

AI ENGINEERING SPECIALIZATION

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Salary Prediction Project

Unlocking Fair Pay

A Data-Driven Approach to Salary Prediction


Building Trust Through Transparent Compensation Analysis


Good morning everyone. Today I'm excited to share insights from our salary prediction project a journey that started with a simple question

'How can we ensure fair and competitive compensation?' What we discovered will help us make better decisions about pay, hiring, and career development

The Challenge I Faced

The Problem: Making Fair Pay Decisions Without Guesswork

 **The Reality:** Salary decisions often feel like educated guessing

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The Questions

- Are we paying fairly across different roles?
- What factors truly drive compensation?
- How do we stay competitive while being equitable?

Our Goal

Build a reliable system to predict and validate salaries



Before this project, salary decisions often felt like educated guessing.

Managers would ask: 'Should this engineer earn more than that analyst?' 'Is our suburban pay competitive?' We needed answers backed by data, not assumptions.

Our Data Story

Meet Our 1,000 Employee Dataset

The People Behind the Numbers:


 **1,000 employees** across diverse backgrounds

 **Education:** High School to PhD

 **Roles:** Analysts to Directors

 **Locations:** Urban, Suburban, Rural

 **Experience:** 1 to 29 years

 **Salaries:** ₦33,510 to ₦193,016



Our story begins with real people - 1,000 employees with diverse backgrounds. From fresh graduates earning ₦33,510 to senior leaders earning ₦193,016, each person represents a unique journey. The average employee has 15 years of experience and earns about ₦105,558.

The Data Detective Work

What Makes Salaries Tick? Our Investigation

Does education level predict higher pay?



How much does each year of experience add?



Does location matter for compensation?



The Detective Process

- **Gathered clues** (collected 6 key factors)
- **Tested relationships** (analyzed each factor's impact)
- **Found patterns**
- **Built predictions** (created my salary model)



Like detectives solving a case, we investigated what really drives salaries. We didn't just assume - we tested every relationship.

Does a PhD always mean higher pay? Does moving from Analyst to Manager guarantee a raise? The answers surprised us."

Smart Data Preparation

Preparing Our Data: The Foundation of Success

A. Education & Job Titles (Ranked by Impact):

- PhD > Master's > Bachelor's > High School ✓
- Director > Manager > Engineer > Analyst ✓
- Why? Clear career progression paths

B. Location (Treated Equally):

- Urban, Suburban, Rural - No ranking ✓
- Why? Each has unique advantages

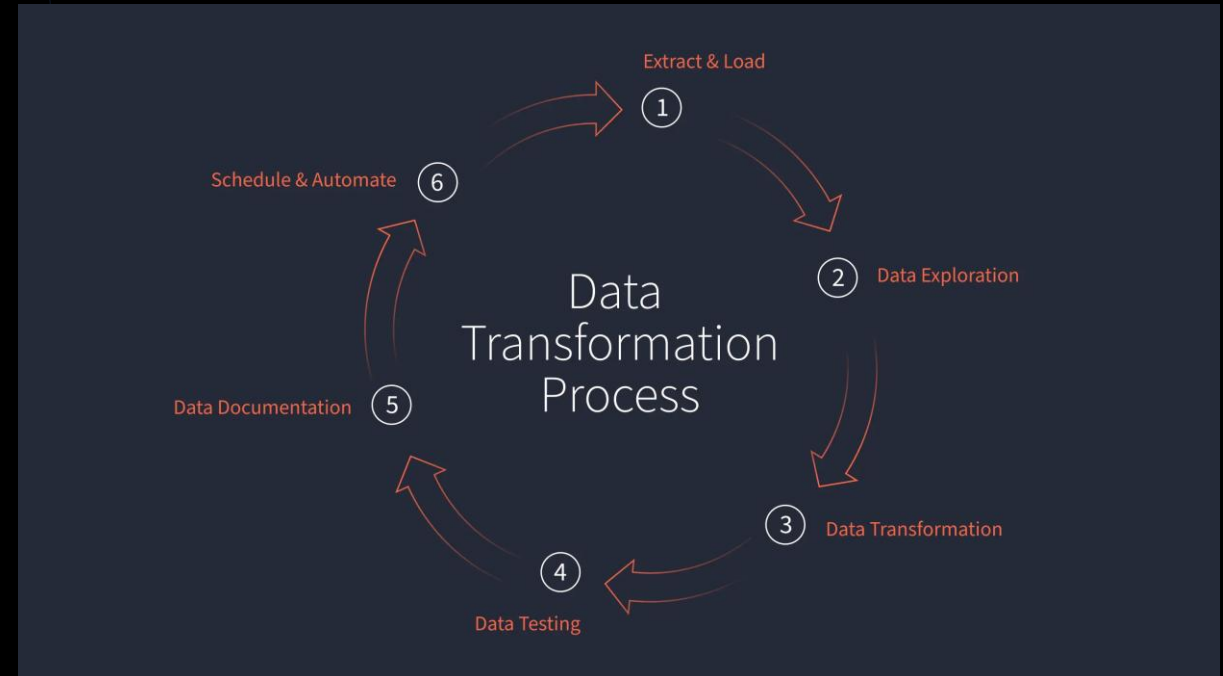
C. Fair Splitting:

- **71 % Training**
- **9% Validation**
- **20% Testing**

I discovered that education and job titles have natural hierarchies - a PhD typically earns more than a Bachelor's. But location? That's complex. Urban areas might pay more, but rural areas offer other benefits. We ranked what made sense and treated the rest equally."

TESA




AI Engineering



The Method: Linear Regression Explained Simply

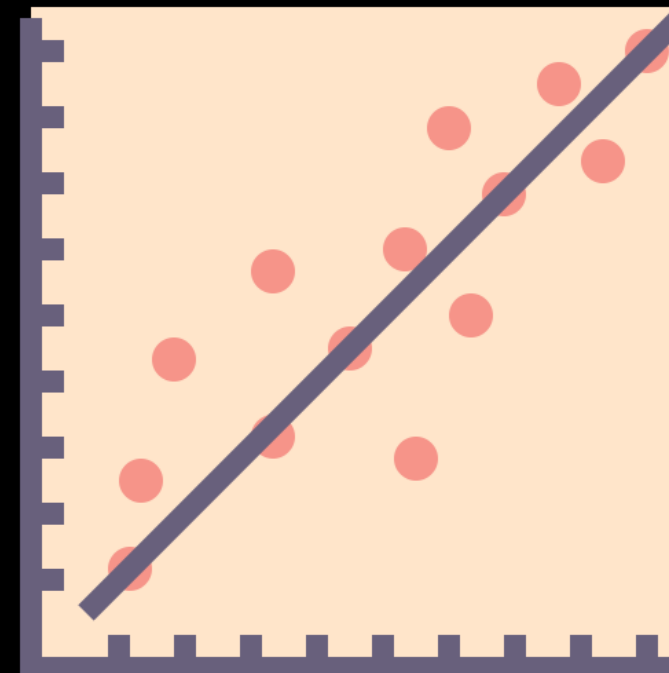
Our Prediction Engine: Simple Yet Powerful

Why Linear Regression?

-  **Transparent:** We can see exactly what drives predictions
-  **Reliable:** Time-tested approach trusted by businesses
-  **Interpretable:** Easy to explain to managers and employees

How It Works: "Think of it like a recipe - each ingredient (education, experience, location) contributes a specific amount to the final dish (salary)"

The Formula: $\text{Salary} = \text{Base Amount} + (\text{Education Points} \times \text{Education Value}) + (\text{Experience Points} \times \text{Experience Value}) + \dots$



We chose linear regression because it's like a transparent recipe. Unlike complex black-box models, everyone can understand how it works. It tells us exactly how much each factor contributes to salary - no hidden secrets, just clear relationships.

The Big Reveal - What Really Drives Salaries

Salary Drivers: Our Key Discoveries

The Power Rankings:

Location - The Game Changer

- Suburban: +~~N~~19,436 impact
- Urban: +~~N~~8,786 impact
- *Translation:* Where you work matters most

Experience - The Steady Climber

- +~~N~~8,187 per experience level
- *Translation:* Every year of experience pays off

Job Title - The Career Ladder

- +~~N~~9,323 per promotion level
- *Translation:* Moving up really pays


Education - The Foundation

- +~~N~~4,385 per degree level
- *Translation:* Education matters, but experience matters more

Here's what shocked us - location matters most! Suburban employees have the biggest salary boost, followed by experience and job level. Education, while important, has less impact than we expected. This tells us we value real-world skills highly

Model Performance - How Good Are We?

Putting Our Model to the Test: The Results

 **Accuracy Score: 87.4%** *"We can explain 87.4% of why salaries differ"*

A. 💰 Prediction Accuracy

- **Average Error:** ₦8,158 (only 8% off!)
- **Typical Range:** Within ₦10,142 of actual salary
- **Translation:** Reliable enough for real decisions

B. ✓ Quality Check - No Cheating:

- Training: 87.8% accuracy
- Validation: 85.5% accuracy
- Test: 87.4% accuracy
- **Verdict:** Consistent and trustworthy across all groups



Our model hits the mark 87.4% of the time - that's like getting 9 out of 10 salary predictions right. With an average error of only ₦8,158, managers can make confident decisions. The consistency across different employee groups proves it's not just memorizing - it's truly learning

The Unexpected Discoveries Plot Twists We Didn't See Coming:

Experience > Education

- A seasoned high school graduate can out-earn a fresh PhD
- **Lesson:** We value practical skills over credentials

Suburban Premium

- Suburban roles command highest location premium
- **Lesson:** Work-life balance locations are in high demand

Gender Fairness

- Only ₦611 difference (statistically insignificant)
- **Lesson:** Our current system shows minimal gender bias

Age Paradox

- Slight negative age effect when controlling for experience
- **Lesson:** We might need to review how we value senior talent

The data revealed some surprises that challenged our assumptions. Who knew suburban locations would command the highest premium? Or that experience could outweigh education? These insights help us understand our organization better than ever before.

Recommendations

Turning Insights into Action: What We Should Do

 Immediate Actions

Use Model for Hiring

- Set fair salary ranges for new positions
- Reduce negotiation guesswork
- Attract competitive talent

Review Location Strategy

- Consider location-based salary bands
- Justify suburban/urban premiums
- Plan remote work compensation

Career Path Clarity

- Quantify promotion value (¥9,323 per level)
- Create transparent advancement expectations
- Motivate career development

Audit Current Salaries

- Identify potential underpaid talent
- Address any unexplained gaps
- Ensure internal equity

Data without action is just interesting numbers.

Here's our roadmap: Start using the model for new hires immediately, review our location strategy, and audit current salaries for fairness. These steps will make us more competitive and equitable."

What Could Go Wrong? Our Safeguards

⚠️ Potential Challenges & Our Solutions



Model Limitations:

- *Risk:* 12.6% of salary variation unexplained
- *Solution:* Use model as guide, not absolute rule

Changing Market:

- *Risk:* Job market evolves, model becomes outdated
- *Solution:* Refresh model quarterly with new data

Individual Uniqueness:

- *Risk:* Special cases don't fit standard patterns
- *Solution:* Allow manager discretion for exceptional circumstances

Over-reliance:

- *Risk:* Forgetting human judgment in decisions
- *Solution:* Model provides recommendations, humans make final calls

Next Steps & Future Enhancements

Looking Ahead: Making Our Model Even Better

More Data, Better Predictions:

- Add performance ratings
- Include industry/department data
- Expand to 2,000+ employee dataset

Technical Enhancements:

- Test 90/10 data split for better accuracy
- Explore advanced modeling techniques
- Add real-time market data

Advanced Analytics:

- Predict salary growth trajectories
- Identify high-risk retention cases
- Benchmark against industry

Timeline:

- Month 1-2: Implementation
- Month 3-4: Data collection expansion
- Month 5-6: Model enhancement and testing

This is just the beginning. We're planning to expand our dataset, add performance metrics, and create even more sophisticated predictions. Imagine predicting not just current salaries, but career growth trajectories and retention risks

Questions & Discussion

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"Let's Talk: Your Questions and Ideas"

Content:  **Common Questions We Anticipate:**

Q: What if the model predicts a salary we can't afford?

A: The model shows market rate - budget constraints are separate business decisions

Q: How often will we update the model?

A: Quarterly reviews with annual major updates

Q: What about confidential salary information?

A: All data is anonymized and access is strictly controlled

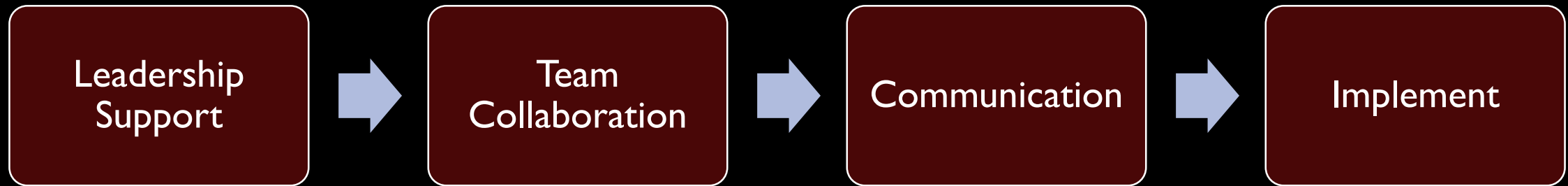
Q: Can managers override model recommendations?

A: Yes, with documented justification for transparency



Call to Action

Ready to Transform How We Think About Pay?



We have the insights, we have the tools, and we have the plan. What we need now is your commitment to making fair, data-driven compensation a reality. Are you ready to transform how we think about pay?

Thank you.