The Promotion Paradox

Fixing Biased Talent Promotion Decisions Through Data-Driven HR Analytics

a project report by Syntax Society

Dataset Phyton Code Github Interactive Dashboard

Our team

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Stage 1: Background.

The promotion paradox

Talent promotion is meant to fuel long-term organizational growth. When the system works, it strengthens efficiency, boosts retention, and builds trust across teams. Yet many organizations struggle to identify the right leaders. Chartered Management Institute (CMI) data shows low managerial engagement, weak trust, and widespread mismatches in leadership roles. This is not just a global issue. It also appears in Indonesia, including within Rakamin.

82%

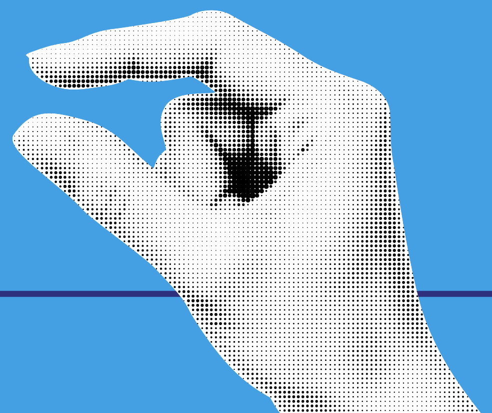
Around 82% companies fail to select the right leaders

31%

Only 31% managers are engage in their workplace

29%

Only 29% employees trust their managers



From our initial assessment, **three major problems emerge**:

1. Weak data integrity leads to slow and biased decisions.
2. Promotion criteria are unbalanced and unclear.
3. Ineffective promotion increases hiring costs.

Loss

47jt

The total cost per hire of 14 new employees at Rakamin.

14%

Save cost

If rakamin chooses to promote their employees instead of hiring

Source: Oculus.hr, Eos Global, Airswift, Salary

From bias to balance

The project aims to transform Rakamin's promotion system from a subjective, manual process into a fair, data-driven decision engine. By integrating machine learning with a real-time dashboard, HR can evaluate talent more accurately, reduce bias, and ensure leadership decisions truly support organizational growth.

Goal:
Develop a data-driven decision-support system that improves HR efficiency in monitoring talent performance and making fair, consistent promotion decisions.

Objectives:

- Build and validate ML models for promotion eligibility and employee characteristics.
- Integrate the models into a real-time insights interactive dashboard.
- Set up continuous monitoring to track system accuracy and impact.

Success Metrics

>95%

standardized and validated HR data.

>90%

model accuracy for promotion eligibility and employee characteristics.

24/7

Real-time, always-on dashboard access.

Stage 2: Data analysis.

Dataset characteristic

Initial description of Rakamin's dataset: 1000 rows and 10 columns, 2 categorical and 8 numerical features, 449 missing values. We also have Promotion_Eligible as target feature that are imbalance.

Descriptive statistic

Statistic	Age	Years_at_Company	Performance_Score	Leadership_Score	Training_Hours	Projects_Handled	Peer_Review_Score	Promotion_Eligible
count	950.0	951.0	950.0	950.0	950.0	950.0	950.0	950.0
mean	40.94	14.968454	2.969474	50.117895	109.286316	10.016842	51.227368	0.294737
std	12.863864	9.319084	1.417977	28.668058	184.616517	5.666507	29.141002	0.456165
min	-3.0	-5.0	1.0	0.0	-50.0	0.0	0.0	0.0
25%	31.0	7.0	2.0	25.0	51.25	5.0	25.0	0.0
50%	41.0	15.0	3.0	51.0	102.5	10.0	51.0	0.0
75%	50.0	23.0	4.0	75.0	150.75	15.0	78.0	1.0
max	200.0	100.0	5.0	99.0	5000.0	19.0	99.0	1.0

Data Type

Employee_ID	**object**
Age	**float64**
Years_at_Company	**float64**
Performance_Score	**float64**
Leadership_Score	**float64**
Training_Hours	**float64**
Projects_Handled	**float64**
Peer_Review_Score	**float64**
Current_Position_Level	**object**
Promotion_Eligible	**float64**

Observation

- There are 1000 rows and 10 column
- There are 2 categorical data and 8 numeric data
- There are 449 missing value
- There are no duplicate data

Baseline

Employees are eligible for promotion
Employees are not eligible for promotion

Target Feature

`Promotion_Eligible`

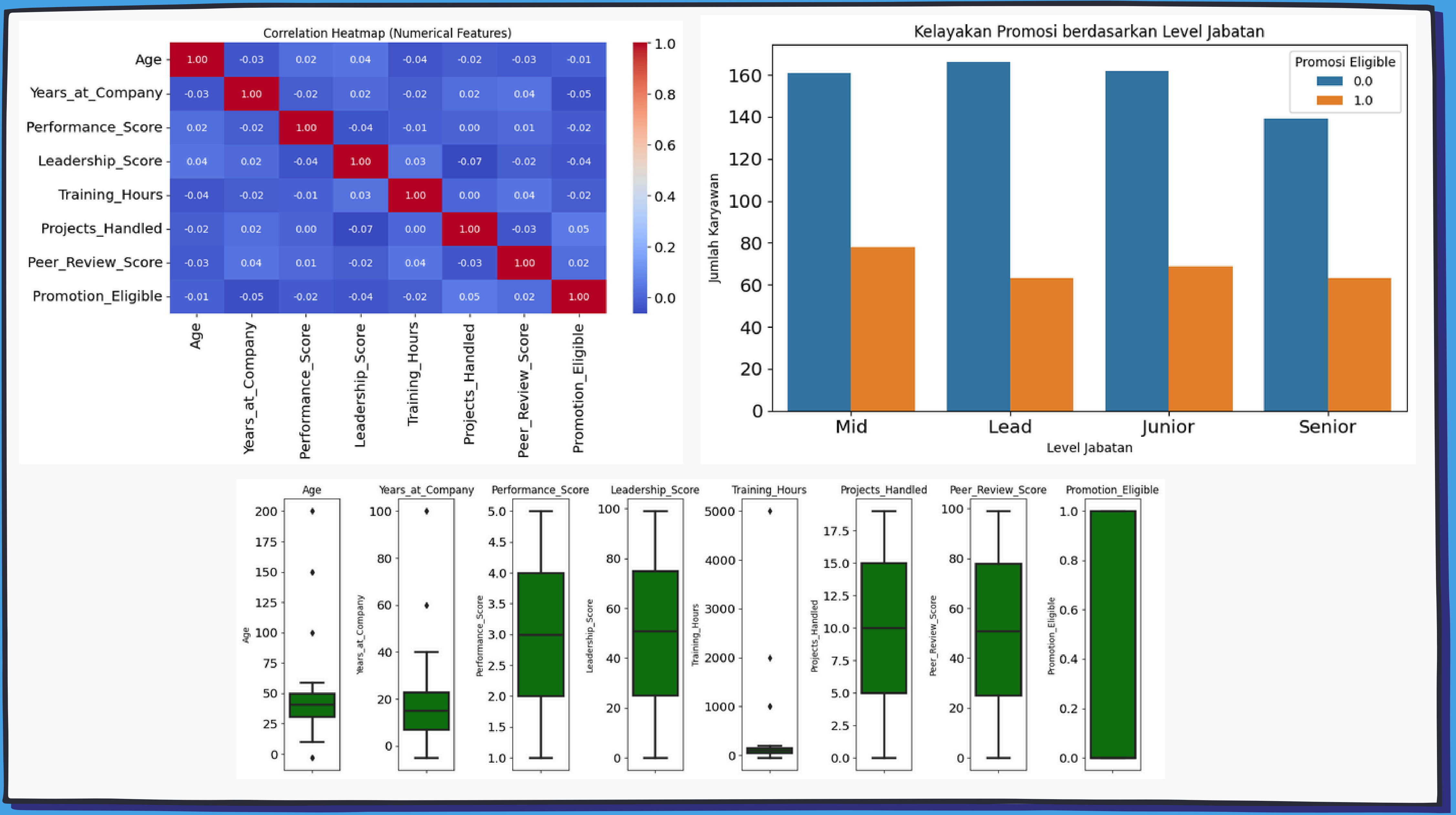
"1" **Employees eligible** for promotion

"0" **Employees not eligible** for promotion

Source: *Rakamin's Talent Promotion dataset*

Distribution & correlation

The data shows several **irregularities** in distribution, including outliers that disrupt normal patterns and indicate inconsistencies in data entry.



- About 1.3% of observations are outliers, contributing to skewed distributions and data quality issues.
- Promotion eligibility is low across all job levels, indicating system-level barriers rather than individual-level differences.
- Projects Handled and Peer Review Score show the highest correlation with promotion, but the associations are weak and not statistically meaningful.
- The weak correlations suggest that **current promotion criteria may not effectively capture true performance** or potential.

Source: Rakamin's Talent Promotion dataset

Data anomalies

The dataset contains several critical anomalies that affect data quality and reliability. These issues range from impossible values, such as negative ages, tenure exceeding age, or extreme training hours, to inconsistencies in leadership scores and job levels. Such anomalies indicate manual entry errors and undermine the validity of any HR decision-making process unless properly cleaned and standardised.

Implausible numbers of Training_Hours

Employee_Id	Training_Hours
EMP0345	-50
EMP0850	999
EMP0379	1000
EMP0394	2000
EMP0926	5000

Negative value in Age, also a lot of Years at Company that is bigger than Age.

Employee_Id	Age	Years_at_ Company
EMP0049	-3	20
EMP0036	22	24
EMP0061	23	29
EMP0095	23	29
EMP0117	23	27
EMP0137	24	26
EMP0164	24	28
EMP0097	26	27

Talents with extremely low Leadership_Score becomes Lead.

Employee_Id	Leadership_ Score	Current_Position _Level
EMP0016	1.0	Lead
EMP0153	1.0	Lead
EMP0366	0.0	Lead
EMP0488	0.0	Lead
EMP0608	1.0	Lead

Source: *Rakamin's Talent Promotion dataset*

Biased target feature

The data shows that promotion decisions rely too heavily on Projects Handled and Peer Review Score, even though both have weak correlations with actual promotion outcomes. These inconsistencies, where strong performers are labeled ineligible and weaker ones are promoted, indicate that the **Promotion_Eligible target itself is unreliable** and does not reflect real employee capability.

At least 418 row has bias related to target feature !!

Employee_ID	Projects_Handled	Peer_Review_Score	Promotion_Eligible
EMP0050	19	98	ya
EMP0324	19	94	tidak

Two employee has similar performance, but one is eligible and the other is not.

Employee_ID	Performance_Score	Leadership_Score	Peer_Review_Score	Promotion_Eligible
EMP0939	1	12	4	ya
EMP0939	5	96	90	tidak

The less qualified employee is the one who is eligible for promotion.

Source: Rakamin's Talent Promotion dataset

Stage 3:
Data preprocessing.

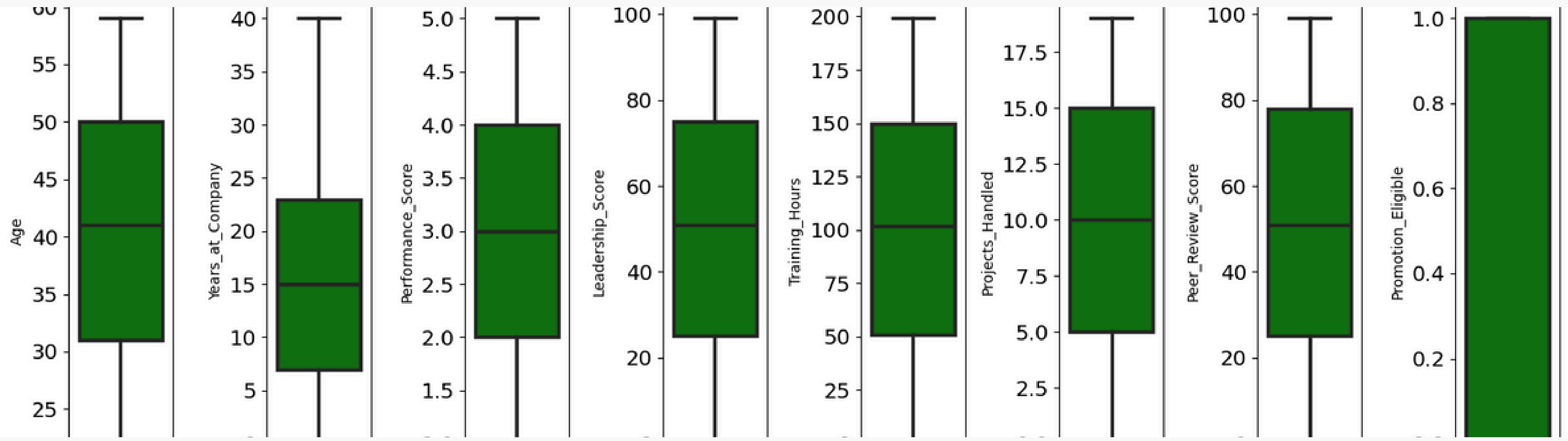
Data cleaning

To ensure the dataset was reliable for modeling, we cleaned missing values and removed invalid outliers. Numeric features were imputed using the median and categorical features using the mode, resulting in a fully complete dataset.

We also removed extreme outliers, particularly in Age and Training Hours, to restore a more realistic distribution and prevent distortion in the machine learning results.

	Feature	Missing Sebelum	Missing Sesudah
0	Employee_ID	0	0
1	Age	48	0
2	Years_at_Company	49	0
3	Performance_Score	50	0
4	Leadership_Score	49	0
5	Training_Hours	49	0
6	Projects_Handled	50	0
7	Peer_Review_Score	50	0
8	Current_Position_Level	50	0
9	Promotion_Eligible	49	0
10	TOTAL	444	0

```
Data columns (total 9 columns):
 #   Column                  Non-Null Count
---  ------                  --------------
 0   Employee_ID             1000 non-null
 1   Age                     950 non-null
 2   Performance_Score       950 non-null
 3   Leadership_Score        950 non-null
 4   Training_Hours          950 non-null
 5   Projects_Handled        950 non-null
 6   Peer_Review_Score       950 non-null
 7   Current_Position_Level  950 non-null
 8   Promotion_Eligible      950 non-null
dtypes: float64(7), object(2)
```



Source: [Rakamin's Talent Promotion dataset]

Feature selection

We selected features based on data reliability and their relevance to employee performance. Features with implausible values, weak conceptual links, or no predictive contribution were removed. We also identified that the **Promotion_Eligible target is biased and inconsistent, meaning it might cannot be used as a trustworthy ground truth** for modeling. However, we still use it for exploratory purposes.

DROPPED

- Employee_Id: Has no effect
- Age : Not reflecting employee quality
- Current_Position_Level: Does not reflect quality
- Years_at_Company: 295 (30%) of data are implausible
- Promotion_Eligible: 418 (40%) Biased and inconsistent

USED

- Performance_Score: Employee performance indicators
- Training_Score: Employee knowledge indicators
- Peer_Review_Score: Indicators of teamwork and skills.
- Project_Handled: Indicators of work experience.
- Leadership_Score: Leadership quality indicators.
- Promotion_Eligible: target feature.

Although their correlations are very low, these features are retained because they may still provide useful information once processed through feature engineering.

Source: *Rakamin's Talent Promotion dataset*

Feature engineering

We engineered six new composite features from the original data to better capture employee potential and performance. These features provide more reliable signals for our clustering and promotion logic than raw metrics alone. Details on how we use these to calculate **Promotion_Score and Eligible_New will be covered in the modeling stage.**

6 New features

We engineered 6 new features to capture deeper signals of performance, leadership, growth, and consistency, providing more reliable inputs for evaluating promotion readiness than the original raw features.

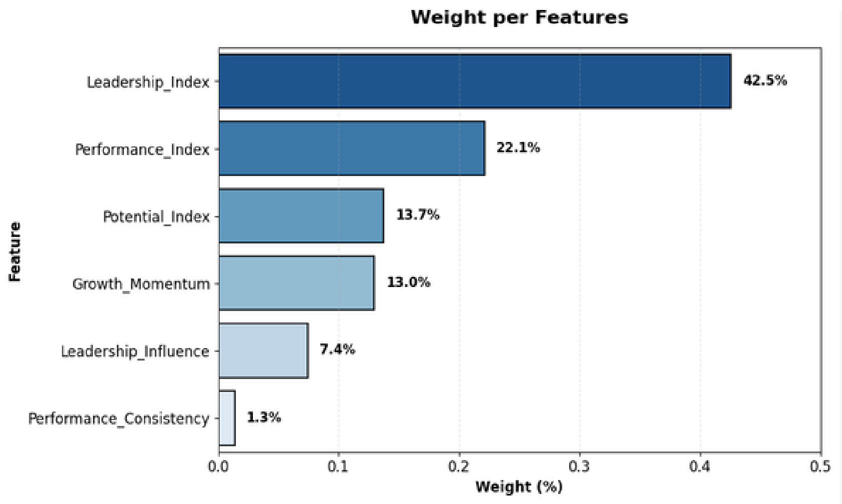
- **Leadership_Index:** Combines leadership and peer review signals to reflect influence and team perception.
- **Performance_Index:** Aggregates performance, experience, and training into a single quality indicator.
- **Potential_Index:** Measures motivation and perceived capability using behavioral and leadership factors.
- **Growth_Momentum:** Captures how quickly an employee converts training into tangible output.
- **Leadership_Influence:** Indicates how colleagues view and trust the employee in collaborative settings.
- **Performance_Consistency:** Highlights sustained performance and reliability over time.

Eligible_New

Promotion_Score > 0.85

Promotion_Score

$$Score = (w_1 \times X_1) + (w_2 \times X_2) + \ldots + (w_n \times X_n)$$



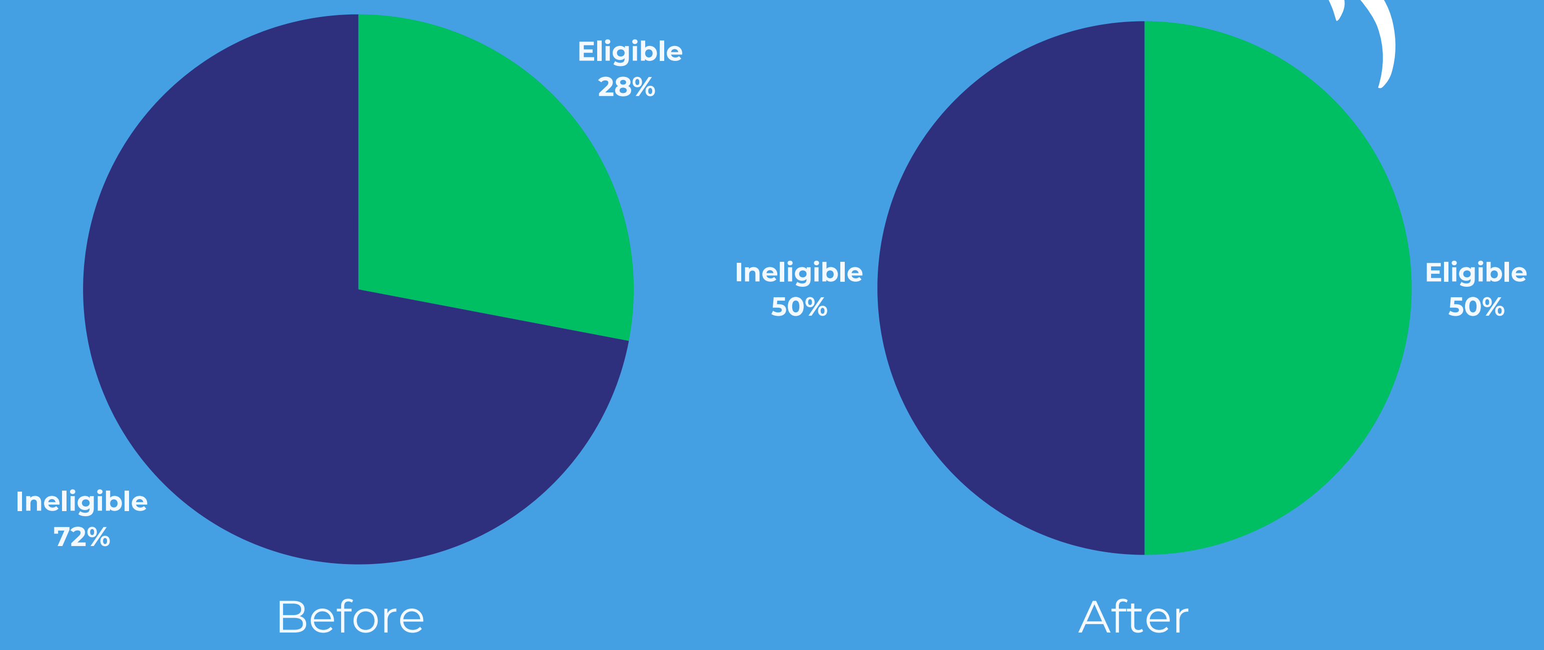
Source: Rakamin's Talent Promotion dataset

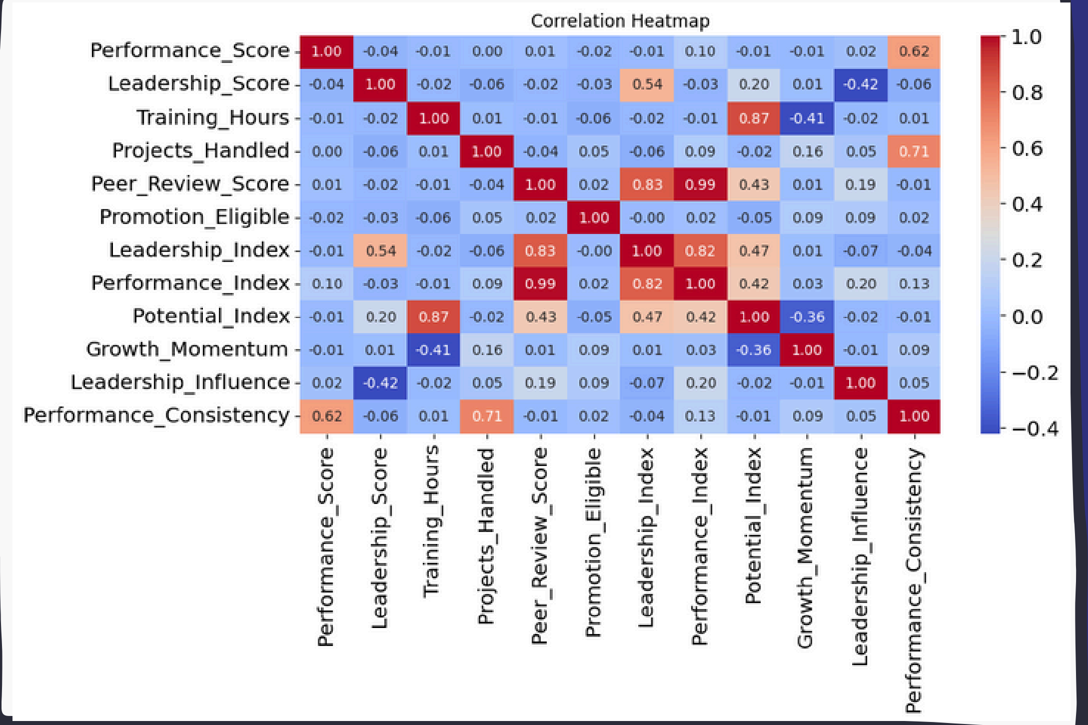
Data standarization

Performance_Score	Leadership_Score	Training_Hours	Projects_Handled	Peer_Review_Score	Promotion_Eligible	Leadership_Index	Performance_Index
-0.7010183561	-0.220183522	-1.03597658	1.627891733	0.3490112651	0	0.1723933596	0.4992035113
1.465699131	-0.1843396928	-0.6100273461	0.1782658027	-1.591787396	0	-1.443854664	-1.437583173
1.465699131	-1.116279251	-0.07759080319	-0.7277504037	1.231192475	0	0.4202841608	1.24591645
0.7434599685	0.03072328213	-1.497421584	-0.7277504037	0.03142602971	0	0.04349014299	-0.002494244397
0.7434599685	0.4966930612	-0.7697583089	1.084282009	0.2784367684	0	0.5095248492	0.4758687319
-1.423257518	0.926819011	0.7565597806	1.627891733	-0.6743189379	1	-0.05566617748	-0.574196338
0.7434599685	0.8909751819	-0.04209503367	-0.908953645	1.407628717	0	1.679569431	1.339255567
0.02122080619	0.6042245486	0.7920555502	-0.3653439211	-1.133053167	0	-0.6208572041	-1.169233211
-0.7010183561	0.8909751819	1.484223056	1.627891733	-0.5331699444	0	0.04349014299	-0.3758507137

Scaling all the numerical features using Standard Scaler.

Balancing the target feature using SMOTE.





Correlation map shows better signals and ready for modeling.

Source: *Rakamin's Talent Promotion dataset*

Stage 4: Modeling + Eval.

Development process

#1 EDA
Found anomalies, missing values, and a biased Promotion_Eligible target.

#2 Data preprocessing
Cleaned the data, removed unreliable features, and created seven new engineered features.

#3 Classification models
Run tree-based and linear models (DT, RF, XGBoost, Logistic Regression, SVM). Accuracy stayed below 85% because the Promotion_Eligible label was noisy and biased.

Supervised learning in which we are using Promotion_Eligible as target feature.

#4 Rule-based calculation
Defined a threshold to label new eligibility (Eligible_New).

#5 Clustering models
Run K-Means, GMM, K-Medoids; selected K=4 based on DBI and Silhouette scores. Used for talent segmentation in the dashboard.

Unsupervised learning to find employee's characteristics.

#6 Dashboard integration
Embedded K-Means for talent mapping and rule-based for promotion probability

ML modeling and evaluation

We explored supervised, unsupervised, and rule-based modeling to support fair promotion decisions. Model performance was assessed using ROC–AUC, F1, recall, and precision, with Silhouette Score and DBI used to validate clustering quality.

Tree-based & linear model (exploratory only)

Model: Decision Tree, Random Forest, XGBoost, Logistic Regression, SVM. **Evaluation metrics:** F1 Score, ROC-AUC.

Clustering model

Model: K-Means, GMM, K-Medoids
Evaluation metrics: Silhouette Score, DBI

Rule-based model

Model: Built from engineered features and weighted coefficients. Replaces the biased Promotion_Eligible target with an objective Promotion_Score.
Treshold: Promotion_Score > 0.85

NOTES: to validate our assumption regarding potential bias in Promotion_Eligible, we used this target feature within all classification model.

Treebased & linear model

We tested tree-based models, logistic regression, and SVM on the promotion eligibility task. The results were disappointing. All models was still unstable and didn't give us the confidence to deploy. This taught us that no algorithm can fix a broken ground truth, which is why we pivoted to rule-based logic instead.

Classification Model	F1 Score	ROC-AUC	Outcome
Tree-based (DT, RF, XGB)	17–27%	48–59%	Weak patterns; struggled even after tuning
Logistic Regression	35–40%	52–55%	Weak patterns; struggled even after tuning
SVM	41–60% (unstable)	Peaked at 59%	Best performer, but not strong enough for reliable prediction

Best tree-based: Random Forest

Train	Pred 0	Pred 1
Actual 0	412	156
Actual 1	38	183

Test	Pred 0	Pred 1
Actual 0	85	58
Actual 1	30	25

Best linear: SVM

Train	Pred 0	Pred 1
Actual 0	227	270
Actual 1	51	142

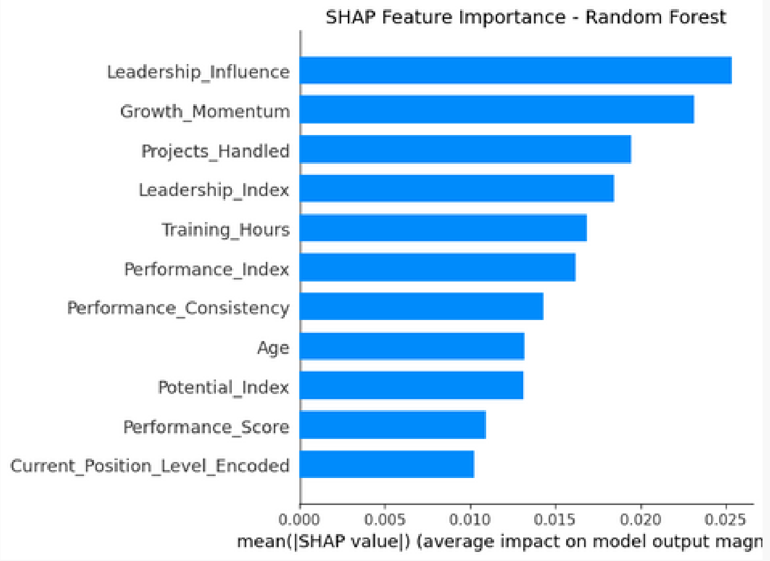
Test	Pred 0	Pred 1
Actual 0	87	127
Actual 1	40	43

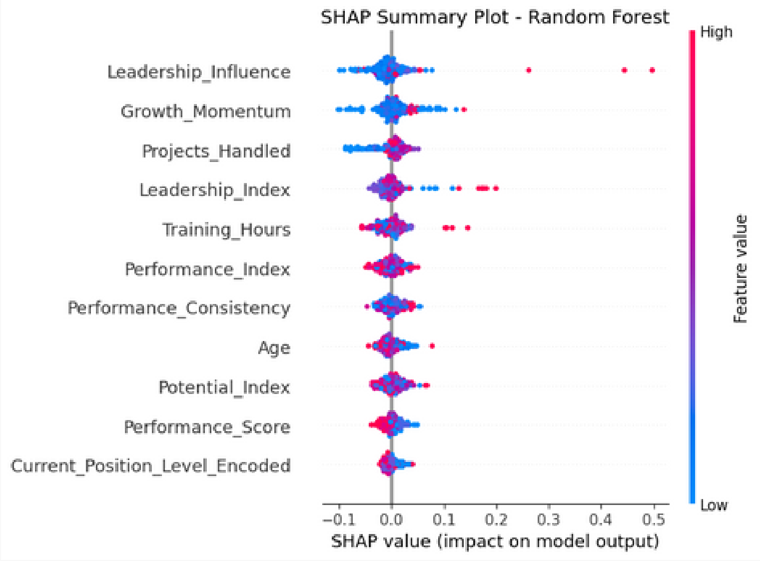
- **Tree-based models:** weak patterns, even after tuning.
- **Logistic Regression:** low signal, struggled to learn any meaningful pattern.
- **SVM:** best result but still unstable and insufficient for deployment.
- **Overall:** most metrics fell below 50%, confirming that the target label is unreliable.

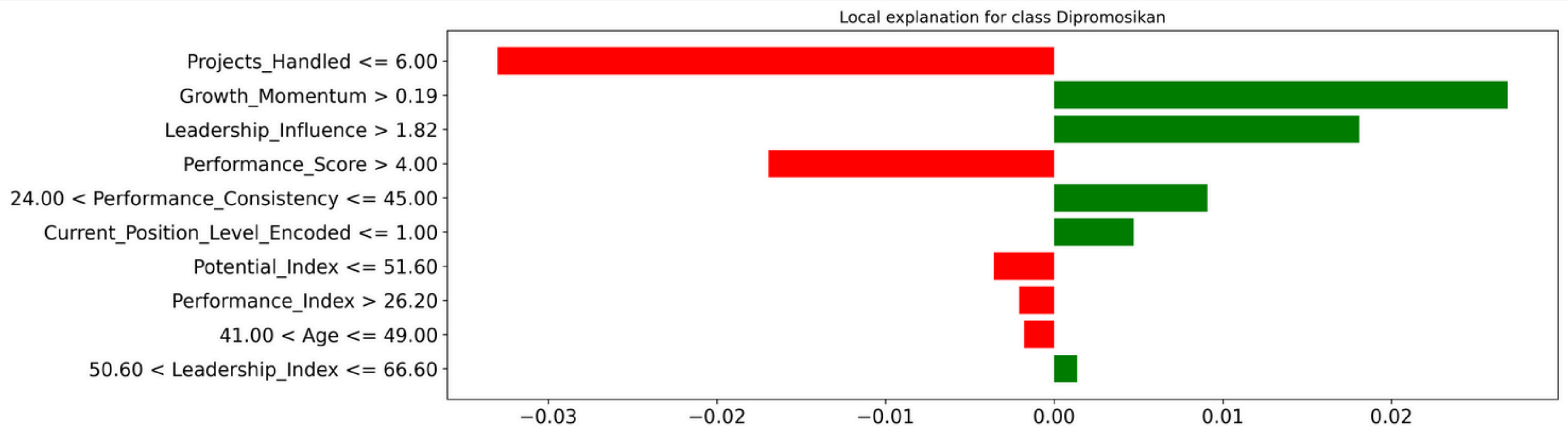
Feature importance

So did we just discard those experiments? No. The tree-based and linear models taught us which features are truly predictive. This knowledge became the foundation for our clustering and rule-based approach, ensuring our logic is grounded in real feature importance.

SHAP & LIME







The SHAP results show that leadership and growth-related features, especially Leadership Influence, Growth Momentum, and Projects Handled are the strongest global drivers of the promotion predictions.

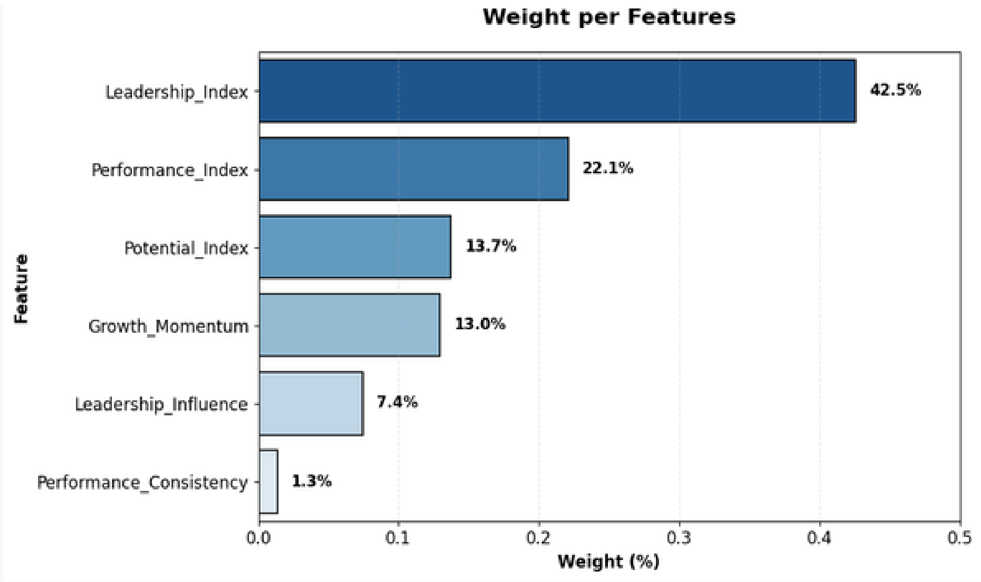
The LIME shows that for the selected employee, strong growth and leadership indicators support the promotion prediction, while low project count and inconsistent performance reduce it.

Rule-based model

We built a transparent rule-based system instead of a black-box model. It combines our features with weights, Leadership Influence (42.3%), Performance Index (22.1%), and others into a single Promotion Score. Scores above 0.85 indicate promotion readiness. Every recommendation is explainable and auditable by HR.

Promotion_Score

$$Score = (w_1 \times X_1) + (w_2 \times X_2) + \ldots + (w_n \times X_n)$$



Eligible_New

Promotion_Score > 0.85

	JUNIOR	LEAD	MID	SENIOR
1	42	32	42	32
0	196	207	254	182

Our rule-based threshold is backed by data. Industry standards show 6-8% is healthy, 8-12% is good, and tech companies average 14% promotion rates. Our system is tuned to match these realistic benchmarks, not arbitrary thresholds.

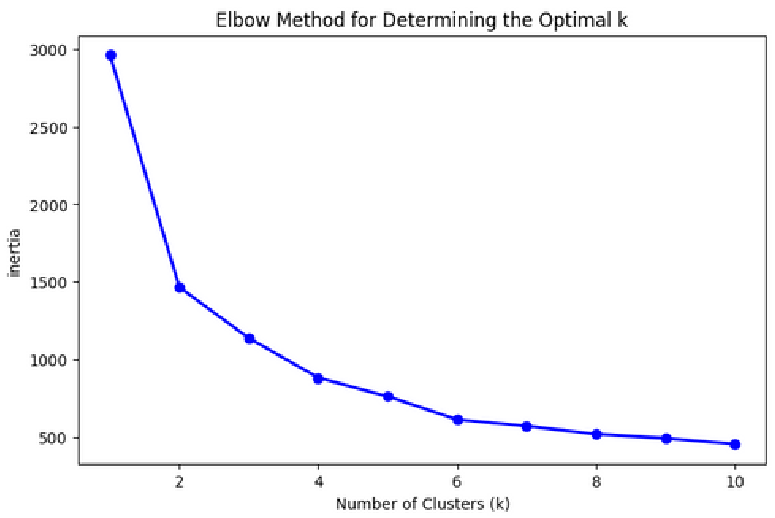
Source: taggd.in, pave.com, aihr.com

Clustering model

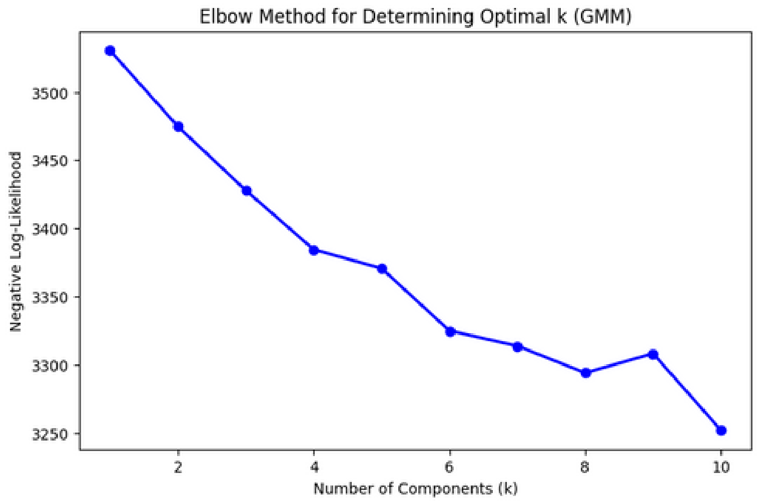
Criteria	K-Means	GMM	K-Medoids
Best K	K = 4	K = 5	K = 5
Silhouette Score	0.320	0.247	0.293
DBI Score	1.00	1.173	1.071
Key Observation	Clearest and most compact clusters.	Lowest performance, overlapping clusters.	Fairly good and stable but not as good as K-Means.

We tested three clustering algorithms: K-Means, GMM, and K-Medoids. K-Means with K = 4 won. It has the highest Silhouette Score (0.320) and best DBI (1.00), with clear, well-separated, and compact clusters. The elbow plots confirm K = 4 is optimal. This interpretability and cluster quality make K-Means perfect for segmenting employee talent profiles.

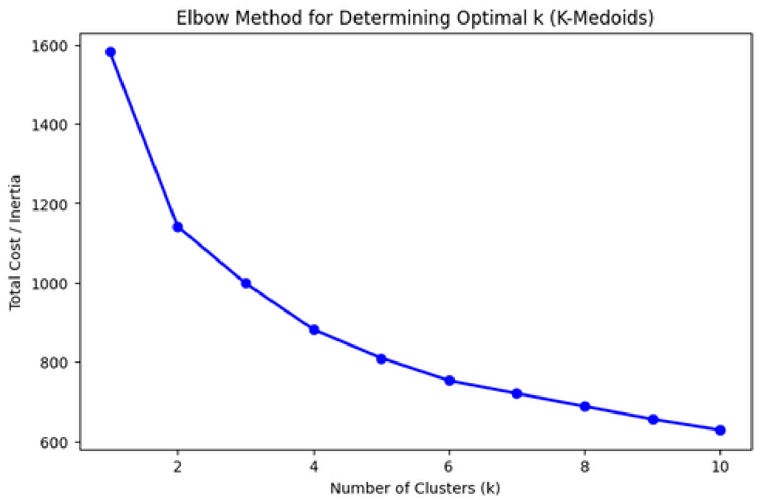
Elbow K-Means



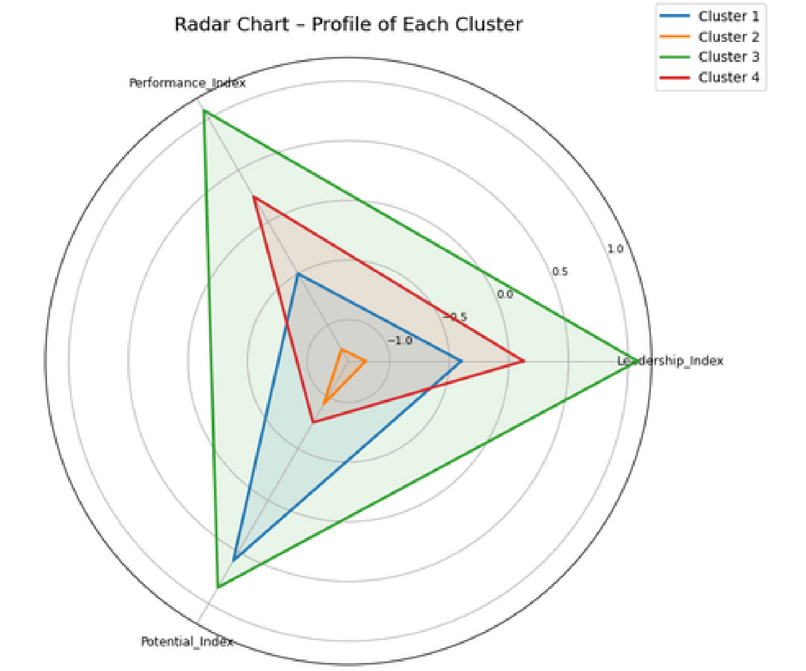
Elbow GMM



Elbow K-Medoids

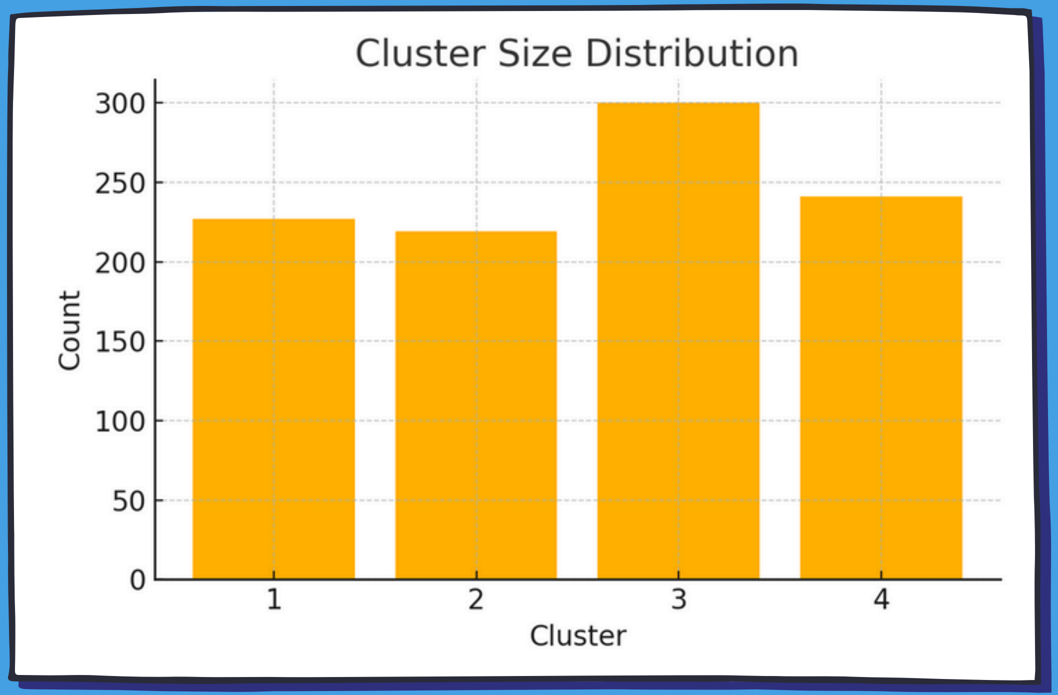


Radar Chart K = 4



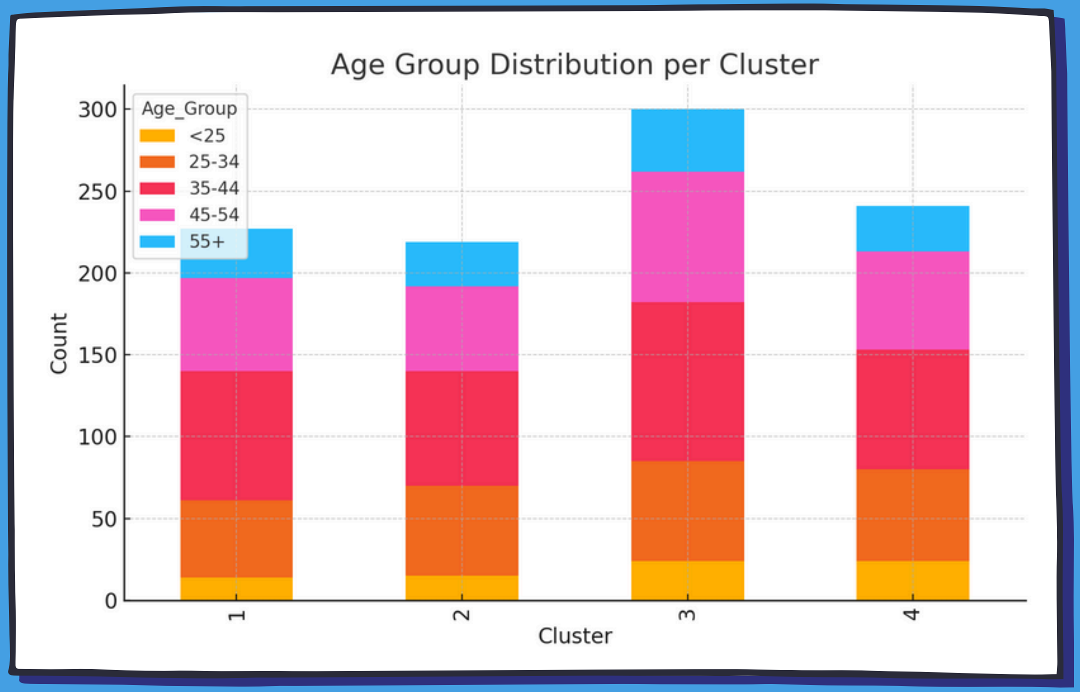
Clustering bias analysis

We validated that K-Means didn't introduce bias. Cluster sizes are balanced, age is evenly distributed, and job levels are mixed, meaning the model segments based on actual performance and capability, not demographics.



Cluster Size Distribution

All four clusters are well-balanced in size. This is important because it means K-Means didn't favor one group over another, reducing bias and ensuring fair representation across all segments.



Age Group Distribution Across Clusters

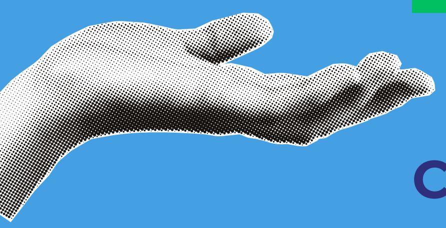
Age is evenly distributed across clusters—we see early, mid, and senior-career employees in each segment. This tells us the clustering is driven by actual performance and capability, not by age bias.

Job Level Distribution per Cluster

Job levels are also balanced across clusters. While some roles appear slightly more in certain segments, no cluster is dominated by a single job tier. The model captured behavioral differences and capability signals rather than just replicating the organizational hierarchy.

Cluster interpretation

K-Means with K=4



Cluster 1: Under Developed With Potential

Technical: Moderate scores in Performance (-0.50) and Leadership (-0.39), but relatively higher scores in Potential (0.58). Stable and fairly consistent, but has yet to demonstrate strong execution skills.
Business: Moderate performance and leadership, but high potential.

Cluster 2: At-Risk & Underpowered

Technical: Lowest values across all three indexes, which are performance (-1.23), leadership (-1.20), and potential (-0.93). Shows stagnation and lack of momentum.
Business: Low across all metrics. They need immediate intervention, such as reskilling, reassignment, or transition planning.

Cluster 3: All Around Top Performer

Technical: Achieves the highest scores in performance (1.08), leadership (1.08), and potential (0.84); highly adaptive and shows strong momentum.
Business: The best candidates for career acceleration and leadership pipeline. A strategic source of potential for the organization's future.

Cluster 4: Consistent Performer or Leader

Technical: Demonstrates consistent execution with average performance (0.24) and leadership (0.12), but low potential (-0.75). This means they are reliable in their day-to-day work but do not yet show strong signs of long-term growth.
Business: Stable execution and reliable. They're the backbone of operations. Keep keep them engaged and valued.

Final models to be utilized

K-Means model

K-Means (k = 4) segments employees into four talent groups, providing HR clear, interpretable categories for decision-making. Clustering turns scattered employee data into structured talent profiles with distinct strengths and risks.

+

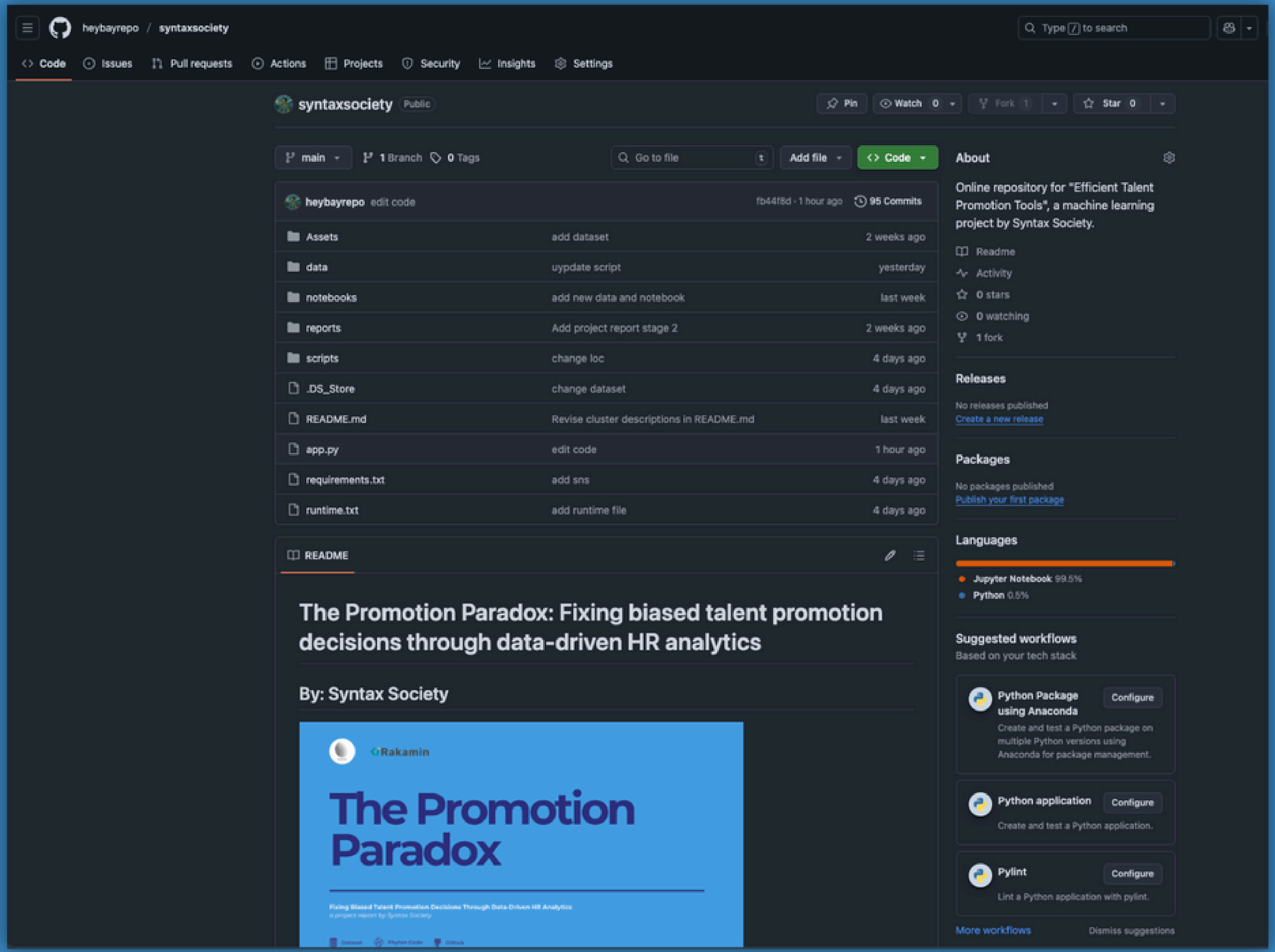
Rule-based

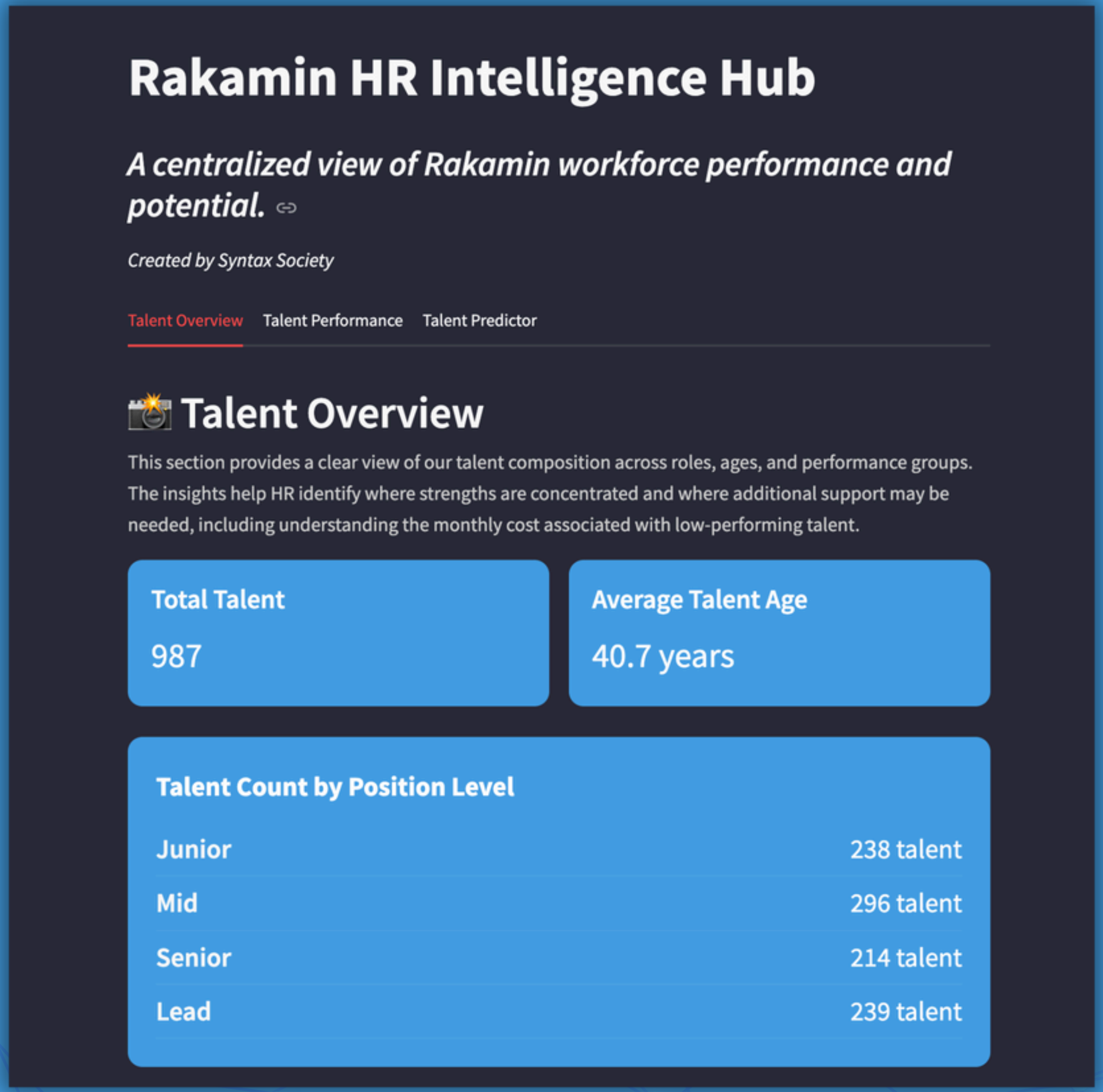
The rule-based method calculates a promotion score using weighted features: Leadership Influence (0.425), Performance Index (0.221), Performance Consistency (0.137), Growth Momentum (0.130), Leadership Index (0.074), and Potential Index (0.013). This transparent, non-black-box approach ensures promotion decisions are explainable and consistent.

Stage 5: Deployment.

From Github to Streamlit

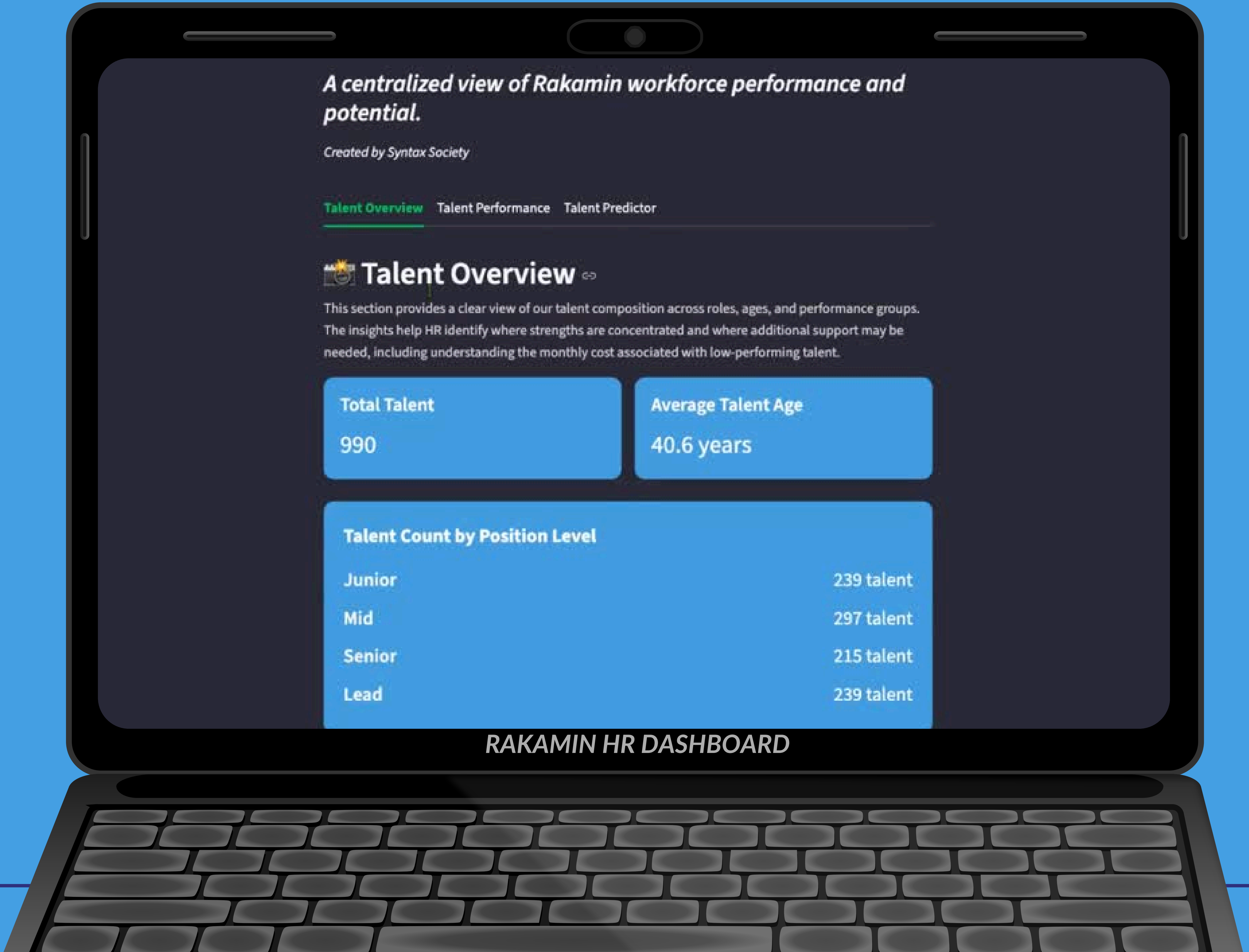
We built the dashboard on Streamlit with GitHub integration. Updates deploy automatically with each code push. The key design philosophy: keep it simple for non-technical users. Clean interface, clear metrics, intuitive workflows. And simplicity enables scalability: easier to maintain, modify, and expand as your needs grow. Check our prototype at https://rakaminhrdashboard.streamlit.app/





Source: Streamlit

App features



Tab 1: Talent Overview. Shows a snapshot of the workforce: total talent, position-level distribution, and potential attrition indicators.

Tab 2: Talent Performance. Displays top and bottom performers across key indexes (performance, leadership, potential) with optional filters for deeper exploration.

Tab 3: Talent Predictor. ML-powered clustering that reveals each employee's group, traits, and risks. Users can input data manually or upload records via CSV.

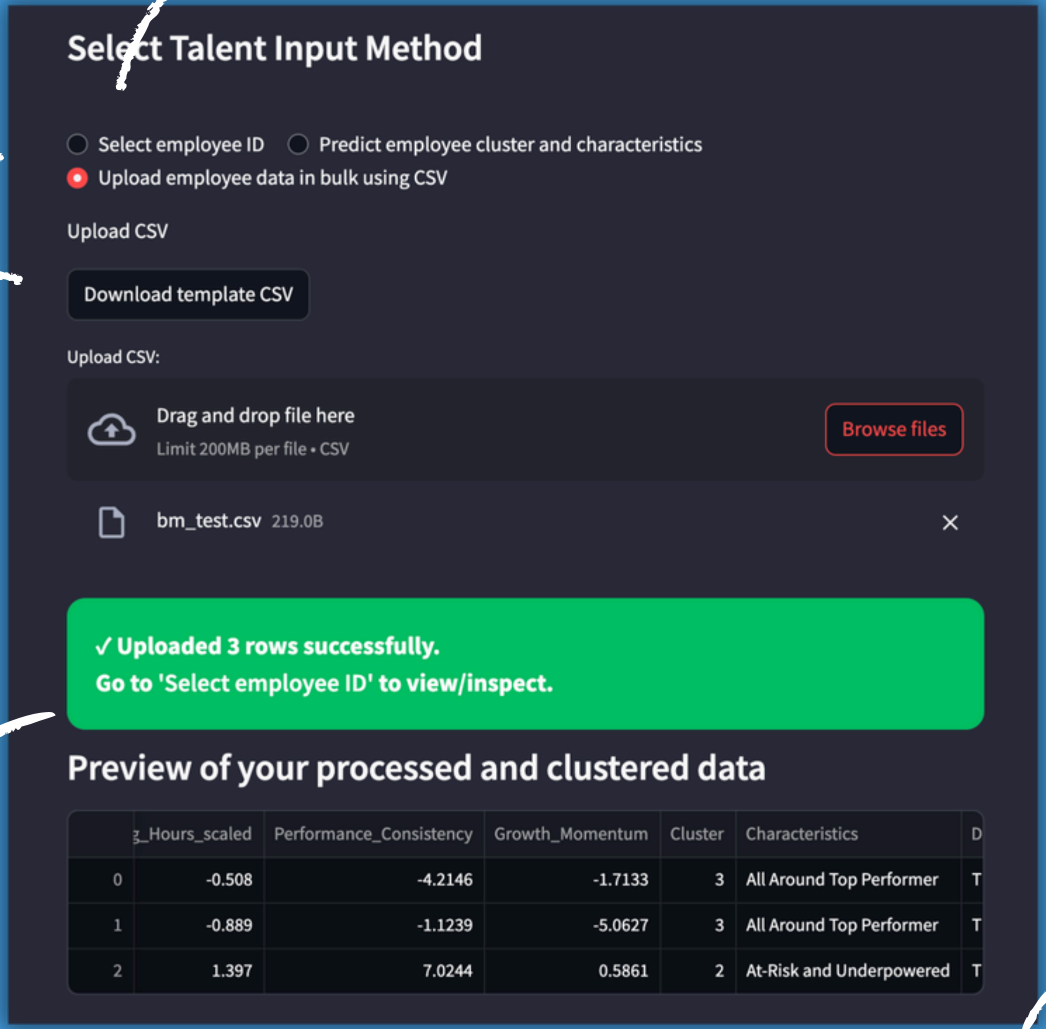
Source: Streamlit

Flexibility & scalability

HR can choose to upload their own dataset

Select employee ID to see specific employee. We're not using name because it is not in the dataset.

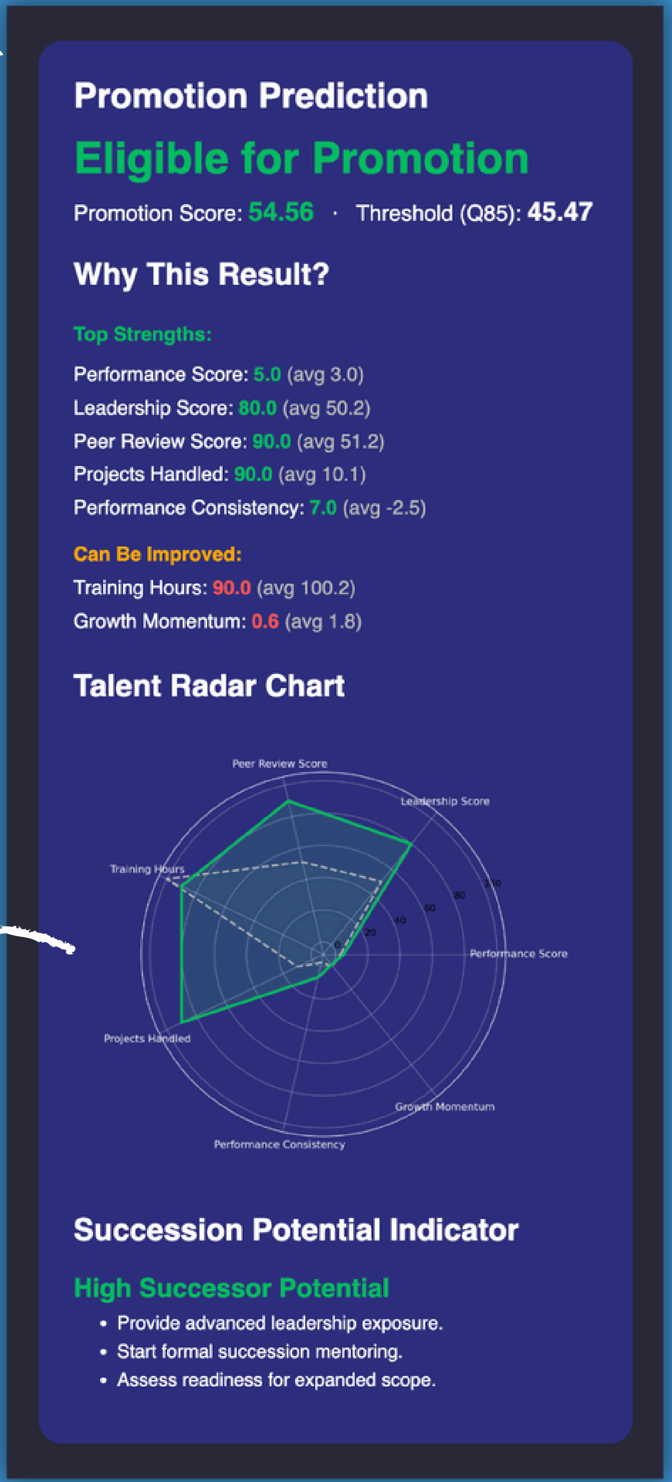
Use the provided CSV template to ensure uniformity



Data upload success notification

Browse uploaded data instantly on any device

Promotion eligibillity calculator can predict employee's readiness, strength and aspects that need to be improved.



Radar chart is shown for quick assessment of employee's quality.

Source: Streamlit

Model usage flow

#1 Talent data input

HR selects an employee or uploads a CSV file containing performance, leadership, and development metrics.

#2 Automated processing

The system applies feature engineering to compute key talent indexes such as performance, leadership, and potential.

#3 Talent clustering

Based on these indexes, the model groups employees into distinct talent clusters to highlight strengths, risks, and development profiles.

#4 Eligibility prediction

The rule-based model evaluates each employee and predicts their promotion readiness using combined performance–potential indicators.

#5 Insight delivery

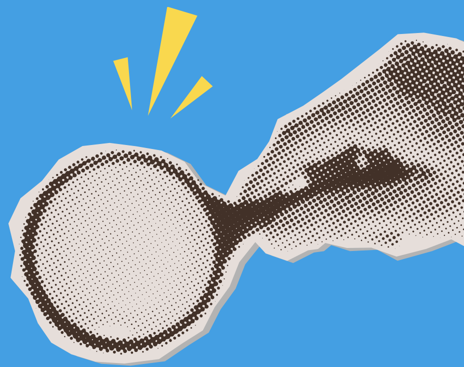
The app displays clusters, key indexes, and promotion eligibility, along with recommended focus areas for HR decision-making.

#6 HR action & decision

HR uses these insights to identify promotable employees, develop top performers, and intervene early with high-risk talent.

Monitoring & retraining

We continuously monitor three things: shifts in employee data patterns (data drift), the health of the cluster structure, and how well the system's recommendations align with actual promotion decisions. When any metric crosses its threshold, it triggers a deeper analysis.



Monitoring strategy

Data drift

- Metric: Population Stability Index (PSI)
- PSI < 0.1 → Stable
- 0.1–0.25 → Run EDA
- > 0.25 → Retrain cluster

Cluster stability

- Metrics: Silhouette & DBI
- Silhouette decrease > 10% → EDA
- DBI increase > 15% → EDA
- Both degrade → Retrain model
- Cluster size shift > ±20% → Retrain

Rule drift

- Check % mismatch between rule output & actual promotions
- >10% mismatch → Review rules
- >20% mismatch → Update rules

Maintenance

Monthly: drift check
Quarterly: cluster & rule review
Semester: retrain if triggered
Annualy: audit system

Retraining Framework

- Refresh latest employee data
- Run EDA + drift analysis
- Refit clustering model
- Recompute Silhouette & DBI
- Update cluster profiles
- Review/update rule logic (if needed)
- Deploy + document changes

Stage 6: Impact.

Business impact

Talent management isn't just about fairness. It's about money. Every time you promote someone who isn't ready, you're paying a senior-level salary for below-par performance. Every time you pass over someone capable, you risk losing them.

⚠️ High Risk Talent

These employees fall into lower performance ranges and may need targeted development, mentoring, or closer support.

Select ranking category: Low Performing

Filter by Position Level: All Levels

Employee_ID	Current_Position_Level	Performance_Index	Performance_Score	Cluster
EMP0010	Mid	1	1	1
EMP0178	Senior	1.3	1	1
EMP0974	Junior	1.8	1	1
EMP0910	Mid	2.1	1	1
EMP0810	Lead	2.6	3	1
EMP0241	Lead	2.7	1	1
EMP0939	Junior	2.7	1	1
EMP0251	Lead	2.8	2	1
EMP0656	Senior	2.8	4	1
EMP0829	Mid	3.1	3	1

Most of the workforce is in the Average Talent category, followed by High Performing Talent, and a fairly large proportion is Low Performing Talent at 219 employee which is the main cause of the estimated loss.

AVG salary based on Dealls!

Level	AVG Salary
Junior	Rp6.500.000
Middle	Rp11.500.000
Senior	Rp22.500.000
Lead	Rp27.500.000

Save 3.5 billions!

22%

Saving by not paying incompetent employees

42%

Improved accuracy in previously biased determinations of promotion eligibility.

Source: Dealls!

Business recommendation

Action items

#1 Overhaul eligibility determination system.
Update it using reliable and reasonable metric calculations to minimize potential bias with online-based data collection.

#2 Conduct a rigorous performance review.
Specifically for employees who fall into Cluster 2 (At-Risk & Underpowered) and make a decision between skill development or, at the worst, employment termination.

#3 Leverage the result of the Talent Clustering.
Identify and map existing skills gaps. Focus development interventions on Clusters 1 and 2 to address the identified gaps. For Clusters 3 and 4, provide targeted training for retention.

Strategic roadmap

Next-Phase Opportunities

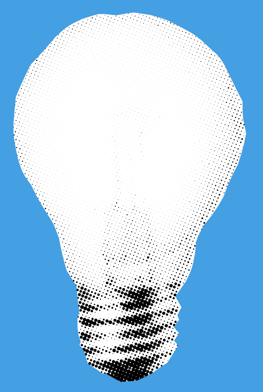
Expand predictive models to additional HR domains like attrition risk, promotion readiness

Scalability & Integration Roadmap

Develop APIs for payroll and attendance systems to enable real-time data flow.

Future Capability Development

Create targeted upskilling programs aligned with model insights and skill gaps.



Thank You!

The Promotion Paradox:

Fixing biased talent promotion decisions through data-driven HR analytics

A project proposal by Syntax Society | Rakamin - Data Science batch 59