International Journal of Informatics and Information Systems
Vol. 7, No. 3, September 2024, pp. 100-110

A Multiple Linear Regression Approach to Predicting AI Professionals' Salaries from Location and Skill Data

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(Received March 1, 2024; Revised June 10, 2024; Accepted August 5, 2024; Available online September 1, 2024)

Abstract

The rapid growth of Artificial Intelligence (AI) industries worldwide has increased the demand for skilled professionals and highlighted the need to understand salary determinants in this sector. This study aims to analyze the factors influencing the compensation of AI professionals globally, with a particular focus on the effects of company location, experience level, and required technical skills. Using a dataset of 15,000 AI job postings collected from multiple countries, a Multiple Linear Regression (MLR) model was developed to identify predictive relationships between independent variables—location, experience, and skills—and the dependent variable, annual salary in U.S. dollars. Data preprocessing included one-hot encoding for categorical variables, standardization of numerical attributes, and vectorization of text-based skill descriptions. Model evaluation produced strong predictive results, with an R^2 of 0.82, a Mean Absolute Error (MAE) of 18,677 USD, and a Root Mean Squared Error (RMSE) of 25,704 USD. Statistical tests confirmed that company location and experience level significantly affected salary outcomes ($p < 0.05$), while technical skills contributed only marginally. These findings suggest that structural factors such as geography and seniority play a more decisive role in determining AI salaries than specific technical competencies. The study concludes that MLR offers a transparent and interpretable analytical framework for exploring salary disparities in the global AI workforce. The results provide practical implications for organizations designing fair compensation policies, professionals assessing market value, and educators aligning training programs with evolving industry demands.

Keywords: AI Salary Prediction; Multiple Linear Regression; Experience Level; Geographic Location; Technical Skills

1. Introduction

The rapid growth of artificial intelligence (AI) is substantially reshaping global labor demand, modifying the skill sets required across various industries. As AI technology becomes embedded in workplaces, there is a noticeable shift toward the demand for high-level digital skills, emphasizing critical thinking and adaptability to new technologies [1], [2]. Emerging estimates reveal a growing gap between available skills and those required by employers, particularly in AI and big data sectors, indicating an urgent need for reskilling initiatives [3] and highlighting salary disparities for digitally skilled personnel compared to lower-skilled roles [4], [5]. Recent reports suggest that jobs requiring AI expertise are proliferating, indicating that the future workforce must prioritize digital literacy and complex problem-solving abilities [6]. This dynamic change not only fosters new employment opportunities but also emphasizes the importance of educational systems in preparing individuals for these evolving market conditions [7].

Past research on AI compensation studies has predominantly focused on descriptive analyses that highlight regional trends rather than a global perspective. Many studies, such as those examining salaries and the gender pay gap among nonprofit executives and higher education faculty, underscore existing disparities but remain constrained to specific institutions or geographic areas [8]. These investigations typically lack a comprehensive, data-driven modeling approach that could effectively gauge compensation variation on a global scale and across diverse industry applications. Moreover, empirical comparisons that analyze the relationship between compensation, location, and requisite skill levels remain sparse. For instance, while Lee and Lee's study establishes a framework for understanding salary disparities among nonprofit CEOs, it does not extend to broader AI-related occupations across multiple regions [8]. Furthermore, while some articles

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DOI: https://doi.org/10.47738/ijiis.v7i3.213

detail how compensation varies across fields, they have not integrated AI-specific data to address these critical comparisons. For example, the study by Liebl et al. discusses gender equity and pay disparities within higher education but does not specifically address AI-related roles or data [9]. The gaps in holistic understanding underscore the pressing need for future research to adopt a global approach to AI compensation, incorporating robust models to facilitate cross-regional and industry-wide comparisons.

Understanding salary determinants in the AI sector is crucial for policymakers, companies, and job seekers as it shapes the landscape of labor market dynamics and informs educational and training programs. Accurate knowledge of how location, experience, and technical skills influence AI salaries can enable more effective policymaking and targeted workforce development initiatives, ultimately supporting economic growth and reducing disparities [10]. The objective of this study is to develop and evaluate a transparent and interpretable regression model to predict AI professionals' salaries based on these key variables. This research makes significant contributions to the field. Firstly, it leverages a comprehensive dataset-based statistical comparison of AI salaries, paving the way for a more uniform understanding across regions [11]. Secondly, it conducts interpretable coefficient analysis, which bridges theoretical frameworks and industry relevance, allowing stakeholders to understand the implications of various factors on compensation [12]. Lastly, this study lays a foundational framework for future non-linear modeling efforts, which could offer deeper insights into the complexities of AI salary determinants [13].

2. Literature Review

2.1 Theoretical Foundations of Salary Determinants

The determination of salary levels in any labor market has long been explained through the lens of Human Capital Theory, which argues that the accumulation of knowledge, experience, and skills serves as a form of economic capital that enhances an individual's productivity and earning potential. In the context of Artificial Intelligence (AI) professions, this theory becomes particularly relevant, as technical expertise, coding proficiency, and advanced analytical capabilities directly contribute to organizational innovation and efficiency. Studies [14] reaffirm that employees possessing higher education levels or specialized technical certifications in AI-related domains command higher salaries due to their ability to develop, manage, and optimize intelligent systems. This reinforces the concept that investment in education and continuous skill development is essential for maximizing individual income potential in a technology-driven economy [15].

Beyond individual qualifications, Human Capital Theory also emphasizes the return on investment in learning and training, both for employees and organizations. As the AI industry evolves rapidly, the shelf life of technical skills shortens, prompting the need for continuous upskilling. Companies that invest in employee development programs—such as data analytics training, AI ethics workshops, or cloud engineering certifications—often experience higher productivity and innovation levels, which justify paying premium wages to retain such talent. Similarly, employees who engage in lifelong learning activities strengthen their market value and career resilience. Thus, the interaction between organizational investment and individual learning behavior creates a feedback loop that drives salary differentiation within the AI sector.

Complementing this, the Compensating Wage Differential Theory provides an alternative yet interconnected perspective by highlighting how external and contextual factors, particularly geographic location and job-related risk, influence compensation structures. Research [16] argue that regional variations in salaries often reflect cost-of-living adjustments and socio-economic disparities between countries or cities. For example, AI professionals employed in global technology hubs such as Silicon Valley, London, or Zurich receive higher salaries not solely due to their skills, but also to offset higher living costs and intense labor-market competition [17], [18]. Similarly, remote or high-risk environments may offer wage premiums to attract skilled workers despite less favorable working conditions.

Integrating both Human Capital and Compensating Wage Differential theories allows for a comprehensive framework to understand salary dynamics in the AI labor market. Human Capital Theory explains intrinsic

ISSN 2579-7069

individual value—education, expertise, and productivity—while Compensating Wage Differential Theory contextualizes these within external socio-economic environments. Together, they reveal that salary formation is both individual-driven and context-dependent, shaped by the dual forces of personal competence and market structure [19]. This dual-theory foundation is essential for contemporary salary studies, especially within the AI industry where regional disparities, rapid skill obsolescence, and cross-border job mobility interact to create complex compensation patterns.

2.2 Machine Learning Approaches in Salary Prediction

Recent years have witnessed the proliferation of machine learning techniques in labor-market analytics, including salary prediction and workforce modeling. Algorithms such as Random Forest, Support Vector Machines (SVM), Neural Networks, and Multiple Linear Regression (MLR) have been widely adopted to identify hidden relationships between job-related factors and compensation outcomes [20]. Among these, Random Forest and Neural Networks are particularly valued for their capacity to model nonlinear patterns and complex interactions between variables. These methods have achieved high predictive accuracy in prior studies examining salary forecasting and job classification [21]. However, their computational complexity and the opacity of their internal mechanisms often result in the so-called “black-box” problem, which limits interpretability for decision-makers in human resource and policy contexts [22].

In contrast, Multiple Linear Regression (MLR) offers simplicity, transparency, and interpretive clarity, making it well-suited for exploratory research. MLR estimates the relative contribution of each independent variable to the dependent variable through statistically interpretable coefficients. For instance, it allows researchers to quantify how much salary changes when experience increases by one level or when the job shifts to a higher-cost region. This capacity for precise, coefficient-based interpretation enables policymakers, HR practitioners, and job seekers to understand the causal direction and magnitude of each factor affecting wages [23]. While MLR may not capture complex nonlinear dependencies as effectively as deep learning models, its analytical transparency provides significant advantages in applied salary research where interpretability is as important as accuracy.

Furthermore, MLR facilitates formal statistical inference, enabling t-tests, F-tests, and confidence intervals that assess the reliability and significance of model parameters [24]. Such inferential capabilities are critical for academic and policy-oriented analyses that seek not only to predict but also to explain and validate observed phenomena. These statistical tests help determine whether differences in salary by region, skill type, or experience level are statistically meaningful or merely due to random variation. This analytical rigor ensures that conclusions drawn from salary prediction models are both empirically grounded and statistically defensible, strengthening the study’s contribution to labor-market research.

Ultimately, the choice of MLR in this study represents a deliberate methodological balance between predictive accuracy and interpretability. While complex models such as Random Forests or Neural Networks might offer marginal gains in prediction precision, they often obscure the relationships that policymakers and practitioners need to understand. By contrast, MLR enables direct interpretation of the coefficients, aligning with the study’s objective to reveal transparent and interpretable patterns in global AI salary determinants. Future research can extend this foundation by comparing linear models with ensemble and hybrid approaches to evaluate trade-offs between explainability and predictive performance in practical salary modeling applications.

3. Method

This section describes the methodological framework employed to perform salary prediction for Artificial Intelligence (AI) professionals. The entire process consisted of three main stages: data collection and variable selection, preprocessing and feature engineering, and model construction and evaluation. Each stage was designed to ensure data integrity, reproducibility, and interpretability of the regression results.

3.1 Data Source and Variables

The dataset used in this study was obtained from the publicly available Kaggle repository [6], which compiles global job postings related to Artificial Intelligence and data science fields. After cleaning and validation, the dataset comprised a total of 15,000 job postings from various countries, representing diverse geographic, industrial, and organizational contexts. The dependent variable in this research is salary_usd, representing the annual salary offered for each job position in U.S. dollars. Independent variables include company_location, indicating the country where the company operates, and experience_level, categorized as Entry-level (EN), Mid-level (MI), Senior (SE), and Executive (EX). The required_skills column, extracted from textual job descriptions, reflects the technical competencies demanded by employers. In addition, remote_ratio is included as a numeric variable to capture the proportion of remote work allowed for each job posting. Collectively, these variables were selected to represent both structural (location, experience) and skill-based (technical requirement) factors influencing salary levels in the AI sector.

3.2 Preprocessing and Feature Engineering

Prior to model construction, several preprocessing steps were conducted to transform the raw data into a suitable analytical format. Categorical variables such as company_location and experience_level were converted into numeric format through one-hot encoding, allowing each category to be represented as a binary feature. Continuous variables, particularly remote_ratio, were standardized using StandardScaler to ensure that all features contributed proportionally to the regression coefficients and to prevent scale-related biases during model training. The required_skills variable, which originally appeared as unstructured text, was vectorized using the CountVectorizer technique, transforming the skill descriptions into a bag-of-words representation. This process enabled the extraction of skill frequency information and facilitated statistical comparison between postings emphasizing different technical domains. Additionally, correlation analysis was performed to identify potential multicollinearity among independent variables. Variables exhibiting strong intercorrelations were examined and adjusted to maintain model stability and interpretability. These preprocessing procedures ensured that the input data were clean, standardized, and analytically meaningful for regression analysis.

3.3 Model and Evaluation

A Multiple Linear Regression (MLR) model was developed using the Scikit-learn library in Python to quantify the relationship between predictor variables and salary. The dataset was divided into 80% for training and 20% for testing to validate the model's generalization capability. The regression model was trained to estimate the coefficients associated with each variable, thereby providing both predictive accuracy and interpretive value for understanding salary determinants. The model's performance was evaluated using several statistical metrics: Mean Absolute Error (MAE), which measures the average magnitude of prediction errors; Root Mean Squared Error (RMSE), which penalizes larger deviations; and R-squared (R^2), which quantifies the proportion of variance in salary explained by the independent variables. Furthermore, inferential tests such as the t-test were employed to assess the statistical significance of individual regression coefficients, while the F-test evaluated the overall model fit. The Variance Inflation Factor (VIF) was also calculated to detect multicollinearity and ensure the independence of predictors. Collectively, these evaluation steps provided a robust quantitative framework for assessing model accuracy, explanatory power, and statistical validity.

4. Results and Discussion

This section presents the results of the multiple linear regression analysis and discusses the implications of the findings in relation to the dataset of AI-related job postings. The discussion focuses on four aspects: the descriptive statistics of salary distribution, the effect of geographic location and experience level, the role of technical skills, and the overall model evaluation and accuracy. Together, these analyses provide a

ISSN 2579-7069

comprehensive overview of how structural and skill-based factors influence compensation in the global AI job market.

4.1 Descriptive Statistics and Salary Distribution

The dataset used in this study comprised 15,000 Artificial Intelligence (AI) job postings from multiple countries, representing a wide variety of organizational scales and industrial sectors. The target variable, salary_usd, exhibited substantial variation, with an average of 115,349 USD, a median of 99,705 USD, and a maximum recorded salary of 399,095 USD. These figures indicate a heterogeneous distribution of compensation across AI professionals, reflecting global disparities in market value and cost of living. The histogram of salary distribution (Figure 1) revealed a right-skewed pattern, where a majority of job offers clustered within the lower-to-middle salary range, and only a small proportion represented high-paying executive or specialized technical roles. This skewness suggests that while AI remains a lucrative field, the majority of positions still fall within moderate compensation tiers, possibly due to regional cost variations or differences in company maturity levels.

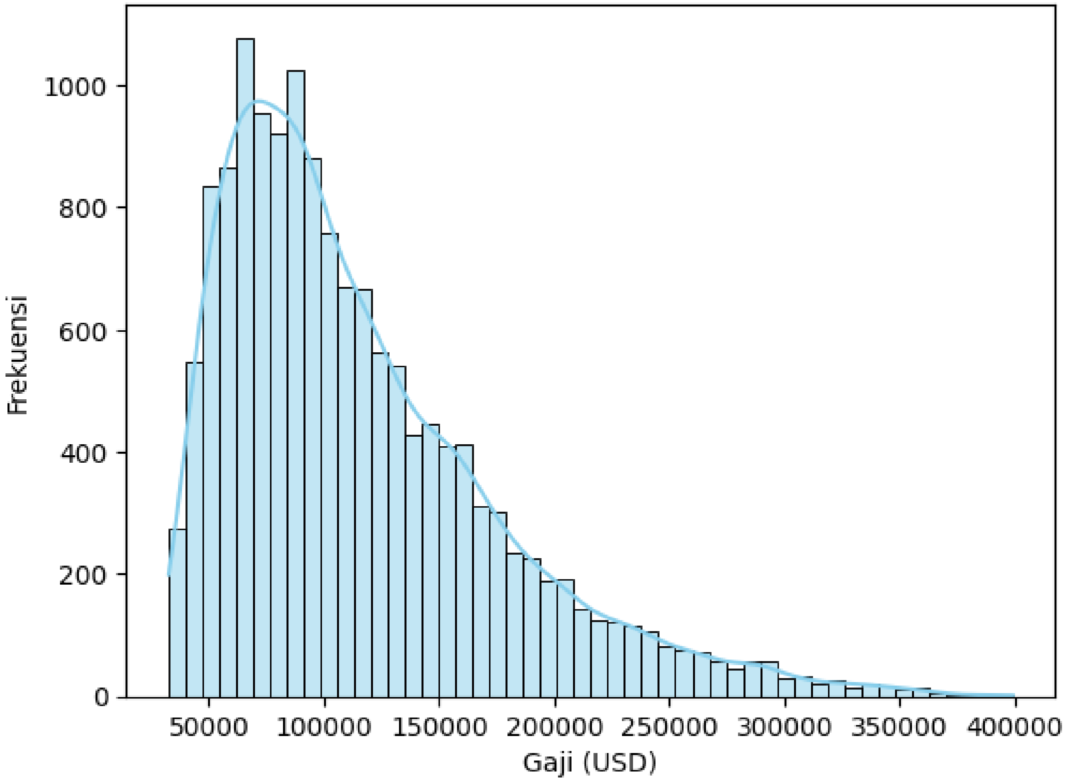

Figure 1. Histogram of AI Salary Distribution

4.2 Impact of Location and Experience Level

The regression analysis confirmed that company location is a major determinant of salary outcomes among AI professionals (Figure 2). Countries such as Switzerland, Denmark, Norway, and the United States exhibited large positive coefficients, signifying significantly higher predicted salaries relative to the baseline country in the dataset. Conversely, locations including India, China, and South Korea displayed negative coefficients, reflecting comparatively lower salary levels. For instance, working in Switzerland was associated with an increase of approximately +57,828 USD in predicted salary compared to the global baseline. These findings align with compensating wage differential theory, where economic conditions, labor costs, and living standards jointly shape salary structures across regions. Experience level was also found to be a critical factor influencing salary variation (Figure 3). The regression coefficients indicated that executive-level (EX) positions commanded the highest salary premium (+71,813 USD), followed by senior-level (SE) roles (+7,413 USD), while entry-level (EN) positions showed a significant negative impact (–

51,790 USD) relative to mid-level employees. This result supports Human Capital Theory, suggesting that accumulated experience and skill maturity substantially enhance earning potential.

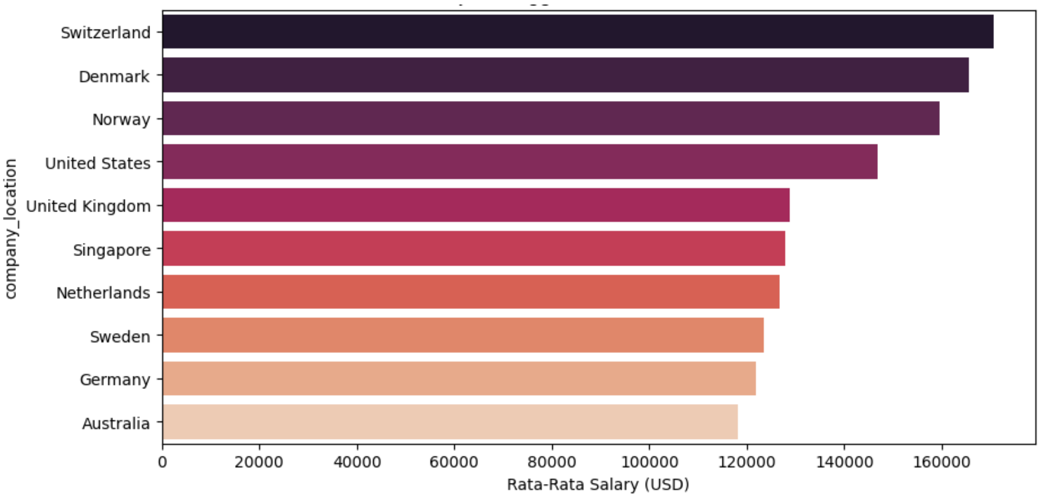

Figure 2. Bar Chart of Top 10 Skills with Highest Average Salary

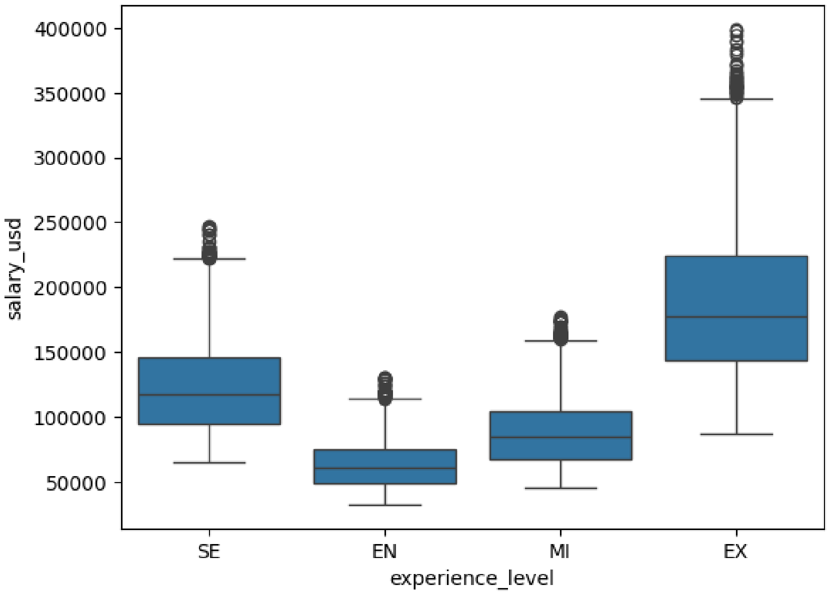

Figure 3. Boxplot of Salary by Experience Level

4.3 Skills Analysis and Salary Impact

The required_skills attribute was processed through text vectorization to generate binary indicators for the presence of specific technical skills within each job posting. The analysis revealed that specialized competencies such as Deep Learning, MLOps, PyTorch, and Cloud Computing were consistently associated with higher average salaries, highlighting their strong demand and strategic value in the AI industry. In contrast, more general or traditional technical skills, including SQL and Excel, showed weaker associations with salary increases, possibly due to their ubiquity across job functions. However, statistical tests indicated that most skill-related features were not individually significant predictors in the regression model. This finding implies that while technical specialization contributes to salary variation, structural factors such as location and experience level exert a stronger and more consistent influence. It also reflects a possible saturation effect, where basic technical qualifications are considered baseline expectations rather than differentiating factors in determining pay scales.

 ISSN 2579-7069

4.4 Model Evaluation and Prediction Accuracy

The multiple linear regression model was tested on a 20% subset of unseen data to evaluate its predictive reliability. The evaluation metrics indicated satisfactory performance, with a Mean Absolute Error (MAE) of 18,677 USD, a Root Mean Squared Error (RMSE) of 25,704 USD, and an R^2 value of 0.8188. The R^2 of 0.8188 suggests that approximately 82% of the variance in salary could be explained by the independent variables used in the model, demonstrating high explanatory power for a linear regression approach. The scatter plot comparing predicted versus actual salary values (Figure 4) displayed a tight clustering along the diagonal, particularly in the mid-salary range, which indicates robust model performance with minimal systematic bias. Overall, these results confirm that the combination of location, experience, and skills provides a reliable foundation for salary prediction within the AI sector. While linear regression offers interpretability and transparency, its limitations in capturing non-linear or interaction effects suggest potential benefits from future work incorporating advanced models such as Random Forest, Gradient Boosting, or Neural Networks for comparative validation.

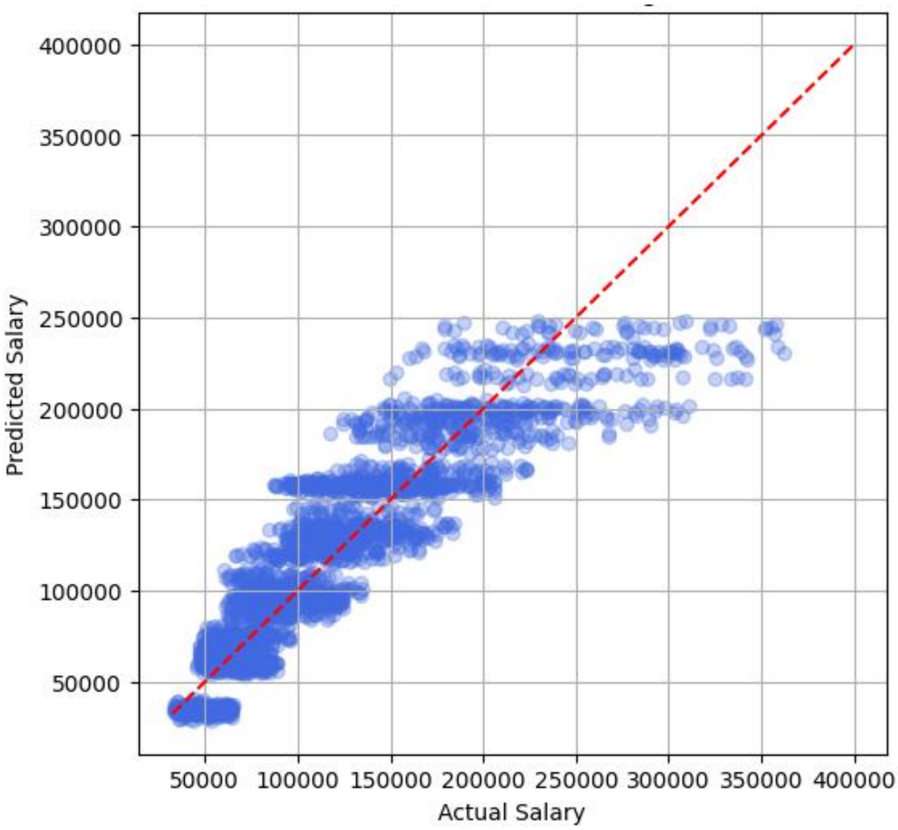

Figure 4. Scatter Plot of Predicted vs Actual Salaries

4.5 Implications

The findings of this study carry several important implications for understanding the global dynamics of AI-related compensation. The most evident insight is that geographic location remains a dominant determinant of salary levels in the Artificial Intelligence job market. Countries with advanced digital economies and higher costs of living, such as the United States, Switzerland, and Denmark, consistently offer substantially higher salaries compared to developing or emerging markets. This suggests that salary disparities in AI professions are not only a reflection of individual merit or skill but are deeply intertwined with macroeconomic structures, national investment in technology infrastructure, and local demand for AI expertise. Therefore, cross-country analyses are essential for accurately interpreting global salary benchmarks and avoiding misinformed comparisons between regions with fundamentally different economic contexts.

A second implication concerns the role of experience as a critical indicator of earning potential. The regression results underscore that professional seniority and accumulated experience significantly elevate salary levels, supporting the principles of Human Capital Theory. From an organizational perspective, this highlights the tangible value of long-term talent development and retention programs within the AI industry. Employers benefit not only from the advanced technical capabilities of experienced professionals but also from their managerial and strategic contributions to data-driven decision-making. Consequently, organizations should view compensation not merely as an expense but as a strategic investment in human capital that drives innovation capacity and project quality.

The findings also reveal a nuanced perspective on technical skills. While specialized competencies in areas such as deep learning, cloud infrastructure, or MLOps correlate positively with higher salaries, their overall influence remains secondary compared to location and experience level. This suggests that, in many cases, technical expertise functions as a qualifying rather than differentiating factor—necessary for entry and advancement but not sufficient to guarantee substantial salary premiums. For professionals and educators, this implies that skill acquisition should be complemented with broader career development strategies, including leadership, project management, and cross-functional collaboration. These capabilities often determine access to higher-paying roles and leadership positions in AI-driven organizations.

Finally, the methodological implications of this research demonstrate the practical advantages and limitations of multiple linear regression in salary prediction. The model's transparency and coefficient interpretability make it particularly suitable for exploratory and explanatory studies in labor economics. It enables stakeholders to quantify how much each variable contributes to salary variation and to identify which factors exert the strongest statistical effects. However, the method's linear assumption restricts its ability to capture complex, non-linear relationships or variable interactions that are likely to exist in real-world data. Future studies should consider hybrid modeling approaches, combining the interpretability of linear regression with the predictive power of non-linear models such as Random Forest, XGBoost, or Neural Networks, to enhance both analytical depth and practical relevance in understanding AI labor markets.

4.6 Limitations

Despite the promising findings and robust statistical performance of the model, several limitations should be acknowledged to ensure a balanced interpretation of the results. The most fundamental limitation lies in the nature of the dataset, which was derived from publicly available job postings on Kaggle. Such datasets often reflect only the advertised salary ranges and may not accurately represent final negotiated compensations or company-specific adjustments. Additionally, postings tend to over-represent positions in developed countries or English-speaking markets, thereby introducing potential geographic sampling bias. Consequently, the model's predictive accuracy may decline when applied to underrepresented regions or emerging economies with limited data availability.

A second limitation concerns the simplification of variables used in the regression framework. While this study incorporated key predictors such as location, experience level, and technical skills, other potentially influential factors—such as company size, industry sector, educational attainment, gender, and job function—were not included due to data constraints. Moreover, the treatment of the required_skills variable through text vectorization may have overlooked semantic nuances or contextual relationships between skills (e.g., "deep learning" versus "neural networks"). These simplifications may have restricted the model's capacity to fully capture the multi-dimensional nature of AI job compensation.

The third limitation relates to the methodological choice of multiple linear regression. Although this model offers interpretability and statistical transparency, it assumes linear relationships among variables and independence of residuals. Real-world salary structures, however, often involve complex, non-linear interactions influenced by dynamic market conditions and organizational hierarchies. This linear constraint might have led to partial underestimation of combined effects between predictors—for instance, how experience moderates the impact of location or technical specialization. Thus, while linear regression serves as a valuable exploratory tool, its explanatory reach remains inherently bounded by its underlying assumptions.

4.7 Future Research Directions

Building upon these limitations, several future research avenues can be pursued to enhance both the breadth and depth of salary prediction studies in the AI domain. First, subsequent studies should seek to integrate larger and more diverse datasets, incorporating regional labor-market statistics, company-reported salary databases, and crowdsourced platforms such as Glassdoor or LinkedIn. By enriching the data pool, researchers can minimize regional and occupational biases, produce more balanced global insights, and explore temporal trends that reveal how AI-related compensation evolves over time.

Future research could also advance the methodological framework by adopting or comparing more sophisticated models. Ensemble learning methods (e.g., Random Forest, Gradient Boosting, or XGBoost) and deep learning architectures could capture complex, non-linear dependencies between predictors. In addition, hybrid or interpretable AI approaches—such as SHAP or LIME for feature attribution—may offer a balance between predictive power and interpretability, allowing for more transparent communication of results to policymakers and industry stakeholders. These methods can also facilitate scenario-based simulations, such as estimating salary shifts under varying economic or technological conditions.

Finally, future studies may broaden the contextual scope of salary analysis to include behavioral and organizational dimensions. For example, integrating factors such as employee satisfaction, workplace flexibility, company culture, and diversity policies could offer a more holistic understanding of what drives compensation beyond technical expertise. Cross-disciplinary collaboration with economists, sociologists, and management scientists would further enrich the interpretation of salary dynamics within the global AI ecosystem. Such expansions would not only strengthen the academic rigor of future research but also contribute to evidence-based policy design and equitable compensation practices in the rapidly evolving field of Artificial Intelligence.

5. Conclusion

This study demonstrates that multiple linear regression (MLR) can serve as an effective and interpretable method for predicting the salaries of Artificial Intelligence (AI) professionals using key predictors such as company location, experience level, and required technical skills. With an R^2 value of 0.8188, the proposed model successfully explains approximately 82% of the salary variance within the analyzed dataset, indicating a high level of explanatory power for a linear statistical model. The findings confirm that salary determination in the AI industry is not random but systematically influenced by both structural and individual factors that can be quantified through regression analysis. This reinforces the notion that transparent, data-driven approaches can provide valuable insights into labor-market dynamics in emerging technology sectors.

The results reveal that geographic location and professional experience exert the strongest influence on compensation levels, both in statistical magnitude and in real-world impact. Professionals employed in countries with advanced digital infrastructures and higher living standards—such as Switzerland, the United States, and Denmark—tend to earn significantly higher salaries compared to their counterparts in developing regions. Similarly, seniority in professional experience consistently translates into higher pay scales, highlighting the cumulative value of expertise in AI-driven industries. In contrast, while certain technical skills—notably Deep Learning, PyTorch, and Cloud Computing—demonstrate a positive correlation with salary, their influence is relatively limited compared to structural determinants. This finding implies that technical competencies are increasingly viewed as baseline qualifications in the AI labor market rather than as exceptional differentiators.

From a practical and policy perspective, the implications of this study are multifaceted. Companies and human resource departments can utilize these findings to develop fair and competitive compensation frameworks aligned with regional cost structures and employee experience levels. Job seekers and professionals can leverage the model's insights to make informed career decisions, negotiate equitable salaries, and identify which skill sets are most valued in the global AI job market. Educational and training institutions, in turn, may adapt their curricula to bridge the gap between academic preparation and labor-market expectations, ensuring that graduates acquire both the technical and professional competencies needed to compete internationally. Looking forward, future research should extend this framework by incorporating non-linear and ensemble-based models such as Random Forest or XGBoost, while also integrating contextual variables—such as company size, industry domain, and macroeconomic indicators—to capture a more comprehensive and realistic picture of salary determinants in the evolving AI ecosystem.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, S.S.M., D.Y., and Y.A.; Methodology, S.S.M. and D.Y.; Software, D.Y. and Y.A.; Validation, D.Y. and Y.A.; Formal Analysis, S.S.M.; Investigation, Y.A. and D.Y.; Resources, D.Y. and Y.A.; Data Curation, Y.A.; Writing—Original Draft Preparation, S.S.M.; Writing—Review and Editing, D.Y. and Y.A.; Visualization, D.Y. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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