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Analyzing the Impact of Company Location, Size, and Remote Work on Entry-Level Salaries a Linear Regression Study Using Global Salary Data

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Abstract

This research explores the key factors influencing entry-level salaries in the global labor market of 2024, emphasizing the roles of company location, organizational size, and the extent of remote work in shaping compensation levels. Drawing on the Global Salary 2024 dataset from Kaggle, which comprises over 5,600 observations across multiple industries and geographic regions, the study applies a multiple linear regression model executed in Python via Google Colab to quantitatively examine salary disparities. The results indicate that company location and size significantly affect entry-level earnings, underscoring how regional economic contexts, cost-of-living variations, and organizational capacity continue to drive wage formation. Conversely, the remote work ratio exhibits a negligible and statistically insignificant effect, implying that flexibility in work arrangements has yet to translate into measurable financial value for early-career professionals. Furthermore, introducing job title as a control variable enhances the model's explanatory power, reaffirming the influence of individual skill specialization and job function in determining compensation outcomes. These findings reinforce human capital theory while extending it by incorporating contextual and organizational dimensions relevant to the digital labor economy. For job seekers, the study offers data-driven insights to guide career decisions and salary expectations across regions, while employers may utilize the results to formulate fair and competitive pay strategies in an increasingly interconnected workforce. Ultimately, this study provides a comprehensive understanding of how structural and individual factors interact to shape entry-level salary dynamics in the modern digital era.

Keywords: Entry-Level Salary, Company Location, Company Size, Remote Work, Linear Regression

1. Introduction

The digital transformation of the labor market is marked by the convergence of Industry 4.0, globalization, and the emergence of new digital professions. Industry 4.0 integrates advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and big data, reshaping production and service sectors worldwide [1]. These developments have generated an unprecedented demand for specialized digital skills, creating new career paths that were non-existent a decade ago. At the same time, globalization accelerates these changes by enabling cross-border collaboration and expanding competition for talent [2]. The resulting global labor ecosystem has redefined salary structures, where technology-driven positions often command premium pay, while traditional roles face stagnation—widening income disparities across industries and regions.

Amid these transformations, salary determination has become increasingly complex. The proliferation of remote and hybrid work models challenges conventional compensation frameworks, as wages now vary not only by role and experience but also by geographic location, cost of living, and company policies [3]. Moreover, a persistent lack of salary transparency and reliance on outdated benchmarks have amplified pay inequities, particularly in fast-evolving technology sectors [4]. Many organizations continue to prioritize traditional determinants such as education and tenure while neglecting contextual and organizational dimensions that shape modern compensation systems [1], [3]. Consequently, workers entering the digital economy often encounter significant inconsistencies in pay expectations, even for similar roles.

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Despite growing attention to workforce digitalization, limited research has quantitatively examined the contextual factors influencing entry-level salaries on a global scale. Existing studies remain focused primarily on individual-level predictors—education, experience, or skills—while overlooking how company location, size, and remote work arrangements interact to determine compensation outcomes [5]. This omission creates a critical knowledge gap, as these variables increasingly shape labor-market competitiveness and equity in the digital era. A comprehensive understanding of such determinants is essential to ensure fairness in workforce planning and to align compensation with the realities of globally distributed work.

Addressing this gap carries both theoretical and practical importance. From an academic perspective, incorporating organizational and geographical factors extends traditional salary-determinant models and enhances the explanatory power of compensation research. Practically, identifying how company context affects entry-level wages supports companies in formulating equitable pay strategies and assists policymakers in developing frameworks that promote inclusivity in the digital economy [6]. It also empowers job seekers to make informed career choices that balance personal aspirations with realistic financial expectations. Accordingly, this study aims to analyze the influence of company location, company size, and remote work ratio on entry-level salaries using the Global Salary 2024 dataset through a multiple-linear-regression approach. By providing empirical insights into these emerging determinants, the research contributes to the broader discourse on pay equity, digital-work transformation, and evidence-based workforce policy in an increasingly interconnected global market.

2. Literature Review

2.1. Theoretical Foundations of Salary Determinants

The determination of salaries has long been grounded in classical economic theories that seek to explain how individual and structural factors shape wage outcomes. Among the most prominent frameworks are human-capital theory, labor-market segmentation theory, and compensation structure models. Human-capital theory, originally advanced by Becker, argues that employees invest in education, training, and skill development to increase productivity, which in turn enhances their earnings potential [7]. Labor-market segmentation theory complements this by emphasizing that the labor market is not homogeneous; rather, it consists of distinct sub-markets—primary and secondary—where workers experience differing degrees of job stability, progression, and income levels [8]. Compensation structure models further explain how organizations align pay systems with strategic goals and competitive conditions, linking internal hierarchies and external benchmarks to overall salary outcomes [9]. Within these theoretical perspectives, salary determination is viewed as a multifactorial process that integrates both individual qualifications and institutional mechanisms. Organizations often employ compensation frameworks to maintain equity between roles, reward performance, and ensure external competitiveness. Meanwhile, macro-economic elements such as labor demand, inflation, and government regulation also shape wage levels. These models collectively underscore the interplay between human investment and organizational context, offering a balanced foundation for understanding salary structures in various industries.

Traditionally, education, work experience, job title, and industry type have been established as the most influential determinants of earnings. Studies consistently show that higher educational attainment and longer tenure correlate positively with income, as these attributes reflect enhanced expertise and productivity [10]. Likewise, job title encapsulates functional responsibility and skill complexity, which directly influence salary differentiation. Industry affiliation introduces yet another layer of variability, as certain sectors—such as information technology or finance—place higher market value on specialized knowledge, resulting in significant wage disparities [8]. Although these conventional determinants provide a robust analytical baseline, they increasingly appear insufficient to capture the realities of the digital economy. Contemporary employment patterns involve diverse forms of work, fluid organizational boundaries, and rapid skill obsolescence, all of which challenge traditional compensation logic. Consequently, modern research must integrate both classic and emergent determinants to explain wage variations in a globalized, technology-driven labor market.

2.2. Emerging Influences in the Digital Era

The digital era has fundamentally transformed the world of work, redefining both employment models and compensation systems. Digitalization and globalization have expanded employers' access to international talent pools while simultaneously heightening competition among workers [11]. This evolution has created new professional categories—data scientists, AI engineers, and UX designers—whose skills are highly valued yet unevenly distributed across regions. The integration of digital technologies into business operations also encourages more flexible work arrangements, compelling organizations to reconsider how and where salaries are determined. As a result, compensation structures are no longer dictated solely by job function but also by contextual factors such as geography and corporate capacity. Company location has become one of the most visible determinants of salary disparity in the digital economy. Regional economic strength, cost-of-living indices, and access to technological infrastructure all contribute to wage differentiation [12]. Urban centers, where economic activities and innovation clusters are concentrated, often command higher wages compared to rural areas [13], [14]. Moreover, multinational operations intensify this gap by setting pay scales that reflect not only local affordability but also global competitiveness. Consequently, geographic context remains an essential explanatory variable in contemporary compensation studies.

Company size likewise exerts substantial influence on salary levels. Larger organizations typically possess greater financial resources, structured career pathways, and comprehensive benefits packages, enabling them to offer more competitive remuneration [15]. Their institutionalized HR systems often embed formal pay-grading mechanisms, whereas smaller firms rely on flexible but less standardized compensation strategies. This structural divergence produces measurable income gaps among employees performing similar functions in different corporate environments. Furthermore, firm size correlates with productivity and market stability, reinforcing its predictive power in wage determination. Finally, remote work introduces a new dimension of complexity. The flexibility associated with remote arrangements enhances employee autonomy and work–life balance but complicates salary normalization across diverse regions. Research indicates that remote workers may accept slightly lower base salaries in exchange for non-financial benefits such as reduced commuting costs and lifestyle flexibility [16]. Nonetheless, empirical findings reveal significant geographic wage differentials within remote contexts, as compensation is often adjusted according to local living costs [17]. These patterns suggest that the digital workplace, while promoting inclusivity, also reproduces existing inequalities through uneven valuation of labor across space.

2.3. Analytical Approaches in Salary Studies

Quantitative modeling has been central to empirical investigations of salary determinants. The most commonly employed techniques include simple linear regression, multiple linear regression, and, more recently, machine-learning methods such as decision trees, random forests, and neural networks. Regression analysis remains the preferred baseline because it allows for direct interpretation of coefficients and straightforward hypothesis testing regarding the influence of independent variables on salary outcomes [18]. In particular, multiple linear regression facilitates the simultaneous evaluation of several predictors—such as company size, location, and job title—thereby capturing the multifaceted nature of compensation systems. The strength of regression-based approaches lies in their interpretability and statistical transparency. Unlike black-box machine-learning models, regression coefficients provide clear indications of direction (positive or negative) and magnitude, supporting theoretically grounded explanations of salary variation. Moreover, the model's ceteris-paribus assumption enables researchers to isolate the average effect of each variable while controlling for others. This characteristic makes regression a valuable first step in exploring relationships before more complex models are introduced for prediction or pattern recognition.

However, these approaches are not without limitations. The assumption of linearity may not always align with the non-linear interactions present in real-world wage data, where variables such as experience or company size may exhibit diminishing or threshold effects. Additionally, omitted-variable bias can arise when key explanatory factors—such as organizational culture or specific technical skills—are excluded from the model, leading to incomplete or distorted results [19], [20]. Multicollinearity among predictors and sensitivity to outliers further complicate analysis, necessitating rigorous data preprocessing and diagnostic checks to ensure validity. Despite these challenges, regression analysis continues to serve as a foundation for salary research, offering both comparability with prior literature and empirical clarity for new studies. It establishes a benchmark against which alternative methods—such as machine-learning algorithms—can be evaluated in terms of accuracy and explanatory power. Recognizing the constraints of linear regression while leveraging its interpretative strengths allows researchers to maintain methodological rigor and contextual awareness, both of which are vital when analyzing compensation patterns in a rapidly evolving digital labor market.

3. Methodology

3.1. Type and Research Approach

This study adopts a quantitative research approach combined with a case study design, allowing for both statistical testing and contextual interpretation. The quantitative approach is chosen because it enables the objective measurement of relationships among variables and supports hypothesis testing through numerical analysis. By quantifying how company location, company size, and remote ratio influence entry-level salaries, this research moves beyond descriptive insights to identify statistically significant determinants. The case study component, focused on the Global Salary 2025 dataset, provides a concrete empirical context for examining real-world salary structures in an international labor market setting. This design allows for the generalization of results within the constraints of the dataset while offering detailed insights into patterns emerging in a digital and globally distributed workforce. Through this approach, the study integrates both analytical precision and contextual understanding to reveal salary dynamics in the digital economy.

3.2. Data Source

The primary data for this research originates from the “Global Salary 2024” dataset available on the Kaggle platform. This dataset is highly relevant because it reflects projected global salary trends and incorporates multiple organizational and demographic attributes. It comprises 5,608 records and 11 variables, including work_year, experience_level, employment_type, job_title, salary, salary_currency, salary_in_usd, employee_residence, remote_ratio, company_location, and company_size. Each record corresponds to an employee’s salary information linked with organizational and employment characteristics. The dataset’s completeness—indicated by the absence of missing values—ensures robust analytical reliability and minimizes the need for data imputation. Furthermore, the presence of core variables directly aligned with this research’s objectives (company location, company size, remote ratio, and salary_in_usd) confirms the dataset’s suitability for empirical analysis. The inclusion of data spanning diverse regions also facilitates comparative evaluation across different economic and organizational contexts, strengthening the global relevance of the findings.

3.3. Research Variables

This study defines entry-level salary in USD as the dependent variable (Y), representing the predicted outcome in the regression model. The dependent variable is drawn from the salary_in_usd column, which standardizes compensation across currencies and enables global comparison. Three independent variables (X) are identified to explain variations in salary: (1) company_location, a categorical variable indicating the geographical base of the employer; (2) company_size, categorized as Small (S), Medium (M), or Large (L), reflecting differences in organizational capacity and resource availability; and (3) remote_ratio, a numerical variable that measures the percentage of work performed remotely (0%, 50%, or 100%). In addition to these, the study incorporates job_title as a control variable to capture the occupational impact on pay differentials, as preliminary analysis indicated that this factor strongly correlates with salary outcomes. Filtering the dataset to include only records where experience_level equals “Entry” ensures that all analyzed cases represent

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comparable early-career positions, thereby reducing heterogeneity and increasing the internal validity of the analysis.

3.4. Data Pre-processing

Before analysis, a comprehensive data pre-processing procedure was implemented to enhance model accuracy and interpretability. First, the dataset was filtered to include only entry-level data, ensuring alignment with the study's objective of examining compensation at the starting point of professional careers. Next, categorical variables such as company_location, company_size, and job_title were transformed into numerical representations through one-hot encoding, a standard technique that converts categorical labels into binary vectors interpretable by the regression algorithm. For example, company_location_US would have a value of 1 for U.S.-based companies and 0 otherwise. This approach preserves categorical distinctions while avoiding ordinal misinterpretation. Following transformation, the dataset was split into training and testing subsets—typically using an 80:20 ratio—to train the model on a majority of the data while reserving a portion for independent validation. This step prevents overfitting and enables objective evaluation of predictive performance. Additional quality checks, including variable normalization and detection of potential multicollinearity, were also conducted to ensure the data met the statistical assumptions of multiple regression.

3.5. Data Analysis Model

The primary analytical method applied in this study is multiple linear regression (MLR), selected for its ability to estimate the linear relationship between a dependent variable and multiple independent predictors simultaneously. The regression model is formally expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

where Y denotes the entry-level salary (in USD), β_0 is the intercept, β_i represents the coefficients for each independent variable X_i, and ϵ captures the random error component. Each coefficient (β_i) reflects the average change in salary corresponding to a one-unit change in the associated variable, assuming all others remain constant (ceteris paribus). Emphasizing this assumption ensures accurate interpretation and prevents overstating causality. The MLR model was chosen because of its transparency, interpretability, and compatibility with the dataset's structure. While it assumes linearity, the model serves as a strong foundation for understanding the general influence of company-related and contextual variables on salary outcomes. Furthermore, residual diagnostics were performed to validate assumptions of normality, homoscedasticity, and independence, ensuring the robustness of model results.

3.6. Analysis Tools

All data analysis was conducted using Google Colab, a cloud-based Python environment that facilitates efficient computation and reproducible research workflows. The analysis utilized several widely recognized Python libraries. Pandas was employed for data manipulation tasks, including filtering, aggregation, and encoding transformations. Matplotlib and Seaborn were used for visual analytics, enabling the creation of descriptive plots such as histograms, box plots, and scatter diagrams that illustrate variable relationships and data distributions. For modeling and statistical evaluation, Scikit-learn was implemented to fit the multiple linear regression model, compute performance metrics such as Mean Squared Error (MSE) and R^2, and assess predictive reliability. The integration of these tools provided a comprehensive analytical pipeline that combined transparency, flexibility, and efficiency. The use of cloud-based computation also ensured scalability and replicability, allowing future researchers to reproduce or extend the analysis using similar datasets.

4. Results and Discussion

4.1. Descriptive Statistics of Data

The initial descriptive analysis reveals a distinctive right-skewed pattern in the distribution of entry-level salaries for 2025, as shown by the histogram and Kernel Density Estimate (KDE) curve. Most salaries cluster

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below the $100,000 USD threshold, representing the dominant concentration of early-career earnings worldwide. This pattern suggests that while the majority of entry-level positions fall within a moderate compensation range, a minority of high-paying positions significantly stretch the upper tail of the distribution, forming what is often termed a “long-tail effect.” This effect commonly appears in global technology and finance sectors, where elite firms offer disproportionately higher pay to attract top-tier talent. The skewed nature of the salary distribution (Figure 1) also reflects the unequal global salary landscape, where only a limited number of markets—mainly developed economies—offer lucrative entry-level opportunities. Such disparities mirror macroeconomic inequalities, cost-of-living differentials, and differences in industry maturity across regions. Additionally, the asymmetry of the salary data emphasizes the concentration of entry-level roles in developing economies, where wage levels remain considerably below global averages.

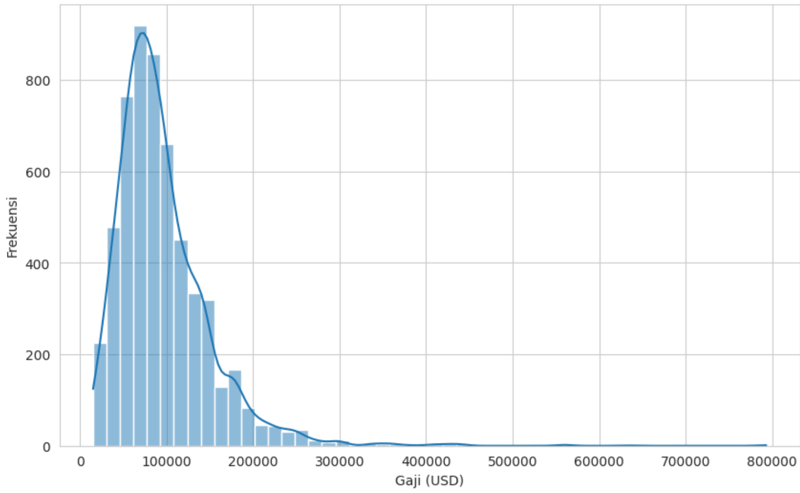

Figure 1. Salary Distribution Plot

From a statistical modeling perspective, this non-normal distribution has implications for the assumptions underlying linear regression analysis. Since regression models assume normally distributed residuals, the presence of skewness may affect model fit and parameter stability. Although this study retains the linear framework for interpretability, the observed skewness underscores the potential for future studies to apply log-transformation or robust regression techniques to address heteroscedasticity.

The box plot visualization for entry-level job titles illustrates notable heterogeneity in salary levels across roles. Technical and analytical positions—such as Research Scientist and Software Engineer—exhibit substantially higher median salaries compared to roles like Data Specialist or Content Analyst. The broader interquartile ranges for technical roles indicate greater salary variability within these job categories, reflecting differentiated valuation of specific technical competencies and project complexities even among entry-level workers.

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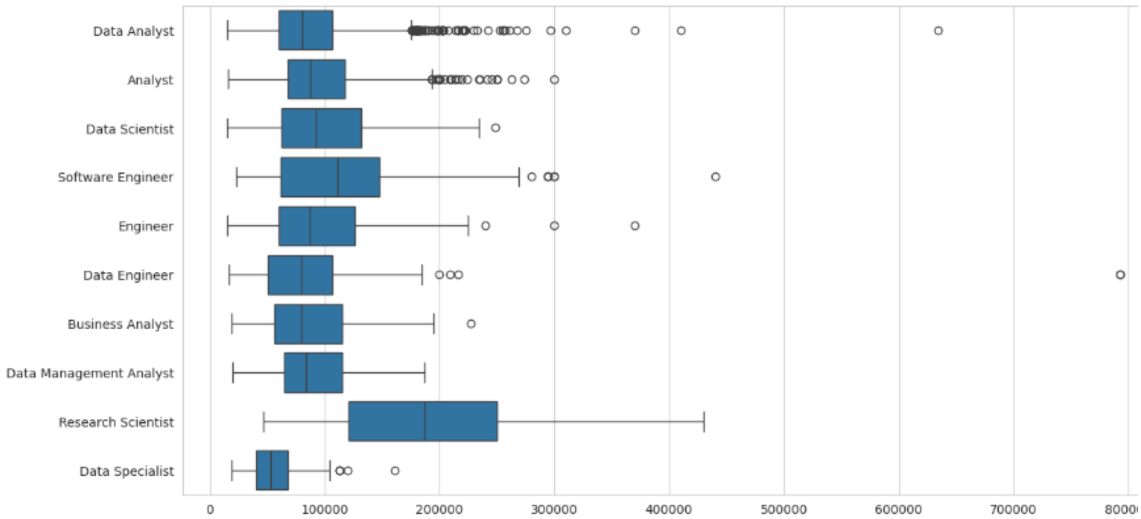

Figure 2. Entry Level Job Title Box Plot

This variation is consistent with global labor-market dynamics, where specialized technical expertise commands a significant premium. High-skill roles in emerging technology fields, including artificial intelligence and software engineering, face persistent talent shortages, driving up market wages. Conversely, non-technical positions often experience wage compression due to oversupply and lower barriers to entry. Thus, the demand–supply imbalance across job types contributes directly to salary disparities, confirming that job title remains one of the most influential predictors of early-career compensation.

The regression coefficients further substantiate this observation. Job_title variables demonstrate some of the largest absolute coefficient values, confirming their strong predictive power relative to contextual factors like location or company size. This dominance suggests that, even at the entry-level, the nature of work and associated skill sets are central determinants of compensation. Market-driven specialization and task complexity therefore outweigh institutional characteristics in shaping pay outcomes.

These findings have both academic and practical implications. They reinforce human-capital theory by demonstrating the economic return to skill specialization and highlight the need for job seekers to strategically invest in technical proficiencies that yield higher entry-level returns. For employers, understanding job-specific wage differentials aids in crafting competitive offers to attract skilled graduates in high-demand fields.

A comparison of salary distributions across company locations reveals pronounced regional disparities. Employees based in the United States (US), Canada (CA), and the United Kingdom (GB) consistently earn higher median salaries with wider ranges, whereas workers in countries such as Slovakia (SK) and Lithuania (LT) receive substantially lower compensation. These findings align with global economic trends, where wage levels reflect variations in productivity, cost of living, and industrial development. The presence of outliers in developed economies indicates that certain firms—particularly in high-tech sectors—offer extraordinary compensation packages to secure talent in competitive markets. Geographical salary disparities can be attributed to several macroeconomic and institutional factors. Higher salaries in advanced economies are often linked to elevated living costs, greater purchasing power, and stronger market demand for technology-oriented roles. Conversely, developing economies, while offering lower pay, may compensate through other benefits such as lower living costs or remote work flexibility. These structural differences underscore that salary cannot be viewed in isolation from the socio-economic environment in which a company operates. Furthermore, the geographical variation emphasizes the global stratification of digital labor. As firms increasingly operate transnationally, they face the challenge of designing equitable pay structures that reconcile global market competitiveness with local affordability. This calls for strategic regional calibration in compensation frameworks, rather than a one-size-fits-all approach.

For job seekers, the implications are equally significant. Understanding how geography influences pay can guide informed career decisions, especially for those considering relocation or remote positions. For organizations, these insights reinforce the importance of adjusting salary bands to local market conditions while maintaining fairness and consistency in global compensation policies. The relationship between company size and salary reveals another layer of differentiation within entry-level compensation structures. The box plots indicate that medium (M) and large (L) companies generally provide higher salaries than small (S) companies. However, the salary ranges for medium firms are notably wider, showing considerable variability. This variation suggests that while some medium-sized companies may offer salaries close to large firms, others still operate closer to small-company compensation norms. This pattern can be interpreted through organizational economics and resource-based perspectives. Larger companies typically possess more robust financial capabilities, enabling them to invest in structured compensation systems and talent retention programs. They also tend to compete in capital-intensive sectors—such as finance, manufacturing, or information technology—where wages reflect higher value creation per employee. Medium-sized firms, on the other hand, often include high-growth startups or specialized technology ventures that offer premium salaries to attract critical expertise, thereby inflating their upper ranges.

In contrast, small companies often operate under resource constraints that limit their ability to match industry pay benchmarks. Instead, they may rely on non-monetary incentives such as flexible work arrangements, skill development opportunities, or equity options to attract talent. This compensation trade-off reflects the entrepreneurial dynamics prevalent in smaller organizations. Collectively, the analysis demonstrates that organizational scale remains an important determinant of entry-level salaries. It shapes compensation through resource endowment, structural hierarchy, and competitive positioning. These insights further justify the inclusion of company size as an explanatory variable in the regression model, as it captures a significant organizational dimension of wage variation.

4.2. Linear Regression Model Results

The multiple linear regression (MLR) model developed in this study evaluates how company location, company size, remote ratio, and job title influence entry-level salaries. The model's overall performance, measured through R-squared (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), provides a quantitative summary of its explanatory power. The resulting R^2 value of 0.31 indicates that approximately 31% of the variance in salaries is explained by the included predictors. Although moderate, this result is meaningful considering the high variability and contextual diversity inherent in global salary data. The MSE (2.59×10^9) and RMSE (≈50,940) reflect the model's average prediction error in dollar terms. These values suggest that, while the model effectively captures major trends, substantial residual variation remains, likely driven by omitted or unobserved variables such as education level or individual performance. Nonetheless, the obtained accuracy is sufficient for interpretive modeling and hypothesis testing within the study's scope. The moderate R^2 value also highlights the complexity of salary determination, which is influenced not only by observable company attributes but also by qualitative factors—organizational culture, market volatility, and employee negotiation power. These nuances cannot be fully quantified through regression but remain essential for contextual understanding. In sum, the model demonstrates reasonable explanatory capability for entry-level salary prediction. It confirms that company-level and contextual variables collectively account for a substantial portion of salary variation while also signaling avenues for future research employing non-linear or machine-learning techniques to capture more complex relationships.

The regression results summarize the estimated coefficients (β), standard errors, t-values, and p-values for each independent and control variable. These values allow for both statistical and substantive interpretation of each factor's influence on salary. Variables with positive coefficients indicate salary-enhancing effects, whereas negative coefficients imply a reduction in expected salary levels. Statistical significance, indicated by p-values below 0.05 or 0.01, validates the robustness of these relationships. From the table, company location and job title emerge as the most influential predictors, exhibiting the highest coefficients and strongest significance levels. Company size shows a positive but smaller effect, suggesting that while firm scale contributes to pay differentials, its impact is less pronounced than geographic or occupational variables. Conversely, remote ratio displays minimal influence, consistent with the hypothesis that remote flexibility is not yet monetized at the entry-level stage. This quantitative evidence corroborates earlier descriptive findings. It reveals that salary variation is largely explained by structural and occupational context rather than flexible work arrangements. These insights confirm the enduring relevance of organizational and market factors in shaping early-career compensation structures. Presenting these coefficients in a unified table enables direct comparison of factor importance, offering practical value to both researchers and practitioners. Such transparency strengthens analytical rigor and enhances replicability in subsequent salary modeling studies.

The scatter plot comparing actual versus predicted salaries (Figure 3) provides a visual assessment of model performance. Most data points align closely along the ideal diagonal (y = x), especially in the lower salary range, demonstrating that the model accurately predicts typical entry-level salaries. However, deviations increase for high-income cases, where observed values significantly exceed predictions. This dispersion indicates that the linear model underestimates extreme salaries—a limitation commonly encountered in wage modeling. This underperformance for higher salaries may result from non-linear effects or omitted variables that become more influential at upper pay levels.

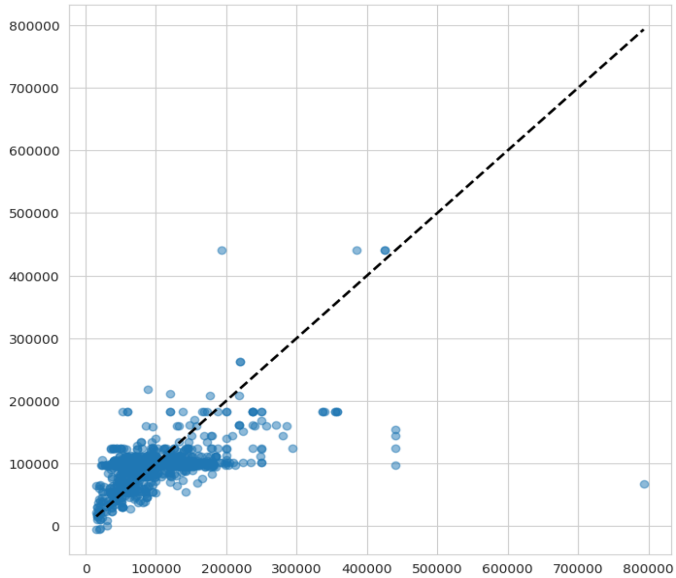

Figure 3. Predicted vs Actual Salary

For instance, elite technical roles, advanced education, or multinational employment benefits may produce salary outcomes that deviate from linear expectations. Thus, while the regression provides general trends, it may not fully capture complex compensation structures in premium segments of the labor market. The observed discrepancies between actual and predicted values reaffirm the earlier conclusion that salary distributions are right-skewed. They suggest that linear regression, while effective for general interpretation, might benefit from alternative approaches such as polynomial regression or machine-learning models to improve prediction accuracy for outliers. Nevertheless, the alignment of most data points around the diagonal demonstrates that the model successfully captures the central tendency of salary variation. This validates the regression's reliability for examining average effects, even if its precision diminishes in extreme cases.

4.3. Discussion of Findings

The results of this study reinforce the central argument of human-capital theory, which posits that individual capability, education, and skill specialization determine economic returns. The finding that job title is the most dominant predictor of salary clearly illustrates this principle: roles demanding advanced technical expertise or higher cognitive complexity yield greater compensation, even at the entry level. At the same time, the substantial effects of company location and company size reveal that contextual and organizational factors remain powerful in shaping salary outcomes. Geographic disparities mirror variations in cost of living, productivity levels, and market demand for digital talent, while organizational scale reflects a firm's financial capacity and compensation philosophy. Together, these insights indicate a paradigm shift in salary determination—away from purely individual attributes toward a more integrated view that combines personal competence with structural and regional influences.

From a job-seeker perspective, these findings carry strategic implications for career planning and market positioning. Entry-level professionals should not rely solely on the availability of remote work as a determinant of financial reward. Instead, they should focus on cultivating competencies aligned with high-value job titles—such as data engineering, software development, or research analytics—while also considering the salary dynamics of different regions. Conducting research on prevailing pay standards in specific geographic and industrial markets enables early-career employees to make informed decisions about where to work and what skills to prioritize. This evidence-based approach can help new entrants bridge the gap between passion, employability, and financial sustainability.

For organizations, the study highlights the importance of adaptive and context-sensitive compensation strategies. Firms operating in high-cost or competitive labor markets must calibrate pay scales that reflect regional realities and company capacity, ensuring fairness while maintaining attractiveness to prospective employees. Conversely, employers offering remote entry-level roles can capitalize on global recruitment opportunities by engaging talent from lower cost-of-living areas, provided that pay expectations are transparently communicated. In such contexts, remote flexibility functions more effectively as a non-financial incentive—enhancing job satisfaction and work–life balance—rather than as a monetary premium. Thus, nuanced compensation management becomes essential for maintaining competitiveness in a diversified global workforce.

Despite its contributions, this study acknowledges several limitations that open avenues for further research. The linear regression framework, while useful for interpretability, is constrained by its assumption of linear relationships and limited ability to model extreme salary outliers. Future analyses could incorporate non-linear or machine-learning approaches to capture complex wage behaviors. Moreover, the dataset omits potentially influential variables such as education level, institutional prestige, individual performance metrics, and fine-grained industry categories. Recognizing this potential omitted-variable bias enhances the credibility of the findings and underscores the need for a more comprehensive analytical model. Addressing these limitations in subsequent research will enable a deeper and more precise understanding of how individual, organizational, and contextual factors jointly determine entry-level compensation in the evolving digital labor economy.

5. Conclusion

The findings of this study demonstrate that company location, company size, and job title are the most influential factors determining entry-level salaries in the global job market of 2025. The results of the multiple linear regression analysis reveal that company location exerts a particularly strong influence, indicating that regional economic contexts—such as cost of living and labor demand—play a decisive role in shaping compensation structures. Company size also contributes significantly, with medium and large organizations generally offering higher and more varied salary packages than small firms. Among all predictors, job title emerges as the most dominant determinant, reinforcing the importance of skill specialization and occupational function in determining pay. In contrast, the remote work ratio has minimal impact, suggesting that remote flexibility, while valuable for work-life balance, does not yet translate into financial advantages for early-career employees.

These findings carry several practical implications for both job seekers and employers. For job seekers, the results highlight the need to strategically develop technical and analytical skills aligned with high-value job titles and to consider regional labor markets that offer competitive compensation. Rather than viewing remote work as a financial differentiator, early-career professionals should regard it as a complementary factor that enhances flexibility and career development opportunities. For companies, the study underscores the

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importance of tailoring compensation strategies according to organizational scale and geographic context. Firms competing in high-cost regions must align pay structures with local living standards to attract talent, while those offering remote positions can optimize recruitment by engaging qualified candidates from regions with lower cost bases. In both cases, compensation must balance fairness, competitiveness, and sustainability in the evolving global economy.

Beyond its immediate insights, this research also points to important directions for future inquiry. The linear regression model employed here captures key determinants but remains limited in addressing complex, non-linear relationships within salary data. Future studies could integrate advanced analytical methods—such as polynomial regression, decision tree algorithms, or machine-learning models—to improve predictive accuracy and capture interactions among variables. Additionally, including other potential determinants such as education level, university reputation, technical certifications, or performance indicators could reduce omitted-variable bias. Longitudinal and comparative studies across industries and regions would also enrich understanding of how salary determinants evolve over time amid digital transformation and shifting economic landscapes. By addressing these dimensions, subsequent research can build upon this foundation to create a more comprehensive and dynamic model of global entry-level salary formation.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, J.K., D.M., and F.S.; Methodology, J.K. and D.M.; Software, F.S.; Validation, D.M.; Formal Analysis, J.K.; Investigation, D.M. and F.S.; Resources, D.M.; Data Curation, F.S.; Writing—Original Draft Preparation, J.K.; Writing—Review and Editing, D.M. and F.S.; Visualization, F.S. 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.

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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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