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Emergence of Artificial Intelligence on Projected U.S. Employment

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Abstract

The recent breakthroughs in artificial intelligence (AI) and its rapid integration into various aspects of life have become a focal point of concern, especially in regards to potential consequences on the workforce. Since AI has seen the most transformation post-2020, this study aims to analyze the role of AI exposure within an occupation on projected 10-year changes in employment using the most recent available data from 2022 (pulled from the U.S. Bureau of Labor Statistics). Through forward selection in ordinary least squares method, after controlling for task offshorability, education, work experience, and on-the-job training, it was found that a 1 standard deviation increase in AI exposure index is associated with a projected decrease of 1.043 percentage points in jobs on average within an occupation. This finding supports the growing concern of AI-driven job displacement and/or unemployment, which could heighten the burden on the government to fund welfare programs and potentially lead to recession. This paper further highlights the need for policy discussions on fostering a more balanced integration of AI into the workforce, possibly through specialized education and retraining programs.

Introduction

Artificial intelligence, or AI, is the ability for machines to perform tasks that require human problem-solving and decision-making skills, which cover many fields from agriculture (such as identifying deficiencies in soils to improve harvests) to health care (such as detecting early onset of diseases and providing accurate diagnoses). The earliest developments in AI began in the 1950s and received major funding from the U.S. military in the 1960s to research the capability of computers to make human decisions (Anyoha, 2017).

Modern AI relies heavily on machine learning techniques, which use sophisticated computer algorithms to find patterns in existing data and make predictions. A major revolution in the AI field was the success of deep learning in the early 2010s. Deep learning is a subset of machine learning which uses multiple layers of neural networks (computational models made up of “nodes” or functions which receive, process, and transmit signals to other nodes) to identify patterns and derive meaning from large amounts of data (Pham 2023). This allows for efficiency as it bypasses the need to spend hundreds of hours of manual coding to account for every possible input. Due to hardware improvements and increased access to vast datasets, these breakthroughs in deep learning have been driving the recent boom in interest and funding for AI. According to a study by Stanford University, 91.9 billion dollars (USD) were spent by global corporations in AI funding during the year 2022 alone (Thormundsson, 2023).

This spike in interest in AI has been raising questions as to the possible repercussions on the workforce. As new technologies render many tasks obsolete, there is a growing concern regarding a possible rise in labor displacement and unemployment, while promoters believe in the potential for job creation, especially within the tech sector. A recent Goldman Sachs report predicted that nearly 300 million jobs will be lost due to generative AI, though it may pave the way for creating new job opportunities, such as AI developers and maintenance specialists (Kelly, 2023).

Due to the novelty of AI technology and consequent lack of extended research, the true impact of AI on employment levels is unknown. Previous research has focused on impacts of AI-related job vacancies on wage growth using data from 2010-2018 (Acemoglu & Restrepo, 2019), a time that saw significantly less AI exposure in corporate settings. Other papers have focused on the effect of robotics and automation rather than AI (Acemoglu et al, 2022). In contrast, this study hopes to look at the most recent data and evaluate current labor market reactions to AI applications via ordinary least squares method to identify the role of AI exposure in various occupations on projected 10-year changes in employment from 2022 to 2032, controlling for various factors such as task offshorability, education needed for entry, related work experience, and typical on-the-job training needed for competency.

Method

Sample

The sample used in this study is U.S. population data from the year 2022. The unit of measurement will be occupation, with a total of 625 occupations defined by the Standard Occupational Classification System, or SOC (U.S. Bureau of Labor Statistics, 2023b). This data with its corresponding estimated statistics for each factor will be collected from the Occupational

Employment and Wage Statistics (OEWS) program by the BLS (U.S. Bureau of Labor Statistics, 2023f).

Dependent Variable

Projected 10-Year Change in Employment

The dependent variable is projected change in employment between 2022 and 2032 by occupation, calculated by the BLS. Note that employment in this paper refers to the 2022 National Employment Matrix developed by the BLS, which defines employment as a total count of *jobs* rather than of individual employees. This accounts for any possible underestimation resulting from a worker holding multiple jobs. Additionally, projected employment for 2032 is calculated by dividing industry employment among occupations "based on expected, structural changes in the demand for those occupations within a given industry" (U.S. Bureau of Labor Statistics, 2023d). These demand changes are determined after reviewing numerous sources from research articles, economic news, historical data, and more (see Appendix 1). Projected long-term change in employment serves as a good indicator of job creation/destruction, workforce participation and economic growth/decline, all of which may be observed as potential consequences of AI developments.

Independent Variables

AI exposure by Occupation

The primary independent variable is AI exposure, measured using the AI Occupational Exposure (AIOE) index developed by Felten, Raj, and Seamans (2021). This index uses AI application data from 2010 onwards from the AI Progress Measurement project by the Electronic Frontier Foundation, applying them to the industrial database by the U.S. Department of Labor. First, the authors calculated ability-level AI exposure scores using data for each ability required within an occupation. Then they weighted each ability-level exposure by that ability's corresponding prevalence in the occupation. These weighted scores were summed to create the aggregate exposure score, which was then scaled by the prevalence weights to result in the "relative" AI exposure score for the occupation. It is important to note that this AIOE measure is standardized so that the mean score across all occupations is 0 and the standard deviation is 1.

This AIOE index was chosen to measure the independent variable due to its extensive data drawn from multiple sources, including existing academic literature, reviews, blogs, and AI-focused websites. Additionally, the index's use of the 6-digit SOC classifications aligns with the BLS data measuring the dependent variable. The index provides a standardized weighted average of AI exposure across all abilities within each occupation, as determined by the Occupational Information Network (O*NET). A higher AIOE score represents a higher relative prevalence and importance of AI in that occupation. Note that negative AIOE scores are not to be interpreted as "negative exposure" to AI, but rather it is a result of standardization which facilitates comparison of relative exposure across occupations (Felten et al, 2021).

The hypothesis is that a higher AI exposure will cause a decrease in projected long-term employment, driven by the idea that services and tasks that can be performed by computers will lead to the replacement of human labor with machines, leading to job loss and lower projected employment rates. Those occupations with higher AI exposure will likely see negative changes in employment over time.

Proxy for Task Offshorability: Physical Proximity

A common driver of domestic unemployment is job offshoring, i.e. outsourcing of a firm's processes and services overseas to reduce business costs. Since changes in employment occur from task offshoring, controlling for this variable is important to prevent potential omitted variable bias. This study considers task offshorability by using a "physical proximity" proxy, as developed by O*NET ("Browse by Work Context: Physical Proximity," n.d.) via survey data. This measure determines the extent to which a job "requires the worker to perform job tasks in close physical proximity to other people," using a numerical scale from 0 (no working near others within one hundred feet) to 100 (very close proximity, near touching).

The hypothesis for this variable is that a lower proximity score is associated with higher offshoring, ultimately leading to decreased domestic employment. This is consistent with the idea that if a job does not require the worker to be in close range with colleagues or clients, then they can just as easily perform their job remotely, incentivizing employers to offshore these jobs to reduce costs.

Education

Based on numerous previous labor studies, education has shown to be a significant determinant of employment (Riddell & Song, 2011). This study uses the typical education level needed for entry to the occupation under focus, drawn from the Employment Projections dataset from the BLS (U.S. Bureau of Labor Statistics, 2023e). This factor is measured as a categorical variable with 8 levels: (1) no formal educational credential, (2) high school diploma or equivalent, (3) some college but no degree, (4) postsecondary nondegree award, (5) associate's degree, (6) bachelor's degree, (7) master's degree, and (8) doctoral or professional degree.

Incorporating education as a potential control facilitates the separation of the effects of education and AI exposure on employment. In alignment with popular literature consensus, it is predicted that a higher level of education leads to better chances of getting employed, which will lead to a positive change in projected employment.

Experience

Another relevant factor is "previous work experience in a related occupation," a requirement for many jobs that could cause considerable differences in employment figures among certain classes of occupations. Therefore, data for this factor is drawn from the same Employment Projections dataset as above to incorporate in the model. This variable is input categorically with 3 levels: (1) none, (2) less than five years, (3) five years or more. The initial prediction indicates that occupations requiring more years of experience will have lower employment rates. Often the related work experience is a flexible requirement, meaning that those with fewer years of experience may still be hired for the job. However, many applicants without this qualification may feel discouraged from applying, leading to a smaller application pool.

On-the-Job Training

Another relevant factor is "on-the-job training needed for competency," as determined by the same Employment Projections dataset. This training is a categorical variable accounting for the skills and knowledge provided to the employees for a particular role, and it is measured in 6 levels: (1) none, (2) short-term, (3) moderate-term, (4) long-term training, (5) apprenticeship, (6) intern/residency.

This study hypothesizes that higher on-the-job training requirements and availability may have mixed effects on employment. On the one hand, the availability of training will likely incentivize the employee to keep their jobs, leading to little or no changes in employment. However, the costs of higher job training may discourage employers from hiring human labor and may resort to technology instead, leading to lower projected employment.

Summary Statistics

Table 1. Summary Statistics of Numerical Variables

Variable	N	Mean	Std. Dev.	Min	Max
Projected Change	625	1.227	8.688	-38.6	44.9
AIOE	625	.65	1.009	-2.670	1.528
Proximity	625	.90	16.346	7	100

Note. AIOE stands for the AI Occupational Exposure index score.

Table 2. Frequency Table of Categorical Variables

Variable	N	Percent
Education	625	
Edu1: None	91	14.6%
Edu2: High School	264	42.2%
Edu3: Some College	4	0.6%
Edu4: Postsecondary	34	5.4%
Edu5: Associate’s	110	17.6%
Edu6: Bachelor’s	40	6.4%
Edu7: Master’s	30	4.8%
Edu8: Doctoral/Professional	52	8.3%
Experience	625	
Exp1: None	561	89.8%
Exp2: < 5 year	53	8.5%
Exp3: 5+ years	11	1.8%
Training	625	
Train1: None	215	34.4%
Train2: Short-term	137	21.9%
Train3: Moderate-term	193	30.9%
Train4: Long-term	51	8.2%
Train5: Apprenticeship	15	2.4%
Train6: Intern/Residency	14	2.2%

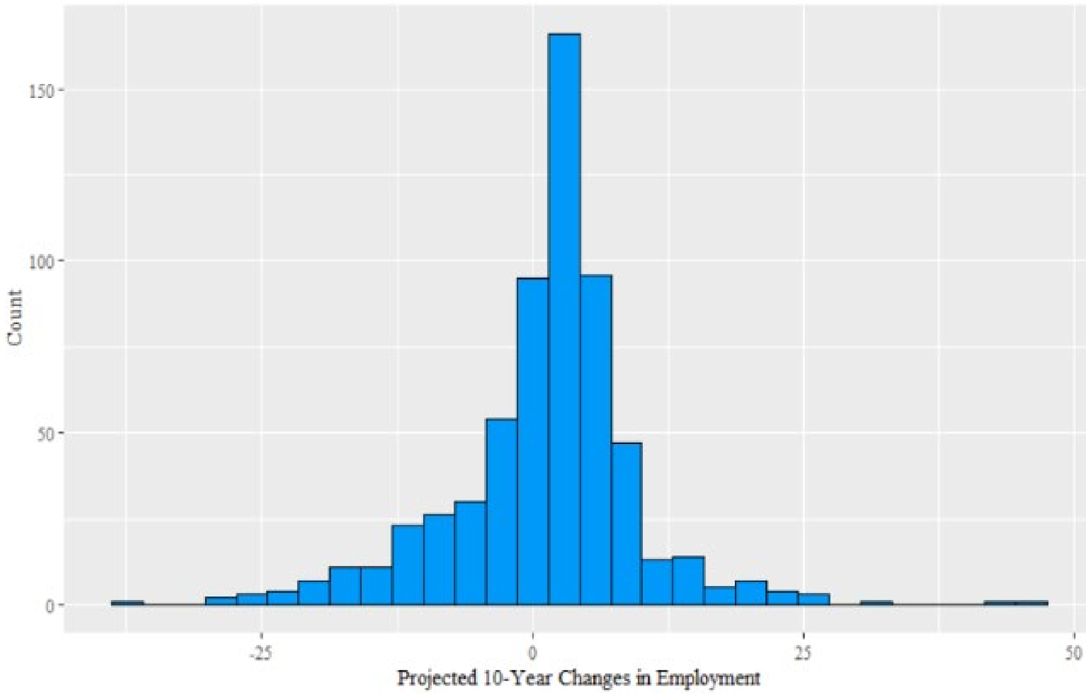

Figure 1: Distribution of Projected 10-Year Employment Changes

This R-generated graph shows the distribution of projected employment estimates by occupation, revealing normal distribution. Residuals were also plotted (excluded from paper) to check for linearity, homoscedasticity, and independence. The Durbin-Watson and variance inflation factor tests also confirmed lack of autocorrelation and multicollinearity. All OLS assumptions were confirmed, allowing the study to continue with the regressions.

Regression and Results

Table 3 reports regression results for varying sets of covariates, with column (4) representing the full model. Adding each categorical factor improved the model, as indicated by consistent increases in adjusted R^2 and greater precision of the estimated coefficient for AIOE. As such, only the coefficients of the full model are interpreted. Note that another specification (excluded from this table) with a quadratic term for AIOE was regressed to check for nonlinearities in the data. Since the model was statistically insignificant for the quadratic term, ruling out the possibility of nonlinearities in the data, that specification was excluded from the results.

AI exposure is statistically significant, with a 1 standard deviation increase in AI exposure associated with an average projected decrease of 1.043% in jobs within an occupation after controlling for all other mentioned factors. For context, a one-unit increase in the AI exposure index means there is a higher perceived exposure of an occupation to AI, as per the AI applications outlined by Felten et al 2021. This aligns with the initial hypothesis (though the magnitude of difference is smaller than expected) since higher relative prevalence of AI within a job can encourage employers to replace workers with computer programs that can perform the same tasks with lower costs and higher accuracy.

The task offshorability proxy, physical proximity, is statistically significant with a significance level of 0.01. On average, a 1 standard deviation increase in "required proximity" for performing job tasks is associated with a projected increase of 1.660% in jobs within an occupation, controlling for other factors. This follows the initial suggestion that if a job requires more close contact between the employee and coworkers/clients, then it would become more difficult to perform remotely. Therefore, the likelihood of offshoring this job decreases, which means domestic employment remains constant or even increases.

Within education, the data observed no statistical significance of levels 2 and 3 (high school diploma or equivalent, some college but no degree) on projected change in employment, compared to an occupation requiring no formal education. However, there is strong statistical significance of the higher levels of education in the positive direction. An occupation requiring postsecondary nondegree education (level 4) is predicted to have about 4.871% more projected jobs, and an occupation requiring an associate's degree (level 5) is predicted to have about 7.334% more jobs than one requiring no formal education. These statistics are higher than that for a bachelor's degree (level 6), which sees a 3.901% increase in projected jobs, which was unexpected during our initial predictions. However, postsecondary nondegree and associate's degree education both target job-specific skills that are directly useful to an occupation, whereas a bachelor's degree is generally broader in coursework. This specialization, along with greater financial accessibility to these programs, may explain the steeper rise in job opportunities. The occupation with the highest projected increase in jobs is one requiring a master's degree (level 7) and is predicted to have about 13.539% more projected jobs on average compared to an occupation requiring no formal education, all else equal. An occupation requiring a doctoral/professional degree (level 8) sees about 8.532% increase in projected jobs than an occupation requiring no formal education. This slightly lower magnitude may occur because doctoral and professional degrees are highly specialized, more so than a master's degree, narrowing the career options for these individuals who would be considered "overqualified" for other jobs. Additionally, hefty tuition fees and longer program lengths act as barriers to entry.

This study did not find any statistical significance of required relevant job experience on projected employment changes, going against our hypothesis of a positive relationship. Perhaps experience has low priority as a hiring criterion, as some applicants choose to apply for jobs despite not meeting the experience requirements and may still get hired, depending on other favorable aspects. Employers may also post more job openings regardless of required listed experience when facing a shortage of skilled workers.

Finally, on-the-job training requirements are statistically insignificant for all levels except for long-term training (level 4), which partially supports the initial prediction. An occupation with long-term training can expect to see about 2.826% more projected jobs compared to an occupation with no required on-the-job training, controlling for other factors. The direction of this relationship follows the lines of reasoning discussed earlier: availability of training could incentivize employees to keep their jobs and well-qualified individuals gain more employment opportunities within high-training occupations. Additionally, the BLS definition of long-term training includes that for dancers, singers, fitness instructors and more. In their words, workers in these categories "typically need to possess a natural ability or talent… [which] must be cultivated over several years" (U.S. Bureau of Labor Statistics, 2023e). Since these occupations require natural talents (many of which are physical), they are less likely to be replaced by AI, which is currently known to be more impactful in areas dominated by "white-collar" workers exercising more cognitive abilities day-to-day (Felten et al, 2021). As for short-term (level 2) and moderate-term training (level 3), these levels may be statistically insignificant due to their informal and occupation-specific (rather than job-specific) nature, implying that these skills are transferable to other jobs within the same occupation. Therefore, it is less likely to see a change in the overall occupation size. Additionally, apprenticeships and internships/residencies (levels 5 and 6, respectively) are more formal certification-based programs, so this may act as a barrier to entry for occupations known to require these trainings for competency, which could slow down the pace of job creation within the occupation.

Table 3. Regression Table

Model	(1)	(2)	(3)	(4)
AIOE	1.953*** (0.349)	-1.065** (0.452)	-1.140** (0.455)	-1.043** (0.463)
Proximity	1.968*** (0.352)	1.628*** (0.331)	1.603*** (0.331)	1.660*** (0.335)
Edu2: High School		0.212 (0.969)	0.136 (0.969)	-0.501 (1.047)
Edu3: Some College		-5.423 (3.970)	-5.266 (3.697)	-6.176 (3.949)
Edu4: Postsecondary		6.168*** (1.642)	6.251*** (1.642)	4.871*** (1.847)
Edu5: Associate's		8.717*** (1.387)	8.627*** (1.388)	7.334*** (1.666)
Edu6: Bachelor's		5.356*** (1.494)	5.135*** (1.499)	3.901** (1.602)
Edu7: Master's		14.404*** (1.832)	14.608*** (1.834)	13.539*** (2.189)
Edu8: Doctoral/Professional		9.644*** (1.621)	9.709*** (1.621)	8.532*** (1.941)
Exp2: < 5 year			1.937* (1.123)	1.889 (1.151)
Exp3: 5+ years			-0.660 (2.342)	-0.766 (2.327)
Train2: Short-term				-1.930 (1.288)
Train3: Moderate-term				-0.702 (1.151)
Train4: Long-term				2.826** (1.439)
Train5: Apprenticeship				-1.021 (2.328)
Train6: Intern/Residency				-1.473 (2.192)
Constant	1.389*** (0.337)	-2.623*** (0.931)	-2.740*** (0.934)	-1.454*** (1.471)
Observations	625	625	625	625
R^2	0.072	0.235	0.239	0.256
Adjusted R^2	0.069	0.224	0.225	0.237
Residual Std. Error	8.383 (df=622)	7.654 (df=615)	7.648 (df=613)	7.590 (df=608)
F Statistic	24.132*** (df=2;622)	20.988*** (df =9;615)	17.487*** (df=11;613)	13.100*** (df=16;608)

Note. *p<0.1; **p<0.05; ***p<0.01. Standard errors are shown in parentheses.

AIOE represents the AI Occupational Exposure Score. The education dummies are relative to level 1 of "no formal educational credential," experience relative to level 1 of "no experience," and training relative to level 1 of "no training required."

Conclusion

While current knowledge of AI impacts is limited and ever-growing, this paper examines the most recent trends in the field associated with projected employment as determined by a particular forecast by the BLS. Controlling for task offshorability, education, experience, and training, there is a significant projected decrease in job count within each occupation known for having a higher prevalence of AI, confirming many recent predictions of the role of AI on unemployment. Due to the novelty of AI studies, this study may have potential limitations. For example, the AIOE index by Felten et al 2021 was developed before the invention of ChatGPT in 2022, which has been one of the most influential innovations in generative AI. A future study could look into calculating a more comprehensive measure of AI exposure accounting for these new tools. This study also paves the way to delve deeper into the wide-reaching effects of technological advancements, such as the perpetuation of biases from data which could potentially affect legal decisions.

The findings emphasize the need to develop strategic policies to address these challenges, finding ways to reskill employees displaced by technology and ensure the workforce at large remains adaptable. This may be done by implementing retraining programs that allow displaced workers to learn skills useful for more tech-oriented jobs that can coexist with AI. As AI becomes more integrated into various facets of society, it is important to find ways to complement and enhance its capabilities, promoting a harmonious collaboration between humans and technology.

Appendix 1: Calculation of 10-Year Projected Employment Changes

Projected employment numbers in this paper are from the BLS National Employment Matrix, which includes counts of two classes of jobs: "nonfarm wage and salary jobs" and "self-employed, agricultural industry, and jobs employed in private households" (U.S. Bureau of Labor Statistics, 2023d). These counts are of individual jobs rather than of workers to account for the possibility of workers holding multiple jobs at once within and across occupations. These counts are available for a base year (2022 in this paper) and a projection for ten years after the base year.

Projected changes are based on "structural changes in the economy which are expected to change an occupation's share of industry employment," and sources that inform these predicted changes include scholarly articles, interviews, current news, and historical data (U.S. Bureau of Labor Statistics, 2023d). In particular, the BLS analyzes factors affecting individual occupational demand, including

- technological innovation,
- changes in business practices,
- replacement of a product/service,
- organizational restructuring,
- resizing of business establishments, and
- offshore outsourcing.

The trends in these factors determine the changes made to the occupational shares of industry employment. These changes are then compared to estimate how much they will cause demand to shift, and these effects are combined into a numerical value that is reported as the projected ten-year change in employment for the specific occupation.

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