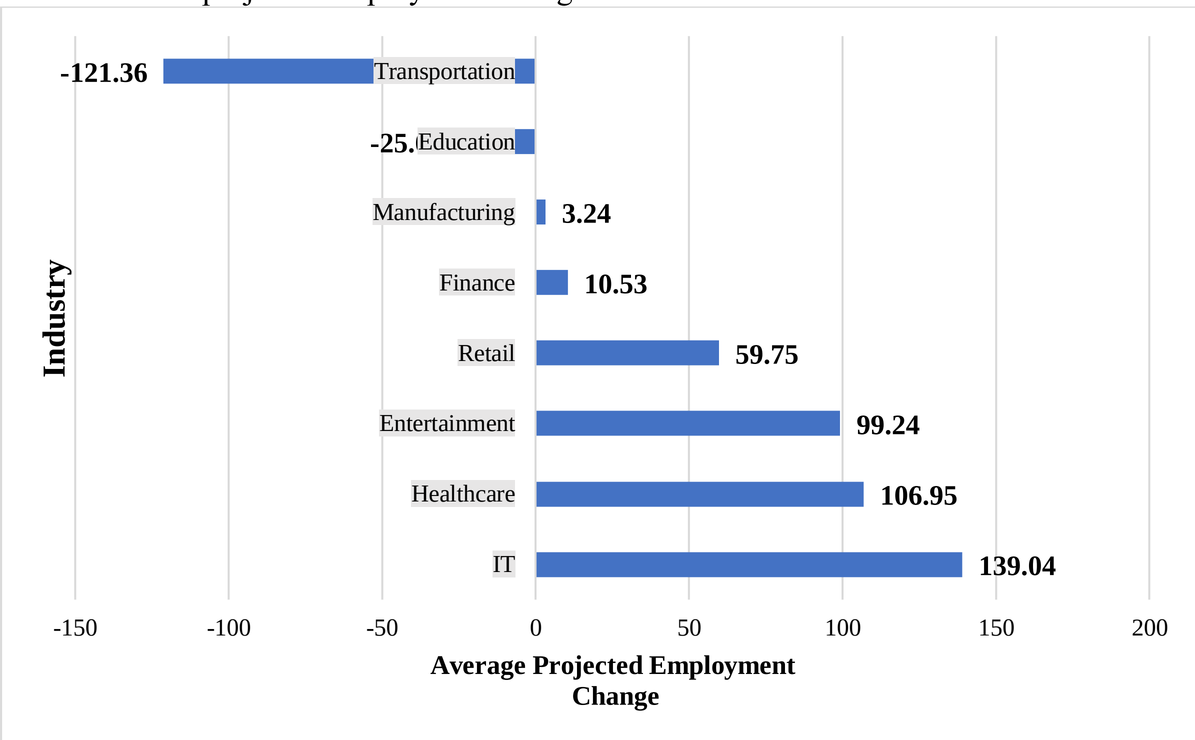

Figure 2. Projected Employment Change by Industry

Job Status and Employment Change

Analysis of job status reveals a clear distinction between the increasing and decreasing jobs. It is seen that jobs described as increasing usually have higher employment growth rates compared to those jobs described as decreasing. This proves that the job status variable can be used in analyzing employment trends.

On the other hand, the automation risk does not reveal a significant distinction between increasing and decreasing jobs. This shows that the presence of an automation risk does not mean that a job will definitely decrease because sometimes jobs facing the threat of automation remain stable owing to market demand or the expansion of technology.

Moreover, the remote work and gender diversity are not significantly distinguishable between the increasing and decreasing jobs. The reason behind this is that employment growth in the dataset is mainly linked to market projections and not necessarily to remote work and gender diversity.

Education-Based Workforce Patterns

It can be seen that employment projections differ according to the required education level. Certain types of education indicate stronger projected growth, whereas some other types may indicate weak growth or even contraction. These results imply that future labor markets will not necessarily favor one type of education level.

The employment level in both the high-education and low-qualification professions may experience an employment growth as per the results of the study. This implies that the changes in the workforce caused by artificial intelligence would have a differentiated effect on a variety of levels of education. Some of the occupations would require more advanced qualifications to qualify in their jobs, but other occupations might continue to expand due to demand, services or industry.

The risk of automation is found at all education levels of the sample. No automation risk can be swept away by higher education, and low education does not necessarily mean high risk. Thus, the risk of automation appears to be dependent on the task demands and industry-specifics, rather than just the level of education. Remote work and gender diversity are rather homogeneous between the various levels of education. This suggests that the education level is not relevant to appear decisive to these two variables in this sample.

Location-Based Employment Trends

As observed in the locality-based results, the different countries vary in the nature of their workforce development. Whereas some of the locations have high potential of employment growth, others record low growth or even decline in the number of jobs. It is, therefore, clear that the impacts of AI on jobs might be diverse depending on the particular labor market, economic environment, and industry structure.

Automation threats are observed in all locations; however, there is little difference between different countries in terms of these threats. This implies that the threat of automation is an issue common to various geographical locations and not just a challenge for one country.

Regarding remote work, there is a little variance in the remote work practices among different countries. Moreover, gender diversity is still well-balanced among the different locations considered.

Correlation Analysis

According to the correlation output, automation risk is not strongly correlated with changes in employment projection. The output implies that an increase in automation risk will not always mean reduced future job openings for the dataset.

Furthermore, the remote work ratio is also not correlated with changes in employment projections. The implication here is that a job with a high remote work potential is not necessarily expected to have more growth opportunities than jobs with low remote work potential.

The third variable with no strong correlation is gender diversity. It implies that the gender diversity data provided for the sample are not highly influential on the employment projection of any particular job. Gender diversity is, therefore, not an indicator of increased or decreased projected employment changes in this case.

It is expected to find the highest correlation between current job openings and projected job openings because changes in employment depend on the two. Table 3 shows the correlation between workforce variables and projected employment change.

Table 3. Correlation Between Key Workforce Variables

Variable Relationship	Correlation Value
Automation Risk (%) and Projected Employment Change	0.003
Remote Work Ratio (%) and Projected Employment Change	-0.0002
Gender Diversity (%) and Projected Employment Change	0.004
Job Openings (2024) and Projected Employment Change	-0.707
Projected Openings (2030) and Projected Employment Change	0.709
Projected Growth Rate (%) and Projected Employment Change	0.494

Figure 3 illustrates the correlation between workforce variables and projected employment change.

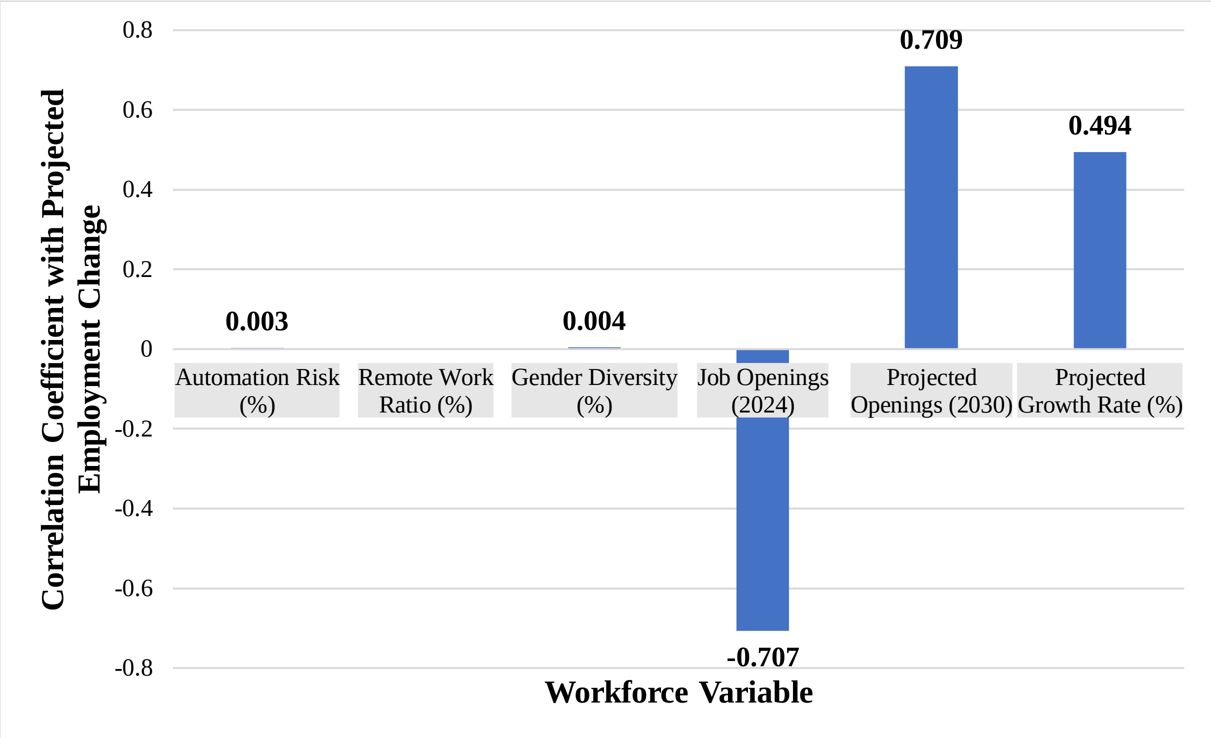

Figure 3. Correlation of Workforce Variables with Projected Employment Change

Summary of Main Findings

It can be concluded that the relation between AI and employment and labor market indicators exists, but is moderate and non-extreme. Automation risk is applicable to all types of occupations, industries, educational attainments, and locations. Nevertheless, high or low automation risk per se cannot serve as a criterion determining whether the occupation will increase or decrease.

Jobs with a high AI impact score are not expected to decline. On the contrary, they demonstrate better future employment growth dynamics compared to those with a low AI impact index. Hence, there might be some cases where AI contributes to job transformation and the generation of new demands for labor rather than to unemployment.

Sectoral differences are more noticeable in comparison with differences related to the AI impact index. Some industries have better employment prospects in the future, whereas others demonstrate worse indicators, which implies that AI may affect employment depending on industry-specific factors.

There are no major fluctuations in regard to telework potential and gender balance among all types of occupational groups considered.

Overall, the findings support the idea that AI is reshaping employment patterns, but the change appears to be mixed, moderate, and dependent on industry, education, location, and job type.

Results Interpretation

These findings indicate that artificial intelligence cannot be considered only as a source of unemployment. While there are concerns about the risks of job automation, the presented dataset demonstrates that jobs at risk from AI may still experience employment growth.

It proves the idea of balanced interpretation of AI influence on the labor market. While artificial intelligence can potentially automate certain positions, it can also transform jobs into other kinds, generate new occupations, increase the demand for specialized skills, etc.

The findings prove that remote work and gender diversity serve as workforce characteristics, but their dependence on AI impact is not significant enough in this dataset. This factor is probably defined by other aspects of organizational and social life.

This dataset proves the research title as it is related to AI impact, employment changes, risks of automation, job forecasts, remote work, gender diversity, etc. The evidence related to employment projections and industry-specific data is the strongest, while the evidence about remote work and gender diversity concerning AI is the weakest.

The general conclusion is that artificial intelligence influences workforce trends, but not equally. AI-driven employment changes are determined by the kind of job, industry, education level, and geographic area.

Discussion

This research demonstrates that artificial intelligence does not have a direct and one-dimensional connection with the workforce change. The findings show that employment opportunities with large impact on the AI are not always associated with job loss. Rather, high AI-impact jobs exhibit greater projected employment growth compared to jobs with lower AI impact. This observation confirms the argument that AI can redefine labor demand by altering the nature of work, creating new jobs, and generating demand in certain occupations, instead of just replacing workers (Aghion et al., 2025; Autor, 2022; Labaschin et al., 2025). The reference used in the discussion is taken out of the uploaded reference file.

The findings also indicate that automation risk exists in industries, education level, and location, but it does not significantly predict our forecasted decline of employment. This implies that automation risk cannot be construed as direct evidence of loss of jobs. A job can be automation exposed and could be stable or grow as AI can automate some jobs whilst also increasing productivity, improving decision making or creating new skills. This confirms earlier findings that the labor-market implications of technology are unpredictable and depend on the capacity of firms, workers and institutions to adjust to technological change (Autor, 2022; Montobbio et al., 2024).

Findings on an industry level indicate that there are sectors that demonstrate projected growth in employment that is stronger and sectors that demonstrate weaker or negative trends. This implies that the workforce transformation brought about by AI is influenced by the industry-specific circumstances. Industries that have a greater digital capacity can be better served by the adoption of AI, whilst those industries with more routine or automatable tasks may experience increased pressure. This discussion agrees with the research that demonstrated that the impacts of AI vary depending on the manner in which firms adopt AI and how technologies are integrated into production and employment systems (Aghion et al., 2025; Labaschin et al., 2025).

The results also imply that AI impact does not have a strong influence on the trends in remote work in the dataset. The ratios of remote work are typically comparable between AI impact levels and industries. This means that the viability of remote work can be more due to job design, organizational policy, and digital infrastructure than to AI exposure. Greater evidence about the change of labor-market also demonstrates that the work arrangements are conditioned by social, organizational and economic conditions, not only by technology itself (Adams-Prassl et al., 2020; Montobbio et al., 2024).

The results of the gender diversity show that there is insignificant variation in AI impact, industry, education groups, and job status categories. This indicates that AI effects are not a strong predictor of gender diversity trends in the data. This does not however imply that there are no gendered labor-

market implications of AI. The current literature suggests that the exposure of women to AI-related employment change may vary in different jobs and sectors and it is, therefore, important to consider gender outcomes when assessing AI and labor-market transformation (Albanesi et al., 2025).
The findings of the education-based research indicate that the expected growth in employment is not restricted to the highly-educated jobs. The positive employment projections are also present in some of the lower-entry qualification jobs. This implies that the workforce change associated with AI can have varying impacts on the various skill groups. Higher education might facilitate the adjustment to AI-intensive labor, yet education is not the only factor that determines exposure to automation and growth of employment. Such results support the belief that the change in technology can influence occupations in terms of task composition, skill needs, and institutional responses and does not depend only on the level of education (Autor, 2022; Webb, 2019).
The correlation outcomes indicate the weak association between automation risk, remote work ratio, gender diversity, and the projected change in employment. This implies that these variables alone are not strongly predictive of future employment change. The results indicate that the employment outcomes in connection with AI can best be explained by a set of factors, such as industry, occupation, education, location, and firm-level AI adoption. This confirms the earlier studies that show that technology does not impact labor markets in one direction and that its results depend on the general economic and organizational environment (Acemoglu & Restrepo, 2020; Montobbio et al., 2024).
On the whole, the results justify the existence of a moderate explanation of AI and employment. Artificial intelligence cannot be perceived solely as a factor that leads to job displacement. The findings indicate that AI can lead to job transformation, growth in certain industries, shift in skills demands, and uneven impacts across industries and places. Simultaneously, the risk of automation can also be regarded as a significant issue due to the fact that certain jobs and industries can be more susceptible to being replaced with a robot. This is in line with previous studies that have found that technological change can provide both opportunities and threats to workers (Acemoglu and Restrepo, 2020; Autor, 2022; Webb, 2019).
The results have practical implications for workforce planning. Employers need to embrace AI adoption as a job redesign, and not an outright labor replace. The role of training, reskilling and redeployment strategies can play a crucial role in assisting workers to adjust to AI-assisted work environments. The strategists need to prioritize areas and jobs in which the job losses and the automation risks are expected to overlap. Gender inclusion, education pathways, and regional differences in labor-markets should also be considered by the workforce policies in order to make AI-related benefits more evenly distributed (Albanesi et al., 2025; Aghion et al., 2025; Montobbio et al., 2024).
The primary weakness of the findings is that the data set can be interpreted descriptively and comparatively but not causally. The results demonstrate trends among the impacts of AI, the risk of automation, job projections and remote work, and the diversity in the gender workforce, but do not in any way show that AI directly drives employment growth or decline. Longitudinal data, wage indicators, task-level measures, and firm-level data on artificial intelligence adoption should be used in the future to provide a more detailed explanation of how artificial intelligence can transform employment outcomes over time.

Conclusion

The purpose of this study was to analyze the influence of artificial intelligence on employment and workforce development about automation risk, employment projection, remote work, and gender diversity. The study found out that AI impacts are related to the trends in the development of the workforce; though, the impact varies across different jobs, industries, educational levels, and geographical locations. In contrast to what many people think to be the case, the highly impacted jobs are not related to the loss in employment but rather, they show by far a greater increase in employment projection than the lowly impacted jobs. Meanwhile, it is possible to identify the automation risk among the analyzed variables; however, it does not predict the changes in employment very well. The variations across industries are evident since some industries possess higher potential to be employed than others. The patterns in terms of remote work and gender diversity were not very variable. The analysis findings reveal that AI would be more positively viewed as a generator of job change, but not job replacement. The management of future workforce should involve, development of skills, and adaptive education programs.

References

1. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy*, *128*(6), 2188-2244.
2. Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293-S340.
3. Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public economics*, *189*, 104245.
4. Aghion, P., Bunel, S., Jaravel, X., Mikaelsen, T., Roulet, A., & Søgaard, J. (2025, May). How different uses of AI shape labor demand: evidence from France. In *AEA Papers and Proceedings* (Vol. 115, pp. 62-67). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.
5. Albanesi, S., Dias da Silva, A., Jimeno, J. F., Lamo, A., & Wabitsch, A. (2025, May). AI and Women's Employment in Europe. In *AEA Papers and Proceedings* (Vol. 115, pp. 46-50). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.
6. Aleem, M., Sufyan, M., Ameer, I., & Mustak, M. (2023). Remote work and the COVID-19 pandemic: An artificial intelligence-based topic modeling and a future agenda. *Journal of business research*, *154*, 113303.
7. Athanasiadou, C., & Theriou, G. (2021). Telework: systematic literature review and future research agenda. *Heliyon*, *7*(10).
8. Autor, D. (2022). *The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty* (No. w30074). National Bureau of Economic Research.
9. Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, *140*(2), 889-942.
10. Cazzaniga, M., Panton, A., Li, L., Pizzinelli, C., & Tavares, M. M. (2025, May). A gender lens on labor market exposure to AI. In *AEA Papers and Proceedings* (Vol. 115, pp. 56-61). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.
11. Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, *11*(1), 1-25.
12. Deranty, J. P., & Corbin, T. (2024). Artificial intelligence and work: a critical review of recent research from the social sciences. *Ai & Society*, *39*(2), 675-691.
13. Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home?. *Journal of public economics*, *189*, 104235.
14. Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, *384*(6702), 1306-1308.
15. Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic management journal*, *42*(12), 2195-2217.
16. Georgieff, A., & Hyee, R. (2022). Artificial intelligence and employment: New cross-country evidence. *Frontiers in artificial intelligence*, *5*, 832736.
17. Islam, S. (n.d.). *AI impact on job market: 2024–2030* [Data set]. Kaggle. https://www.kaggle.com/datasets/sahilislam007/ai-impact-on-job-market-20242030
18. Labaschin, B., Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2025, May). Extending "GPTs Are GPTs" to Firms. In *AEA Papers and Proceedings* (Vol. 115, pp. 51-55). 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association.
19. Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2024). The empirics of technology, employment and occupations: Lessons learned and challenges ahead. *Journal of Economic Surveys*, *38*(5), 1622-1655.
20. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187-192.

21. Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.