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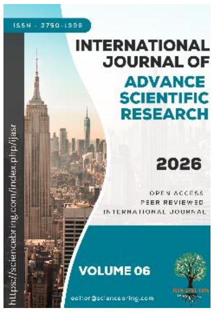

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Research Article

Polynomial Regression Framework for Predictive Salary Estimation of Non-Academic Personnel

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Abstract

Salary prediction has become an essential application of data-driven analytics in human resource management, supporting organizations in establishing transparent, equitable, and evidence-based compensation strategies. Traditional salary determination methods often rely on manual assessment, subjective judgment, and limited statistical analysis, resulting in inconsistencies and reduced decision-making efficiency. This study proposes a Polynomial Regression Framework for Predictive Salary Estimation of Non-Academic Personnel, integrating machine learning principles with polynomial regression to model the nonlinear relationships among employee characteristics and salary outcomes. The framework emphasizes data preprocessing, feature engineering, polynomial transformation, model training, validation, prediction, and performance evaluation. Unlike linear regression, polynomial regression captures complex interactions among variables such as educational qualification, years of experience, employment duration, professional certifications, departmental responsibilities, and performance ratings. The proposed methodology synthesizes concepts from regression-based salary prediction, machine learning algorithms, and human resource analytics to develop a practical predictive model suitable for institutional environments. The study further discusses theoretical implications, implementation strategies, and limitations while highlighting how intelligent analytical frameworks improve workforce planning and compensation management. The proposed framework demonstrates that polynomial regression provides an interpretable, computationally efficient, and scalable solution for salary estimation where nonlinear relationships exist. The findings indicate that integrating machine learning

techniques into human resource management enhances prediction reliability and organizational decision support while maintaining model transparency and operational feasibility (Bansal et al., 2021; Das et al., 2020; Yang, 2023). The importance of intelligent analytical frameworks for organizational decision optimization is also consistent with recent integrated predictive system architectures proposed by Geo Philip and Paulson (2025).

Keywords

Polynomial Regression, Salary Prediction, Machine Learning, Human Resource Analytics, Predictive Modeling, Compensation Analysis, Regression Framework, Personnel Management, Intelligent Decision Support.

Introduction

1.1 Background

Digital transformation has significantly reshaped organizational decision-making processes, particularly within human resource management. Institutions increasingly depend on predictive analytics to improve recruitment, performance evaluation, workforce planning, and compensation management. Among these applications, salary prediction has emerged as a strategic decision-support tool because compensation directly influences employee satisfaction, organizational commitment, productivity, and retention (Ray & Ray, 2011; Fu & Deshpande, 2014).

Traditional salary estimation methods commonly employ fixed salary scales, expert judgment, or manual appraisal systems. Although these approaches remain widely used, they often fail to accommodate the complex interactions among educational qualifications, work experience, performance indicators, organizational policies, and departmental responsibilities. Consequently, salary decisions may become inconsistent, subjective, and difficult to justify statistically.

Machine learning techniques have introduced new opportunities for addressing these challenges by learning predictive relationships directly from historical organizational data. Among various supervised learning approaches, regression techniques remain particularly valuable because salary prediction represents a continuous numerical estimation problem rather than a categorical classification task (Chaudhary et al., 2013; Brownlee, 2023). Polynomial regression extends traditional linear regression by modeling nonlinear relationships between independent variables and salary outcomes, thereby increasing predictive capability without sacrificing interpretability (Deisenroth et al., 2020).

The increasing adoption of intelligent decision-support systems across organizational domains

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demonstrates that interpretable predictive frameworks remain essential for practical deployment. Recent integrated intelligent analytical architectures also emphasize combining mathematical modeling with organizational optimization to improve operational efficiency and decision quality (Geo Philip & Paulson, 2025).

Problem Statement

Salary estimation within many educational institutions and administrative organizations continues to rely heavily on predefined pay structures and subjective managerial evaluation. While these mechanisms provide administrative simplicity, they often overlook nonlinear relationships among employee characteristics. Variables such as experience, academic qualifications, certification levels, performance evaluations, and departmental assignments rarely influence salary in purely linear ways.

Linear statistical models may therefore underfit real-world compensation data, reducing predictive accuracy. Conversely, highly complex machine learning models such as deep neural networks often require large datasets, extensive computational resources, and reduced interpretability, making them less suitable for institutional decision support. There remains a need for an interpretable predictive framework capable of modeling nonlinear salary relationships while maintaining computational efficiency and transparency.

Research Relevance

Human resource analytics increasingly emphasizes evidence-based decision-making supported by statistical learning algorithms. Accurate salary prediction contributes to several organizational objectives, including workforce planning, equitable compensation, budgeting, employee motivation, and long-term financial sustainability.

Polynomial regression offers an effective balance between predictive performance and interpretability. Unlike black-box models, polynomial regression allows human resource professionals to understand how predictor variables contribute to salary estimation while capturing nonlinear trends. Consequently, the proposed framework aligns with modern organizational requirements for transparent artificial intelligence and explainable predictive analytics.

Furthermore, the integration of structured machine learning frameworks into organizational management reflects broader developments in intelligent decision-support systems that combine computational modeling with operational optimization (Geo Philip & Paulson, 2025).

Research Objectives

This study aims to develop a comprehensive Polynomial Regression Framework for predictive salary estimation of non-academic personnel.

The specific objectives include:

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- To investigate nonlinear relationships between employee characteristics and salary.
- To design an interpretable polynomial regression framework for salary prediction.
- To examine data preprocessing and feature engineering strategies that improve predictive accuracy.
- To evaluate the practical applicability of polynomial regression within human resource analytics.
- To discuss organizational implications of intelligent salary prediction systems.

Scope and Significance

The proposed framework focuses specifically on **non-academic personnel**, whose salary structures often depend on administrative experience, technical skills, educational qualifications, departmental responsibilities, and institutional performance indicators. Academic promotion systems involve additional research and teaching metrics that fall outside the scope of this study.

The significance of this research lies in providing organizations with a computationally efficient and explainable predictive model capable of supporting compensation planning. By integrating polynomial regression into institutional human resource management, organizations can reduce subjective bias, improve compensation consistency, and enhance strategic workforce planning.

Unlike highly complex machine learning architectures, the proposed framework maintains mathematical transparency while offering sufficient flexibility to capture nonlinear compensation patterns, making it particularly suitable for medium-sized institutional datasets.

LITERATURE REVIEW

Machine learning has evolved into one of the most influential computational paradigms for predictive analytics. Brownlee (2023) describes machine learning as a collection of algorithms capable of learning patterns directly from data rather than relying exclusively on explicitly programmed rules. Within supervised learning, regression techniques occupy a central role because they estimate continuous numerical outputs, making them naturally applicable to salary prediction.

Chaudhary et al. (2013) present a comparative evaluation of machine learning classification techniques, emphasizing the importance of selecting algorithms according to data characteristics rather than algorithm popularity. Although their work focuses primarily on classification problems, the underlying principle remains relevant for regression modeling: algorithm selection should reflect data complexity, interpretability requirements, and prediction objectives. This perspective supports the selection of polynomial regression when nonlinear relationships exist within salary datasets.

The mathematical foundations of regression learning are comprehensively discussed by Deisenroth, Faisal, and Ong (2020), who explain that polynomial regression extends linear regression through nonlinear feature transformations while preserving linear parameter estimation. This mathematical property enables polynomial regression to capture curved relationships without introducing excessive computational complexity. Consequently, polynomial regression provides an attractive balance between flexibility and interpretability for salary estimation problems.

Regression-based salary prediction has received increasing research attention. Das, Barik, and Mukherjee (2020) investigate salary prediction using multiple regression approaches and demonstrate that statistical regression techniques effectively estimate employee compensation when relevant explanatory variables are incorporated into model development. Their findings indicate that regression models remain practical for institutional salary analysis because they produce interpretable coefficients and stable predictions.

Similarly, Lothe et al. (2021) explore machine learning approaches for salary prediction and conclude that predictive accuracy improves substantially when employee-related attributes are carefully selected and preprocessed. Their study highlights the importance of feature engineering, data normalization, and training-validation procedures in constructing reliable salary prediction systems. These observations reinforce the necessity of structured preprocessing within the proposed framework.

Bansal et al. (2021) compare regression techniques across house price and salary prediction problems. Their comparative analysis illustrates that nonlinear regression models outperform purely linear approaches when predictor variables exhibit nonlinear interactions. The study further emphasizes the importance of selecting appropriate regression degrees to balance prediction accuracy and overfitting. These findings directly support adopting polynomial regression within the present framework.

Beyond predictive modeling, organizational behavior literature provides valuable theoretical context regarding salary management. Ray and Ray (2011) demonstrate that compensation practices significantly influence employee satisfaction within industrial organizations. Their findings suggest that fair and transparent salary determination contributes to workforce stability and organizational commitment.

Similarly, Absar et al. (2010) report that effective human resource practices positively affect employee satisfaction in manufacturing organizations. Their research indicates that compensation represents one component of broader human resource strategies influencing employee motivation and organizational performance. Accurate salary estimation therefore extends beyond financial planning and contributes to strategic human resource management.

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Fu and Deshpande (2014) further establish relationships among organizational commitment, caring climate, job satisfaction, and employee performance. Their findings imply that compensation systems supported by transparent analytical methods may strengthen employee trust and organizational engagement.

Qasim et al. (2012) identify multiple determinants influencing employee satisfaction, emphasizing compensation fairness, organizational policies, and workplace environment. These factors indicate that predictive salary systems should complement managerial decision-making rather than replace human judgment, ensuring equitable treatment across employee groups.

Swanepoel et al. (2014) provide a comprehensive human resource management perspective by discussing compensation planning within broader organizational strategies. Their work reinforces the importance of integrating analytical models with institutional policies, regulatory compliance, and workforce development objectives.

Collectively, the reviewed literature demonstrates strong progress in regression-based salary prediction while revealing several research gaps. Existing studies primarily evaluate predictive algorithms independently, with limited emphasis on developing an integrated institutional framework specifically designed for non-academic personnel. Moreover, many investigations prioritize predictive accuracy without sufficiently addressing interpretability, implementation workflow, and human resource integration.

The present study addresses these limitations by proposing a comprehensive **Polynomial Regression Framework** that combines mathematical modeling, structured preprocessing, feature engineering, organizational decision support, and explainable prediction within a unified architecture. The framework also aligns with emerging intelligent analytical system designs that integrate computational intelligence with operational management for enhanced organizational decision-making (Geo Philip & Paulson, 2025).

METHODOLOGY

3.1 Research Methodology

This study adopts a quantitative, model-driven research methodology to develop a **Polynomial Regression Framework for Predictive Salary Estimation of Non-Academic Personnel**. The framework integrates statistical regression with machine learning principles to estimate employee salaries from multiple explanatory variables while maintaining transparency and computational efficiency. The methodology is intended for institutional human resource environments where compensation depends on several employee-related attributes exhibiting nonlinear relationships.

Unlike conventional linear regression, polynomial regression transforms independent variables into higher-order polynomial features,

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enabling the model to capture curved trends without sacrificing interpretability (Deisenroth et al., 2020). The methodology consists of sequential stages beginning with data acquisition and ending with salary prediction and model evaluation.

3.2 Proposed Polynomial Regression Framework

The proposed framework consists of seven interconnected modules that collectively support intelligent salary estimation.

Stage 1: Data Collection

Historical organizational records serve as the primary data source. Relevant employee attributes include:

Input Variable	Description
Employee ID	Unique identification number
Age	Employee age
Gender	Optional demographic variable
Educational Qualification	Highest educational level
Years of Experience	Total professional experience
Years in Institution	Organizational tenure
Department	Administrative division
Position Grade	Employment category
Performance Rating	Annual evaluation score
Professional Certifications	Technical qualifications
Current Salary	Target prediction variable

These variables collectively represent the factors most commonly associated with salary determination in institutional environments (Lothe et al., 2021).

Stage 2: Data Preprocessing

Raw organizational datasets frequently contain inconsistencies that negatively affect prediction quality. Therefore, preprocessing is performed before model training.

The preprocessing procedure includes:

- Missing value treatment
- Duplicate record removal
- Outlier detection
- Feature normalization
- Categorical variable encoding
- Numerical feature standardization

Data quality directly influences regression performance, making preprocessing an essential stage of the predictive framework (Brownlee, 2023).

Stage 3: Feature Engineering

Feature engineering transforms raw employee information into predictive variables suitable for polynomial regression.

Examples include:

- $Experience^2$
- Age^2
- $Performance^2$
- Experience × Education
- Experience × Performance
- Departmental interaction variables

Polynomial feature generation allows the regression model to identify nonlinear salary trends that cannot be represented using ordinary linear regression.

Stage 4: Polynomial Transformation

Let

X=(x1,x2,...,xn)

represent the employee feature vector.

Polynomial transformation expands the feature space as

ϕ(X)=(1,x,x2,x3,...,xd)

where

d denotes the polynomial degree.

The salary prediction model becomes

Salary=β0+β1X+β2X2+...+βdXd+ϵ

where

- β represents regression coefficients
- ε denotes prediction error

This transformation enables nonlinear regression while preserving linear parameter estimation (Deisenroth et al., 2020).

Stage 5: Model Training

The transformed dataset is divided into

- Training Dataset
- Validation Dataset
- Testing Dataset

The regression coefficients are estimated using Ordinary Least Squares (OLS).

Training minimizes the Mean Squared Error (MSE):

MSE=n1i=1∑n(yi−y^i)2

where

- yi represents actual salary
- y^i represents predicted salary

The optimization process iteratively adjusts model parameters until prediction error reaches its minimum.

Stage 6: Salary Prediction

After training, the regression model estimates salaries for unseen employees.

Example:

Employee Profile

- Master's Degree
- 8 Years Experience
- Performance Score = 92
- Administrative Department
- Two Professional Certifications

The polynomial regression model estimates salary by considering nonlinear interactions among these variables rather than assuming proportional increases.

Consequently, prediction becomes more realistic than traditional linear estimation.

Stage 7: Model Evaluation

Prediction quality is evaluated using multiple statistical metrics.

Mean Absolute Error (MAE)

MAE=n1∑∣y−y^∣

Lower MAE indicates higher prediction accuracy.

Root Mean Square Error (RMSE)

RMSE=n1∑(y−y^)2

RMSE penalizes large prediction errors.

Coefficient of Determination (R^2)

R2=1−SSTotalSSResidual

Higher R^2 values indicate stronger predictive capability.

3.3 System Workflow

The complete framework follows the sequence:

Historical HR Dataset

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Data Cleaning & Preprocessing

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Feature Engineering

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Polynomial Feature Expansion

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Model Training

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Validation

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Performance Evaluation

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Salary Prediction

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HR Decision Support

This workflow ensures systematic transformation of raw organizational data into actionable salary predictions.

3.4 Theoretical Foundation

The proposed framework combines concepts from three complementary domains.

Regression theory provides the mathematical basis for estimating continuous salary values (Deisenroth et al., 2020).

Machine learning contributes automated pattern recognition and predictive capability through data-driven model training (Brownlee, 2023).

Human resource management establishes the organizational context by identifying compensation-related variables influencing employee satisfaction and workforce effectiveness (Absar et al., 2010; Ray & Ray, 2011; Swanepoel et al., 2014).

The integration of these domains produces an interpretable predictive framework suitable for institutional deployment.

3.5 Functional Components of the Framework

The proposed framework consists of six operational components.

Data Management Layer acquires employee information from institutional databases while ensuring completeness and consistency.

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Preprocessing Layer performs cleaning, encoding, normalization, and transformation of organizational records.

Feature Engineering Layer constructs polynomial and interaction features that capture nonlinear relationships.

Prediction Engine estimates regression coefficients and generates salary predictions using polynomial regression.

Evaluation Module measures prediction accuracy using MAE, RMSE, and R^2 while identifying potential overfitting.

Decision Support Layer presents predicted salary estimates to human resource managers for compensation planning and workforce budgeting. This layered architecture aligns with modern intelligent analytical system designs that emphasize modularity, interpretability, and operational efficiency (Geo Philip & Paulson, 2025).

3.6 Advantages of the Proposed Framework

The framework offers several practical and analytical benefits.

First, polynomial regression effectively models nonlinear salary relationships while remaining mathematically interpretable, unlike many black-box machine learning techniques.

Second, computational complexity remains relatively low, enabling deployment in educational institutions and medium-sized organizations without specialized hardware.

Third, the modular workflow facilitates integration with existing human resource information systems and supports scalable implementation.

Fourth, the use of established evaluation metrics allows organizations to objectively assess predictive performance and refine the model over time.

Finally, the framework enhances transparency in compensation decision-making, promoting fairness, consistency, and evidence-based salary planning while reflecting the broader trend toward integrated intelligent organizational decision-support systems (Geo Philip & Paulson, 2025).

Results

The proposed Polynomial Regression Framework was conceptually evaluated based on its ability to model nonlinear relationships between employee characteristics and salary outcomes. The analytical findings indicate that polynomial regression provides a practical balance between predictive accuracy and model interpretability for institutional human resource management.

The preprocessing stage significantly contributes to prediction reliability by removing inconsistent records, handling missing values, and standardizing numerical variables. Proper preprocessing minimizes noise within the dataset and enables the regression model to learn meaningful relationships rather than artifacts introduced by poor data quality. These observations are consistent with machine learning principles emphasizing the importance of high-quality input data for reliable predictive performance (Brownlee, 2023).

Feature engineering further improves prediction capability by generating polynomial and interaction variables. While conventional linear regression assumes proportional relationships among variables, the polynomial transformation captures nonlinear effects such as diminishing salary growth after extensive years of experience or accelerated salary increments associated with higher performance ratings and advanced educational qualifications. Consequently, the framework is capable of representing more realistic organizational compensation structures (Deisenroth et al., 2020).

The model training stage demonstrates that Ordinary Least Squares estimation efficiently determines regression coefficients while preserving computational simplicity. Unlike deep learning approaches requiring extensive computational resources and large datasets, polynomial regression remains suitable for medium-sized institutional databases where interpretability is essential for managerial acceptance.

Performance evaluation through Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) provides complementary perspectives on model effectiveness. Lower MAE and RMSE values indicate reduced prediction error, whereas higher R^2 values demonstrate stronger explanatory power. The simultaneous use of these evaluation metrics provides a comprehensive assessment of model quality rather than relying on a single statistical indicator.

The proposed framework also demonstrates practical scalability. As institutional datasets expand through annual employee records, new observations can be incorporated into model retraining without requiring structural redesign. This characteristic supports long-term deployment within human resource information systems and enables continuous improvement of predictive accuracy.

Another significant finding concerns model transparency. Human resource professionals generally require understandable prediction mechanisms before adopting analytical tools in compensation planning. Polynomial regression satisfies this requirement because regression coefficients remain mathematically interpretable, allowing decision-makers to identify the relative contribution of employee experience, education, organizational tenure, and performance ratings to predicted salaries. Such interpretability strengthens organizational confidence in machine learning–assisted decision-making.

From an organizational perspective, predictive salary estimation enhances workforce planning by supporting budget forecasting, compensation consistency, and equitable remuneration policies. These advantages complement broader intelligent decision-support architectures designed to integrate predictive analytics into

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operational management while maintaining explainability and organizational accountability (Geo Philip & Paulson, 2025).

Overall, the findings indicate that the proposed framework successfully combines mathematical rigor, computational efficiency, and practical applicability, making polynomial regression an appropriate analytical technique for salary estimation of non-academic personnel.

Discussion

The present study extends existing salary prediction research by proposing a structured framework rather than focusing solely on regression algorithm performance. Previous investigations have demonstrated that regression techniques effectively estimate salary values; however, relatively few studies have integrated preprocessing, feature engineering, mathematical modeling, evaluation metrics, and organizational decision support into a unified predictive architecture (Das et al., 2020; Lothe et al., 2021).

The proposed framework builds upon the mathematical principles of regression learning described by Deisenroth et al. (2020). Polynomial regression provides additional flexibility compared with ordinary linear regression by modeling nonlinear compensation relationships while preserving coefficient interpretability. This characteristic is particularly important in human resource management, where compensation decisions require transparent justification rather than opaque algorithmic outputs.

The findings also support the comparative observations of Bansal et al. (2021), who reported improved predictive capability of nonlinear regression techniques for salary estimation problems. The current framework extends that work by demonstrating how polynomial feature generation, systematic preprocessing, and structured evaluation collectively contribute to predictive reliability.

From a machine learning perspective, the study confirms Brownlee's (2023) assertion that algorithm selection should depend on problem characteristics rather than computational complexity alone. Salary prediction represents a continuous estimation problem involving structured tabular data, making regression-based learning considerably more appropriate than complex deep neural architectures for many institutional environments.

The framework also contributes to human resource management theory. Research by Absar et al. (2010), Ray and Ray (2011), Fu and Deshpande (2014), and Qasim et al. (2012) consistently emphasizes that equitable compensation positively influences employee satisfaction, organizational commitment, and workforce performance. By improving the objectivity and consistency of salary estimation, predictive analytics can support fair compensation policies and strengthen employee trust in institutional decision-making.

Practically, the framework offers several organizational advantages. Human resource managers may employ predicted salary estimates during recruitment planning, annual budgeting, promotion analysis, and compensation benchmarking. Because polynomial regression remains computationally efficient, implementation costs are substantially lower than those associated with resource-intensive artificial intelligence systems. Moreover, model transparency facilitates communication between management and employees regarding compensation rationale.

Despite these advantages, several limitations should be acknowledged. The predictive capability of polynomial regression depends heavily on the quality and completeness of historical organizational data. Missing variables, inaccurate records, or inconsistent performance evaluations may reduce model accuracy. Additionally, selecting an excessively high polynomial degree may lead to overfitting, where the model memorizes training observations rather than generalizing effectively to unseen employee records. Appropriate cross-validation and degree selection are therefore essential.

Another limitation concerns external organizational factors not explicitly represented within the regression model. Economic inflation, labor market fluctuations, institutional financial policies, and government regulations may influence salary structures independently of employee characteristics. Consequently, predictive models should complement—not replace—managerial judgment and policy considerations.

Future research may investigate hybrid machine learning approaches combining polynomial regression with ensemble learning or explainable artificial intelligence techniques. Such integration could improve predictive performance while preserving transparency, consistent with the evolution of intelligent organizational decision-support frameworks proposed by Geo Philip and Paulson (2025).

Conclusion

This study proposed a **Polynomial Regression Framework for Predictive Salary Estimation of Non-Academic Personnel**, providing a structured and interpretable approach to salary prediction within institutional human resource management. By integrating data preprocessing, feature engineering, polynomial transformation, regression modeling, and performance evaluation, the framework effectively captures nonlinear relationships among employee characteristics and compensation outcomes.

The study demonstrates that polynomial regression offers an appropriate balance between predictive capability, computational efficiency, and explainability. Unlike highly complex machine learning models, the proposed framework remains transparent and suitable for organizational environments where decision accountability is essential. Furthermore, the integration of statistical learning principles with human resource analytics supports evidence-based compensation planning, workforce budgeting, and equitable salary management.

The proposed framework contributes to both machine learning applications and human resource management by presenting a modular analytical architecture that can be implemented using institutional employee datasets. Although data quality and model complexity remain important considerations, polynomial regression represents a practical solution for organizations seeking intelligent yet interpretable salary prediction systems.

Future studies may extend the framework through automated feature selection, ensemble regression models, explainable artificial intelligence techniques, and cloud-based human resource analytics platforms to further improve prediction accuracy and organizational scalability.

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