Gender Bias in Earnings Across Different Industries

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Gender bias in earnings continues to persist across various industries despite efforts to narrow the gap. Previous studies have mostly relied on traditional statistical methods to analyze incomplete datasets to understand gender bias in earnings. However, this project applies more advanced analytical techniques to comprehensively analyze high-dimensional population datasets from the U.S. Bureau of Labor Statistics and UCI income dataset, discussing the earnings gaps between men and women, as well as the intersectionality with factors such as race and education. This study explores discriminatory practices and stereotypes that influence earnings differentials, with an example analysis of the gender earnings gap in male-dominated STEM fields. Machine learning algorithms are applied to predict earnings based on various features to quantify their impact. Through broad industry analysis and sector-specific research, this project aims to contribute to the development of strategies for creating inclusive and equitable workplaces.

Keywords: Gender bias, Earnings inequality, Workplace diversity, Gender pay gap, Intersectionality, STEM industry, Machine learning, Data analysis

I. INTRODUCTION

Gender inequality has long been a pervasive issue in society, and the workplace is no exception. Despite efforts to promote diversity and inclusivity, gender bias in earnings remains a significant challenge. Historically, women have been systematically undervalued and underpaid compared to their male counterparts, contributing to widespread earnings disparities across various industries. [1]

This project aims to delve into the complexities of gender bias in earnings by conducting a thorough analysis of earnings differentials between men and women across different sectors. By using data from reputable sources such as the U.S. Bureau of Labor Statistics [2] and the UCI income dataset, we seek to quantify the extent of earnings inequality and explore the intersectionality of gender with other factors such as race, and education.

Understanding the root causes of gender bias in earnings is crucial for devising effective strategies to mitigate these disparities. Discriminatory practices in hiring, promotion, and compensation, along with societal stereotypes, contribute to perpetuating earnings gaps. [3, 4]

Taking the male-dominated STEM (Science, Technology, Engineering, and Mathematics) industry as an example, this project considers factors such as education level, job roles, and social expectations to conduct an in-depth investigation into the gender earnings gap. [5] It is worth noting that in industries traditionally dominated by females, the median earnings of women are also lower than that of men, indicating that gender bias in earnings is not limited to male-dominated industries, but a pervasive issue that spans various industries.

To shed light on these issues, this project employs advanced data analysis techniques, including machine learning algorithms, to predict earnings based on various factors. Specifically, we explore several data-based debiased techniques to mitigate gender bias in machine learning models. We use various criteria to balance gender representation. For example, we examine debiasing by unawareness, which omits gender information in the dataset, and data augmentation, which creates new entries that only differ by gender. We also test different machine learning models and architectures, such as linear regression, random forest, decision tree, and neural network, to identify less biased approaches. [6] By comparing the fairness metrics of the model, we seek to quantify the impact of gender on earnings inequality.

Through a combination of broad industry analysis and focused research on specific sectors such as STEM, this project aims to identify actionable insights for promoting gender equity in the workplace and fostering inclusive environments. Additionally, the article will outline future research directions to investigate the gender earnings gap and propose suggestions for mitigating these biases through technological innovations and policy interventions.

II. RELATED WORK

In recent decades, research on the persistence of gender bias in earnings has revealed compelling insights. Blau and Kahn [7] conducted a longitudinal analysis from 1980 to 2010, revealing a shifting pattern in which traditional determinants of earnings like human capital variables have become less relevant over time. However, gender disparities in occupations, and industries, and the presence of potential discrimination continue to have a significant impact. In addition, cross-sectional studies by Rice et al. [8], Browne and Misra [9], and Tsui [10] delve into the nuanced interactions between gender and other factors such as race, social class, and education, revealing how these intersections can exacerbate income disparities over time.

In the STEM field, Sterling et al. conducted three-wave NSF-funded longitudinal surveys, focusing on engineering and computer science graduates. The study revealed a gender pay gap for these graduates, suggesting that it emerges upon entry into the workplace. This gap is linked to cultural beliefs that shape an individual's self-efficacy, and the authors emphasize the need to address these beliefs to close the gap. [5]

In addition, machine learning and data mining techniques have become tools for predicting earnings based on demographic attributes. For example, Chakrabarty and Biswas utilized the Gradient Boosting Classifier model to achieve high accuracy in predicting earnings. [11] However, rather than only predicting earnings, our paper will focus on the potential biases in these predictions, especially those related to protected features such as gender. By examining any sources of bias in prediction models, people can better address inequality and promote fairer outcomes.

While previous research has laid the groundwork for understanding gender bias in earnings, our paper aims to advance the field by utilizing comprehensive, high-dimensional demographic datasets, considering multiple cross-cutting factors, focusing investigations within specific industries, and applying advanced analytical techniques. By doing so, our paper will enhance the understanding of the gender income gap and develop effective strategies for improvement through a more comprehensive research approach.

III. METHODS

A. Analyzing Gender Earnings Gap Using Statistical Methods

1. Median Earnings Gap Between Men and Women in Different Industries

The dataset from the U.S. Bureau of Labor Statistics contains detailed information on the median earnings, margin of error, and gender-to-gender earnings ratio for the United States by gender, race, education, occupation, industry, and other demographic factors in 2022. The population included in the dataset is full-time, year-round workers aged 16 and above in the United States with earnings. To study the gender earnings gap in the United States, we select the median earnings of male and female workers in different industries from the dataset. [12] In Table I, it is evident that male workers earn higher incomes than female workers in all 20 industries. We subtract the median earnings of men from the median earnings of women to obtain the earnings gap and draw a bar chart (Figure 1) to better illustrate the magnitude of the earnings gap within each industry.

The earnings gap varies significantly across industries. The largest gaps appear to be in finance and insurance, followed by professional, scientific, and technical services, and management of companies and enterprises. These industries traditionally have higher salaries, which may reflect a larger gender gap in higher earnings groups. This may be because women often choose majors and jobs with lower earnings in their own fields, and even highly accomplished women are not as proactive as men when negotiating salaries with companies. The salary structure of these industries may lack transparency, exacerbating gender pay disparities. Moreover, the family responsibilities bestowed upon women by society may prevent them from working long and hard hours, but it is crucial to invest time and effort in promoting them to higher positions. This contradiction also leads to a wider gender earnings gap in high-paying jobs.

Moreover, from traditionally male-dominated fields like construction and manufacturing to sectors with a more balanced gender distribution such as healthcare and

	Industry	Male	Female	Earnings Gap
0	Agriculture, forestry, fishing and hun...	43989.0	35136.0	8853.0
1	Mining, quarrying, and oil and gas ext...	80462.0	76784.0	3678.0
2	Construction	54413.0	52478.0	1935.0
3	Manufacturing	63450.0	50795.0	12655.0
4	Wholesale trade	63033.0	52228.0	10805.0
5	Retail trade	45929.0	37207.0	8722.0
6	Transportation and warehousing	56932.0	44761.0	12171.0
7	Utilities	88513.0	72963.0	15550.0
8	Information	89547.0	70285.0	19262.0
9	Finance and insurance	101653.0	62358.0	39295.0
10	Real estate and rental and leasing	63417.0	58627.0	4790.0
11	Professional, scientific, and technica...	104551.0	75427.0	29124.0
12	Management of companies and enterprises	103070.0	74703.0	28367.0
13	Administrative and support and waste m...	45956.0	40887.0	5069.0
14	Educational services	63813.0	55317.0	8496.0
15	Health care and social assistance	69090.0	50850.0	18240.0
16	Arts, entertainment, and recreation	49575.0	43305.0	6270.0
17	Accommodation and food services	37028.0	31196.0	5832.0
18	Other services (except public administ...	50240.0	40728.0	9512.0
19	Public administration	78389.0	61408.0	16981.0

TABLE I. Median Earnings (in Dollars) of Workers by Sex in 2022

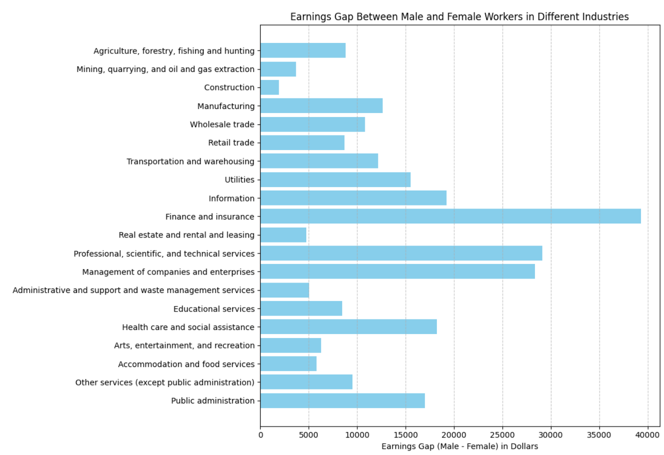

FIG. 1. Earnings Gap Between Male and Female Workers in Different Industries

education, women consistently earn less than their male counterparts, indicating the pervasive nature of gender pay disparities across diverse industries.

2. *Impact of the Intersection of Gender and Other Factors on Earnings*

Initially, we investigated the intersection of gender and race concerning earnings. As depicted in Table II, a clear earnings disparity emerges between males and females across all racial demographics. We utilized a scatter plot (Figure 2) to illustrate the comparison of median earnings across various race categories and genders, distinguishing between males and females with distinct colors. It's evident that while White and Asian individuals tend to have higher median earnings across both genders, the earning gap between males and females is more pronounced among Whites and Asians. In contrast, other racial groups like Black and American Indians have relatively smaller earning disparities between genders. Specifically, for White individuals, the median earning gap between males and females is $14,224, whereas for Asians, it amounts to $17,050. Moreover, Asian males lead with the highest median earnings at $83,743, while American Indian and Alaska Native females have the lowest median earnings at $41,228, excluding the "Some other race" category.

	Race	Median earnings (dollars) - Male	Median earnings (dollars) - Female
0	White	68677.0	54453.0
1	Black or African American	50001.0	44131.0
2	American Indian and Alaska Native	45036.0	41228.0
3	Asian	83743.0	66693.0
4	Native Hawaiian and Other Pacific ...	51510.0	45926.0
5	Some other race	44352.0	38219.0

TABLE II. Median Earnings (in Dollars) of Workers by Sex and Race in 2022

Furthermore, we investigated the correlation between gender and educational attainment in terms of earnings. As outlined in Table III, a notable earnings gap emerges between males and females across all levels of educational attainment. To visually illustrate this comparison, we utilized a scatter plot (Figure 3), where median earnings across various educational attainment categories are contrasted for males and females, each distinguished by unique colors. Remarkably, the plot reveals that the median earnings disparity between genders widens as the level of educational attainment increases.

It is also clear that females with higher levels of educational attainment may still have lower earnings than males. For instance, females with a graduate or professional degree have lower median earnings than males with a bachelor's degree. Even when females attain one level of education higher than males, their median earnings remain lower than those of males with one educational attainment level lower. The only exception is for females with a bachelor's degree, who have slightly higher median earnings than males with some college or associate's degree, albeit only by $1,893.

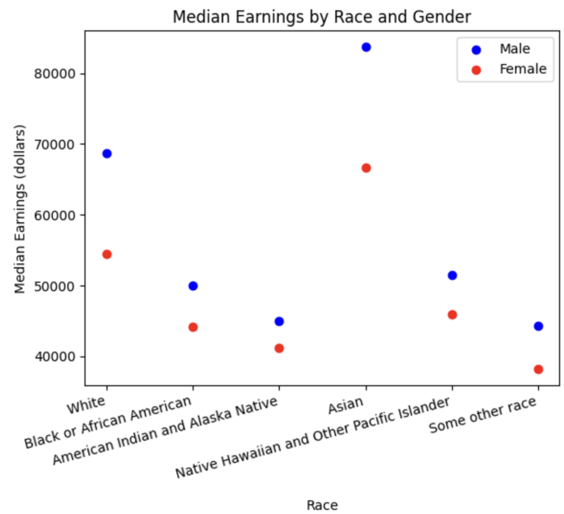

FIG. 2. Earnings Gap Between Male and Female Workers in Different Races

	Education Attainment	Median earnings (dollars) - Male	Median earnings (dollars) - Female
0	Less than high school graduate	35428.0	23370.0
1	High school graduate (includes equival...	43403.0	30411.0
2	Some college or associate's degree	53020.0	36994.0
3	Bachelor's degree	78869.0	54913.0
4	Graduate or professional degree	103049.0	72582.0

TABLE III. Median Earnings (in Dollars) of Workers by Sex and Education Attainment in 2022

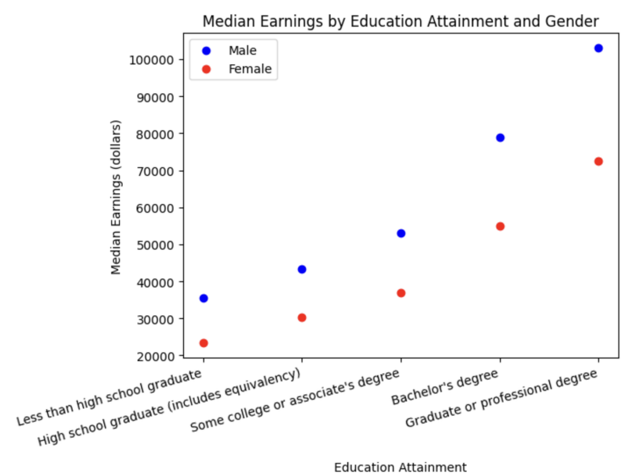

FIG. 3. Earnings Gap Between Male and Female Workers in Different Education Attainment

Examining the intersection of gender with other factors, such as race and education, reveals significant disparities in earnings, shedding light on the multifaceted nature of economic inequality. Notably, research suggests that the gender earnings gap is more pronounced among White and Asian individuals compared to other racial groups. Furthermore, as education levels rise, the disparity in earnings between males and females widens further. It can be seen that gender, race, and education have complex interactions in shaping economic outcomes.

There are several factors that may lead to higher median earnings for White and Asian individuals, as well as more pronounced gender earnings disparities within these groups. Firstly, historically, compared to other ethnic groups in many countries, White and Asian populations have often had higher levels of education. Higher education levels are often associated with higher-paying job opportunities. When they are attracted by the high-skilled immigration policies in the United States and enter the high-paying industries here, the median earnings of their population increase. Moreover, the proportion of White and Asian workers is often higher in high-paying industries, such as technology, finance, and engineering. This occupational segregation may lead to a higher median overall earnings. The gender pay gap is greater for Whites and Asians than for other groups, possibly because traditional gender roles and societal expectations often steer women into lower-paying occupations or discourage them from pursuing leadership positions. It causes their earning potential to decline relative to men. This occupational divide perpetuates inequalities in earnings, particularly among White and Asian individuals who may be more entrenched in culturally defined gender roles. [3]

The reasons for the widening earnings gap between men and women with higher education levels are also varied. For example, highly educated men and women differ in their career choices. The proportion of men in high-paying fields is higher; in contrast, women may be more prevalent in sectors like education and healthcare, which are vital but typically offer lower salaries. In addition, even with higher levels of education, women still face obstacles to career advancement and leadership opportunities. Discriminatory practices, unconscious biases, and gender stereotypes contribute to this phenomenon, hindering women's ability to access commensurate earnings through education. [4] Women's work performance and ability are often undervalued, affecting their earnings and career advancement.

3. *Example: Gender Bias in Earnings in STEM Fields*

The data in the line chart (Figure 4) is sourced from the U.S. Bureau of Labor Statistics and illustrates women's earnings as a percentage of men's earnings in STEM (Science, Technology, Engineering, and Mathematics) occupations from 2015 to 2022. Across all STEM fields, the median earnings of women have been lower than that of men over the years, but the percentage of women's earnings to men's earnings has been increasing, from 81.65% to 83.57%, indicating a gradual narrowing of the gender pay gap within STEM occupations. Despite advancements in gender equality advocacy and initiatives promoting diversity and inclusion in STEM fields, these industries need to address the significant pay disparities that favor male professionals.

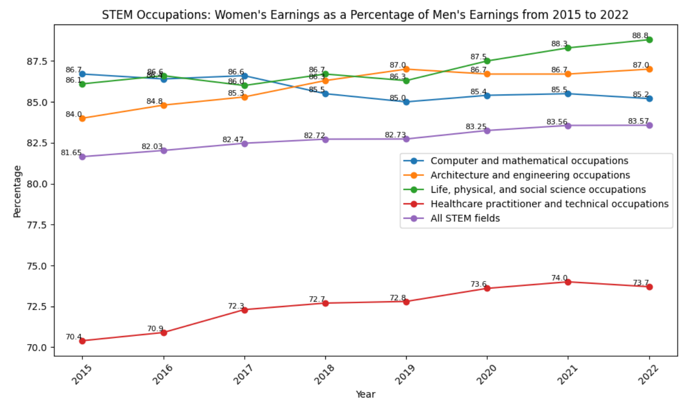

FIG. 4. STEM Occupations: Women's Earnings as a Percentage of Men's Earnings from 2015 to 2022

There's variation in the level of gender pay gap across different STEM fields. For instance, healthcare practitioners and technical occupations consistently show the largest gender pay gap compared to other STEM fields. Even though there's improvement over the years, the gap remains relatively wide, with women earning 73.7% of what men earn in this sector by 2022.

It is worth noting that the gender pay gap starts as soon as individuals enter the workforce, rather than arising over time. The cultural beliefs regarding the suitability of women and men for STEM professions shape an individual's self-efficacy, that is, their confidence in their ability to complete the tasks required to achieve their goals, which can influence their starting salary. Even considering factors such as degree type and GPA, women's income after graduating from university is lower than that of men. [5] In fact, gendered beliefs may not only affect how women and men evaluate their abilities when deciding which majors to pursue in college but also how they evaluate their abilities when entering the labor market. People with lower levels of self-efficacy earn less in their initial STEM occupations, while the self-efficacy level of women is generally lower than that of men. [5] This is why there is an earnings gap between male and female workers in the STEM field over time. However, such research also provides some insights for practitioners in the STEM field, that is, addressing the confidence gap is crucial for narrowing the gender earnings gap in the STEM field.

B. Income Prediction

In this section of the paper, we aim to examine the multiple factors that influence individual income. Our primary objective is to explore the effectiveness of predicting income levels with and without gender as a feature variable. The central focus is on understanding the role of gender in income prediction. Furthermore, we introduce and discuss various methods aimed at mitigating potential gender bias within our predictive models.

1. *Data Pre-processing and Exploration*

The UCI income dataset is a widely cited dataset in the field of machine learning modeling. It is derived from the 1994 U.S. Census data and contains over 48,000 data points. Each entry contains 15 features, including variables such as age, education, occupation, gender, race, and salary. It is noteworthy that the 'income' feature is a binary label that encodes whether an individual earns more or less than $50,000. We believe it is reasonable to assume the benchmark of $50K because the average U.S. annual salary is about $50K/year according to the U.S. Bureau of Labor. [16]

Initially, we preprocessed the data by cleaning and transforming the raw data to ensure compatibility with the statistical model. We removed all missing values in the columns 'workclass', 'occupation', and 'native-country'. Additionally, we converted the 'sex' and 'salary' features to binary form to improve simplicity and computational efficiency.

Subsequently, we conducted data exploration to gain insights into the dataset. We found a clear gender imbalance, with twice as many males as females in the dataset [5]. There is also a clear income gap between genders, with about one-third of males reportedly earning more than $50,000, while only one-fifth of females earn the same. Notably, the dataset shows a significant difference in the number of data points between the male and female categories, particularly in terms of higher incomes. [6]

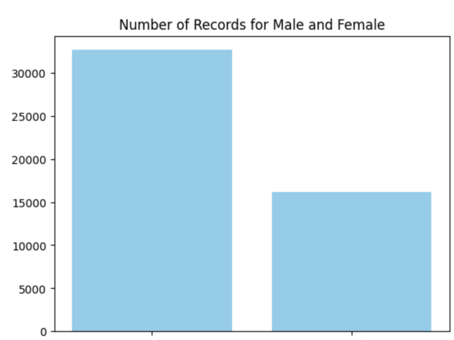

FIG. 5. Number of Records for Female and Male

2. *Model*

Our goal is to train machine learning models to predict an individual's annual income, and then we will use a

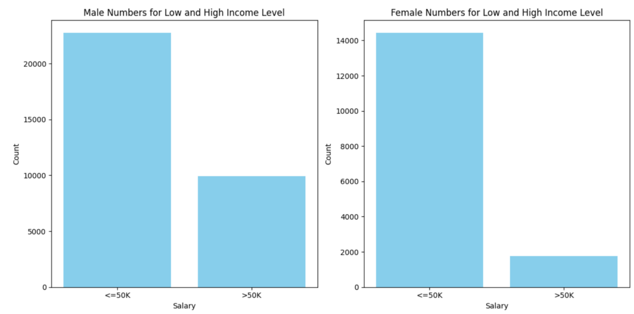

FIG. 6. Number of Males and Females for Low and High Income Level

variety of methods to mitigate potential gender bias in our model. We will use gender as our protected feature to develop a more fair and unbiased model.

We applied the standard machine learning approaches to analyze the dataset. First, we split the dataset into training and test data. Next, we performed the model selection, choosing four commonly used algorithms: Logistic Regression, Random Forest, Decision Tree, and Neural Network. Subsequently, we trained each selected model using the training data. Finally, we leveraged the trained models to make predictions on the test data.

To evaluate the performance of these machine learning models, we rely on three metrics: Accuracy, Statistical Parity, and Equal Opportunity. Accuracy is a metric to measure the percentage of correct predictions made by the model among all predictions it has made. Statistical Parity is a fairness metric to assess whether different demographic groups in a dataset have roughly the same probability of a positive outcome. Equal Opportunity is also a fairness metric used to assess whether the model consistently correctly predicts positive instances for all demographic groups by measuring whether the model provides similar true positive rates (sensitivity). Upon examining the results presented in Table IV, it is clear that all four models exhibit similar performance levels. However, the Neural Network model showed relatively good performance with better accuracy and fairness compared to the other models. Consequently, we selected the Neural Network model for further analysis.

Model	Accuracy	Statistical Parity	Equal Opportunity
Logistic Regression	0.8249428761	-0.2027192681	-0.09607001467
Random Forest	0.8233950026	-0.1832887850	-0.08045947794
Decision Tree	0.8229527530	-0.1804056412	-0.08376863077
Neural Network	0.8266381661	-0.2063329933	-0.09213174851

TABLE IV. The Evaluation Metrics for All Three Models

3. *Mitigate Gender Bias*

We employed two common methods to mitigate potential gender bias in our predictions. The first method involves mitigating bias through unawareness, which is achieved by removing the gender attribute from the dataset. Secondly, we used a data augmentation technique to mitigate gender bias by diversifying the training dataset. [13]

4. Result

In Table V, it becomes evident that employing methods to mitigate gender bias has led to slight improvements in statistical parity and equal opportunity metrics, while the accuracy remains similar or becomes a little bit higher. However, it's noteworthy that mitigating gender bias is a continuous process, so further exploration and refinement of these methods may yield more substantial improvements.

Method	Accuracy	Statistical Parity	Equal Opportunity
Original	0.8266381661	-0.2063329933	-0.09213174851
Remove Gender Attribute	0.8273752488	-0.1783335107	-0.07528794606
Augment Trainning Set	0.8264170414	-0.1746016859	-0.07147547769

TABLE V. The Evaluation Metrics Before and After Mitigating Gender Bias

IV. DISCUSSION

Nowadays, many measures have been proposed or implemented to promote equal pay for men and women. For example, the Paycheck Fairness Act was introduced in 2023, aiming to address wage discrimination based on sex. [17] However, legislative efforts alone may not be enough to eliminate gender bias in income and our income prediction model can become an effective tool with a wide range of real-world applications:

Salary Equity: This model can be used to manage how employees are paid and treated in a company. Employers can use this model to ensure that everyone is paid fairly for their work based on their job performance and qualifications without discriminating based on gender. This is beneficial to promote fairness and diversity in the workplace and reduces the risk of gender-based pay disparities.

Policy Development: This model can help inform policy decisions to reduce income disparity and improve economic equality. By utilizing these models and mitigating gender bias, policymakers can gain insights into the various factors that influence income levels and ensure that their decisions are not influenced by discriminatory practices. Therefore, policymakers can develop targeted interventions and policies to support marginalized groups and promote inclusive economic growth.

Overall, the income prediction model offers a comprehensive approach to addressing gender-based income inequality. With the help of data-driven insights and bias mitigation, this model can be an effective tool in a variety of real-world applications.

V. CONCLUSION AND FUTURE WORK

Our findings reveal pervasive gender bias in earnings across industries and the complex interactions between gender and other intersecting factors such as race, age, and education. By using advanced analytical techniques and high-dimensional demographic data sets, we aim to comprehensively understand the root causes of income disparities and contribute to the development of strategies to promote equity in the workplace.

Our analysis shows the persistence of the gender pay gap across all industries. Regardless of whether an industry is a traditionally male-dominated one (e.g. STEM) or one that is more balanced in terms of gender representation, females consistently earn less than males in the same industry. This reflects the systemic nature of gender bias in earnings, and simply increasing female representation in certain industries may not be sufficient to address the underlying issues contributing to the earnings gap. [14]

Additionally, our analysis shows significant differences in income due to intersecting factors such as race and education. Whites and Asians tend to experience larger gender pay gaps than other racial groups, suggesting that cultural beliefs and social expectations may exacerbate inequality. [15] While education is often touted as a path to economic advancement, our findings suggest that even with higher levels of education, women may still face barriers to achieving equitable earnings.

Within STEM industries, our analysis highlights the progress and ongoing challenges in closing the gender pay gap. While overall trends suggest that the gap has narrowed over time, significant disparities remain across STEM fields. Factors such as occupational segregation, differences in specialization, and negotiation practices may contribute to these differences, emphasizing the need for targeted interventions to address specific industry dynamics. [5]

For income prediction models, our analysis demonstrates the importance of considering gender as a potential source of bias. While machine learning algorithms can achieve high accuracy in predicting income, we also need to consider mitigating gender bias through methods such as removing gender attributes or data augmentation, which has shown promising results in improving fairness metrics.

Overall, our study highlights the multifaceted nature of gender bias in earnings and the importance of taking a holistic approach to address disparities. Efforts to promote equity in the workplace must consider not only gender but also intersectional factors such as race, age, and education.

Future work on the gender pay gap could involve multiple aspects. First, future studies will consider using a wider range of datasets, such as datasets that include more cross-cutting factors that may influence earnings. This will help people discover more valuable information about the interrelationships between factors and their impact on earnings. Second, more sophisticated technical methods will be used to process and analyze these datasets. In terms of exploring the relationship between gender and earnings using machine learning, developing more advanced debiased methods will help capture and compare earnings differences among different groups of people more fully. For example, when there are features related to gender to varying degrees in the dataset, it becomes difficult to remove bias, and future work will focus on addressing these issues. Third, understanding the direct and indirect causes of gender bias in earnings will help develop strategies to mitigate bias. For example, qualitative research that provides insight into an individual's experience and the systemic barriers he or she faces will help understand the reasons behind bias. Fourth, conducting long-term follow-up research is necessary because it will help evaluate the effectiveness of gender equality measures across different industries.

Reducing the gender pay gap is a multidimensional issue that involves multiple aspects like technology and policies. When analyzing large amounts of career data through machine learning models, people can identify and predict potential factors that contribute to earnings disparities, such as gender bias in recruitment and promotion. Based on these factors, companies can improve their salary decisions and ensure a more inclusive and equitable working environment where all individuals are fairly compensated regardless of gender or other demographic characteristics. In addition, improving equal pay laws and strengthening anti-discrimination policies in the workplace are guarantees for men and women to receive equal treatment and opportunities at work. In short, working to alleviate gender earnings inequality can promote economic development and improve social justice.

DATA AVAILABILITY

Data is available at:

The U.S. Bureau of Labor Statistics: `https://data.census.gov/table/ACSST1Y2022.S2002?q=earning`

The UCI income dataset: `https://archive.ics.uci.edu/dataset/20/census+income`

CODE AVAILABILITY

Code is available at `https://github.com/meiyizhong/DSCI531_Project`.

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