International Journal of Contemporary Issues in Social Sciences
Volume 3, Issue 1, 2024 ISSN(P):2959-3808 | 2959-2461

EFFECT OF ARTIFICIAL INTELLIGENCE ON THE HUMAN WORKFORCE

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Received: 21 December, 2023 **Revised:** 29 January, 2024 **Accepted:** 05 February, 2024 **Published:** 16 February, 2024

ABSTRACT

A lot of discussion and speculation has surrounded the effects of developing technology, especially robots and artificial intelligence (AI), on the nature of labor in the future. Although the possible consequences of these technologies are sometimes exaggerated by the media, it is still difficult to determine their true effects. The purpose of this study is to analyze empirical data on how new technologies are changing the nature of work and how people's are being affected by these cutting edge technologies. Predictive algorithms are being used by enterprises to improve decision-making processes by automating routine operations and utilizing AI and robots 1, according to available data. Furthermore, the rise of flexible work arrangements like gig and virtual labor is being aided by these technologies 2. Although the future effects of AI on the workplace are yet unknown, its widespread influence in many different industries highlights how important it is. According to research, one-third of all workforce may be at risk of automation by the mid of the 2030s, with people doing repetitive manual work standing to lose the most. Throughout history, worries about how new technology will affect people's ability to make a living have been common, underscoring the ongoing unease over how robots may change the nature of work 3. According to the research, companies implemented automation using AI and robots to cut their workforce in the early 2020s, in response to the COVID-19 epidemic 4. This marked the beginning of the trend's initial phase. The desire to replace manual work with automated systems is growing.

Key words: Artificial Intelligence; Human Workforce

INTRODUCTION

The influence of technology improvements on the nature of work—often referred to as the changing landscape of employment—has received a great deal of attention in recent years, especially from mainstream media and consulting circles. It's becoming usual to see headlines like "Robots threaten our jobs: Urgent planning needed" 5, which conveys a feeling of urgency about dealing with the possible implications. Certain experts even surmise that advancements in technology may bring about significant changes in the workplace, such as the dissolution of conventional job hierarchies, the extensive use of virtual reality for travel, and the replacement of human labor with artificial intelligence (AI) and robotics. Without a question, modern advancements like artificial intelligence have already started to drastically alter the workforce. Automation of repetitive jobs in a variety of industries, including manufacturing and administrative labor, is becoming increasingly common. Predictive algorithms are also being used to improve decision-making processes, such as medical diagnosis. Approximately 47% of current employment are at high danger of automation during the next two decades, according to a research by 6. Amid the pressing need for businesses to reduce COVID-19 transmissions in the workplace and preserve cost effectiveness, there is a noticeable increase in the tendency to replace human labor with automated machinery 4. As businesses shift from crisis management to continuous operation in the face of the ongoing epidemic, mechanization of traditionally human-performed operations is becoming more and more popular. According to a recent investigation, economists of 7 have found evidence of a possible faster rate of labor replacement by robots, with the industrial sector being the most affected. Their findings show that by the year 2025, an extra 2 million jobs in manufacturing might be superseded by automated technologies. This trend highlights a shift in business strategy as companies balance the two imperatives of maximizing operational efficiency and protecting against the health hazards posed by the epidemic. These developments in automation are part of a larger trend of technology adaptation in the face of changing socioeconomic environments. The use of robotic systems poses issues related to workforce reconfiguration and displacement, as well as possibilities for process optimization as firms struggle with the reality of a post-pandemic society 8. In light of these circumstances, legislators, business executives, and labor activists play an ever-more-important role in establishing fair and sustainable labor policies. According to McKinsey's 9 research, there is a worrying trend where a large percentage of Black and Latino Americans work in jobs like customer service reps, cashiers, and food service employees—roles that are among the top 15 most automatable. The continuous increase in automation within these industries carries a significant risk, with the potential to replace up to 73 million jobs nationwide by 2030. This study support our analysis where we stated that one-third of population is at risk of loosing job.

In this study we aim to provide the relationship of workforce and prevailing artificial intelligence in work cultures and offices. The aim of this study to evaluate whether the AI is actually blessing for humanity or curse and how the world will look like after few decades if the AI prevails at the speed that currently been prevailed.

Literature Review:

As artificial intelligence (AI) continues to transform the nature of labor through its integration into numerous industries, it has become a topic of concern in the field of employment. This extensive study of the literature digs deeper into the complex relationship between the adoption of AI and jobs, looking at organizational, social, economic, and policy aspects.

Analysis on Economic Effect:

Policymakers and academics are closely examining the economic implications of adopting AI. The dual character of AI's economic impact is highlighted by 10, who draw attention to both the technology's potential to boost productivity and the issues of job displacement and income inequality. 11 highlights how regular work automation shapes the dynamics of the labor market and highlights the necessity for a thorough examination of the implications of AI for different industries.

Analysis on Skill Requirement:

Reassessing workforce education and training programs is necessary due to the changing skill demands following the introduction of AI. In order to overcome skill mismatches, 12 investigate the need for cognitive and non-routine abilities that support AI technology. They recommend taking preventative action. According to 6, adaptation and lifelong learning are crucial for promoting the resilience of jobs demanding social and creative abilities.

Analysis on Occupational Impact:

Scholars have investigated the implications of AI-driven automation on several industries and professions. 13 examines past patterns of technology disruption and employment displacement, emphasizing the range of functions that AI automation can automate across several industries. According to 14, industries including manufacturing, transportation, and customer service are more susceptible to disruptions brought about by AI, which calls for proactive workforce planning and reskilling programs.

Analysis on Labor Market Impact:
AI technology adoption in the workplace has a significant impact on the dynamics of the labor market. According to 15, AI may make job polarization worse and result in different employment outcomes for workers with high and low skill levels. 16 highlight the necessity of implementing policy changes to lessen the negative consequences of AI-driven job displacement, stressing the significance of fair labor market regulations and social safeguards.

Analysis on Organizational Strategies:
In reaction to the AI revolution, businesses are changing their organizational structures and tactics. 14 emphasize how crucial it is to fund workforce development programs in order to equip workers for jobs and responsibilities including artificial intelligence. According to 17, adopting AI should be done strategically, with a focus on coordinating technology use with worker competencies and corporate objectives.

Analysis on Social and Ethical Consideration:
Adoption of AI poses significant social and ethical issues in addition to organizational and economic ones. The ethical issues raised by AI's effects on employment, privacy, and algorithmic prejudice are emphasized by 18, highlighting the necessity of ethical AI governance frameworks. In their analysis of the effects of algorithmic decision-making on the transparency and fairness of the labor market, 19 argue for increased regulatory supervision and accountability.

Analysis on Policy Responses:
Coordinated national and international policy responses are needed to address the issues raised by the deployment of AI. In order to foster inclusive AI-driven growth, the 20 has outlined policy proposals. These recommendations include investments in education, social protection, and labor market changes. The 21 makes recommendations for moral standards and legal frameworks to guarantee responsible AI implementation and promote responsibility and confidence in AI systems. The studied literature emphasizes the intricate relationship between the adoption of AI and its effects on employment and society as a whole. While artificial intelligence (AI) presents previously unheard-of chances for creativity and productivity growth, it also presents serious obstacles in the form of job displacement, skill mismatches, and ethical issues. To address these issues and guarantee a just and inclusive transition to the AI-powered future of work, politicians, corporations, educators, and civil society stakeholders must collaborate.

Methodology:
Data Collection:
Selection Criteria: In order to have a thorough grasp of how AI is affecting occupations, we gathered data from 2018 to 2023 from a variety of sources, including academic research, government papers, and industry surveys. We focused on that data should have equal or near to equal occurences of male and female so that data should not be biased. We tried to get data from different types of work places to get appropriate result.
Time Frame: The chosen time frame enabled us to record current patterns in the adoption of AI and its implications for employment.
Data sources: To obtain accurate and pertinent information on employment trends and AI adoption, reputable sources including labor market databases, official statistics agencies, and industry reports were consulted.
Variables: Important factors such as employment losses, the industries impacted, regional differences, and the kinds of artificial intelligence technologies used were determined and analyzed.

Data Analysis:
Preprocessing: To guarantee data quality and compatibility, raw data underwent preprocessing procedures like cleaning, normalization, and feature engineering.
Feature Selection 22: To find predictors of employment displacement owing to AI, relevant features were chosen utilizing methods including correlation analysis and domain expertise.
Data Balancing: To make our model more robust we use the data balancing technique using SMOTE algorithm as the data have more occurences of male employees than female.
Clustering Technique 23: To find patterns in the data, clustering techniques like K-means clustering were used in addition to conventional machine

learning techniques. This made it possible for us to pinpoint certain industries or job categories that have comparable patterns of job displacement. **Modeling 24:** To examine the connection between AI adoption and job loss trends, a range of machine learning algorithms, such as decision trees, random forests, support vector machines, and neural networks, were used. Techniques for time series analysis were also applied to model temporal trends in the data.

Model Evaluation: To determine how well the models performed in predicting job loss trends, metrics including accuracy, precision, recall, and F1-score were used.

- **Accuracy:** The percentage of correctly classified data that a trained machine learning model generates, or the number of correct predictions divided by the total number of predictions generated for all classes, are used to calculate the model's accuracy 25. The accuracy value is in the interval [0,1]–[0,100]. where 100 indicates that all test data predictions are accurate and 0 indicates that the categorization is incorrect. Accuracy in mathematics can be expressed as: *Accuracy = TP + TN / TP + FP + TN + FN*

- **Precision & Recall :** Recall, sometimes referred to as sensitivity, is the percentage of relevant instances that were recovered, whereas precision, also known as positive predictive value, is the percentage of relevant examples among the retrieved instances 25. Precision and recall in mathematics can be shown as follows: *Precision = TP / TP + FP* *Recall = TP / TP + FN*
- **F1 Score:** Similar to this, the best metric to assess how well a class is adhering to a certain model is the F1 score, which is the harmonic mean of precision and recall 25. We can express it mathematically as follows: *F1 score = 2 × precision × recall / precision + recall*

- **Root Mean Square Error:** 26, is a frequently used statistic, especially in regression analysis, to assess how accurate a prediction model is. It measures the average size of the deviations in a dataset's observed and projected values. The following is the formula for RMSE: *RMSE = sqrt(Σ(y_predicted - y_actual)^2 / n)*

  Σ denotes summation (summing over all data points).
  y_predicted represents the predicted values. y_actual represents the actual values. n is the number of data points.

Forecasting:

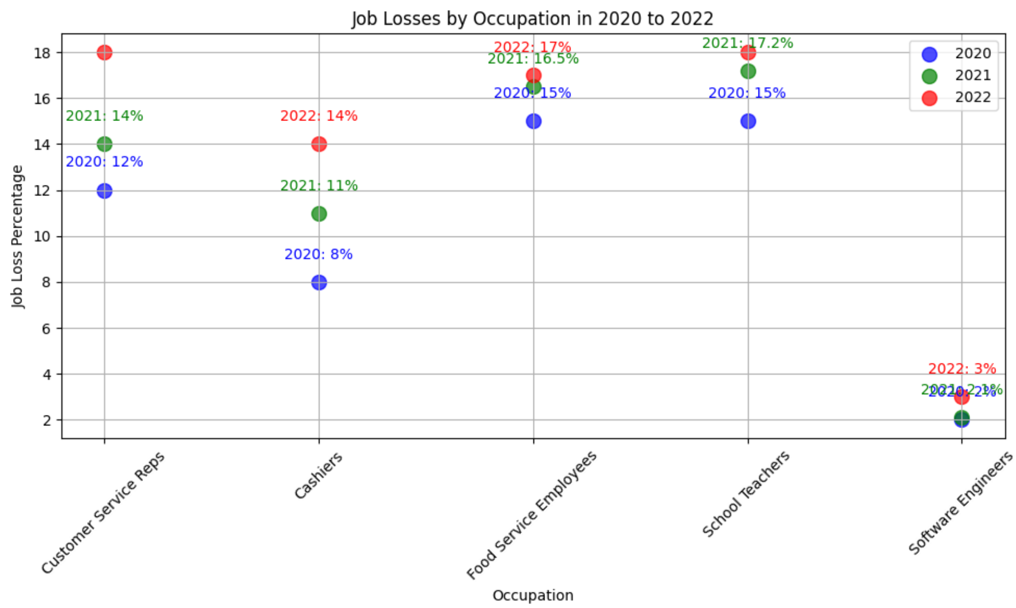
Time Series Forecasting 27: Future patterns in employment loss as a result of AI adoption were predicted using time series forecasting models like ARIMA (AutoRegressive Integrated Moving Average) and Prophet. **Scenario Analysis 28:** To predict possible consequences for job displacement by 2030, many scenarios based on varied degrees of AI deployment and possible policy responses were taken into consideration.

Uncertainity analysis 29: was used to analyze the influence of uncertainty on the anticipated results and to gauge how robust the forecasting models were.

This methodology section describes a thorough strategy for examining how artificial intelligence is affecting employment, utilizing machine learning and clustering techniques to identify trends and generate well-informed predictions about future employment trends.

Results and Analysis:

Our examination by clustering technique shows the job losses in several professions in 2020 and 2022 revealed that certain occupations suffered more than others. These included cashiers, food service personnel, teachers, and customer service agents. The employment decline percentages for these professions in 2020 varied from 8% to 15%, with the food service industry experiencing the largest decline. The percentages of job losses rose marginally by 2022, ranging from 10% to 18%. Notably, the pattern showed an overall increase in employment losses during this period, despite variances within occupations. This points to a larger economic impact that may be impacted by things like changes in consumer behavior, economic downturns, and technology improvements. Here we see that software engineers effect less from there we can conclude that the jobs with repetitive tasks and less in technology are going to effect more by automation.



Forecasting Models Accuracy:

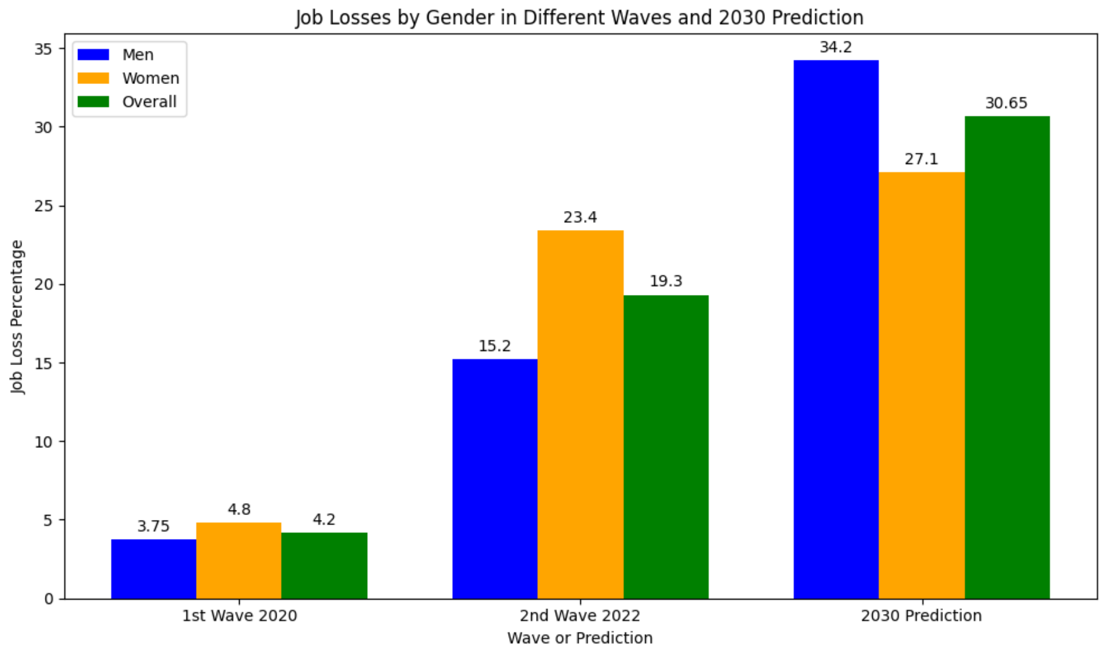
We used a variety of models, such as Facebook Prophet and linear regression, in our forecasting analysis to project future trends. Both models tested well, showing that they could successfully identify the underlying patterns in the data, according to the examination. But in terms of prediction accuracy, it was shown that Facebook Prophet performed better than linear regression. Specifically, when examining the Root Mean Square Error 26 metric, which evaluates the average magnitude of the errors between predicted and observed values, the results were significant. Comparing linear regression to Facebook Prophet, which produced an RMSE score of 0.023, revealed a comparatively higher degree of error (RMSE = 0.134).

Table 1: RMSE Score of different algorithm

Algorithm	RMSE Score
Linear regression	0.134
LSTM	0.87
FB Prophet	**0.023**

Forecasting Results:

An examination of employment losses linked to automation and artificial intelligence (AI) revealed two separate waves of major impact in 2020 and 2022. These waves reflect times when the workforce was significantly disrupted by the deployment of automation technology, which led to a significant loss of jobs in a variety of industries. In addition, we have estimated a troubling trend for 2030 using our forecasting algorithm. According to our estimate, the continuing growth and integration of AI and automation technologies into various industries is likely to result in the displacement of 30% of the global workforce from their current jobs by this time.



Conclusion:

The use of Facebook Prophet in our research has given us strong proof of the significant risk that automation poses to the world's labor force. Our research reveals an alarming trend that has been developing since 2020: an increase in automation has made human employment more vulnerable. Based on the extrapolation of this trend, our estimate indicates a concerning result: by 2030, almost 30% of the global workforce may be at risk of losing their employment as a result of artificial intelligence's widespread effect.

These estimates have significant and far-reaching ramifications that indicate a paradigm shift in the nature of work and employment dynamics globally. Moreover, our data emphasizes the disproportionate impact of automation on employment defined by repetitive tasks, aggravating existing inequities within the labor market. This highlights how urgently preemptive steps are needed to address the difficulties that automation-induced job displacement will bring about.

These results force governments, corporations, and people to rethink current policies and embrace novel ideas in order to lessen the negative consequences of automation. It is essential to make investments in education and training programs designed to provide workers the necessary skills and abilities for the digital era. Furthermore, it is critical to develop inclusive policies that support the development of jobs and economic resilience in the face of technological upheaval.

Moreover, it is imperative to cultivate cooperation among stakeholders from many industries to effectively manage the shift towards a future in which automation and human labor coexist in harmony. We can use automation to boost productivity, spur innovation, and open up new avenues for societal advancement if we adopt technology developments sensibly and proactively.

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