4. RESULTS AND DISCUSSION

4.1 AHP Results per Function and Final Weightings

Eight sets of pairwise comparisons are conducted to get the weightings of each potential criterion in each function. The pairwise comparison matrices for each function are presented in the table below:

Table 4.1

Pairwise Comparison for P&T

	Training	Assess	Education	PDP
Training	1.00	3.00	5.00	0.33
Assess	0.33	1.00	1.00	0.20
Education	0.20	1.00	1.00	0.20
PDP	3.00	5.00	5.00	1.00

Table 4.2

Pairwise Comparison for F&A

	Training	Assess	Education	PDP
Training	1.00	1	0.33	0.25
Assess	1	1.00	0.5	0.5
Education	3	2	1.00	1
PDP	4	2	1	1.00

Table 4.3

Pairwise Comparison for Non-Sales

	Training	Assess	Education	PDP
Training	1.00	3	3	0.5
Assess	0.33	1.00	1	0.5
Education	0.33	1	1.00	0.25
PDP	2	2	4	1.00

Table 4.4

Pairwise Comparison for Other

	Training	Assess	Education	PDP
Training	1.00	0.5	0.5	0.2
Assess	2	1.00	0.5	1
Education	2	2	1.00	1
PDP	5	1	1	1.00

Table 4.5

Pairwise Comparison for Distribution

	Training	Assess	Education	PDP
Training	1.00	4	4	1
Assess	0.25	1.00	1	0.25
Education	0.25	1	1.00	0.25
PDP	1	4	4	1.00

Table 4.6

Pairwise Comparison for T&C

	Training	Assess	Education	PDP
Training	1.00	0.5	0.33	0.2
Assess	2	1.00	1	0.33
Education	3	1	1.00	0.5
PDP	5	3	2	1.00

Table 4.7

Pairwise Comparison for Human Capital

	Training	Assess	Education	PDP
Training	1.00	0.33	0.33	0.33
Assess	3	1.00	0.5	0.5
Education	3	2	1.00	0.5
PDP	3	2	2	1.00

Table 4.8

Pairwise Comparison for Sales

	Training	Assess	Education	PDP
Training	1.00	3	4	0.33
Assess	0.33	1.00	1	0.2
Education	0.25	1	1.00	0.2
PDP	3	5	5	1.00

Table 4.9

Final Weights and Consistency Ratios for Potential Criterias in Each Function

Functions	Training	Assessment	Education	PDP	CR
P&T	28.24%	9.31%	8.57%	53.88%	4.36E-02
F&A	12.16%	15.90%	34.58%	37.36%	1.73E-02
Commercial Non-Sales	31.42%	14.18%	11.40%	43.00%	4.45E-02
Distribution	40.00%	10.00%	10.00%	40.00%	-1.68E-16
HC	9.81%	20.81%	28.75%	40.63%	4.58E-02
Sales	26.85%	9.48%	9.02%	54.65%	2.85E-02
T&C	8.93%	18.96%	23.28%	48.83%	9.35E-03
Other	10.22%	14.19%	29.63%	45.96%	6.32E-02

The tables presented above illustrate eight pairwise comparisons of four potential criteria across eight functions. Through each of the eight pairwise comparison matrices, the consistency test is performed for each function to test its logical coherence and validate the results for each AHP matrix. The consistency ratio is calculated as shown on the table above, indicating that all sets of pairwise comparison matrices are acceptable given their value is less than 0.1. Preference values of each criterion in each function are consistent.

The final sets of criteria weightings are illustrated in Table 4.9. As previously mentioned, a notable highlight from the results has illustrated that Personalized Development Plan (PDP) is consistently rated highly across functions. The highest PDP weights are found in the Production & Technical (53.88%) and Sales functions (54.645%). Education is weighted significantly higher in functions such as F&A (34.58%) and HC (28.75%) functions. This emphasis suggests that employees in functions such as F&A and HC value formal qualifications and specialized knowledge, which are often essential for roles demanding critical thinking and analytical skills, in contrast to positions that primarily rely on practical skills and experience. In some functions, such as Sales, Distribution, Commercial Non Sales, and P&T, training is valued higher than education due to the practical nature of their roles. Employees in sales need training on Price Negotiation (Price increase) to enhance their skills in raising product prices, effectively to drive higher sales. Similarly, PT XYZ also does training on preventive maintenance measures within Production & Technical functions for positions like production operator and maintenance operator. For the evaluation of competencies and foundational skills, assessment is emphasized more on Human Capital, Technology & Compliance, and Finance & Accounting.

Generally, the different weight distributions across functions reflect the unique skills and required capabilities within each function.

4.2 AHP-TOPSIS Results

Criteria weights from AHP for each function are then implemented in the TOPSIS methods. For each function, we iterate and do the following TOPSIS algorithm in RStudio:

Algorithm 1 TOPSIS Algorithm

```
procedure TOPSIS(Function_IDs, merged_data)
  results_list ← ∅
  for function_id ∈ Function_IDs do
    subset_data ← merged_data[merged_data$Function_ID = function_id]
    criteria ← subset_data[Training.Full.Score, Assessment.x, Education.Level.Score, PDP.Score]
    weights ← subset_data[Training, Assessment.y, Education, PDP]
    norm_factors ← √(Σ(criteria² for each column))
    normalized_criteria ← criteria ÷ norm_factors
    weighted_normalized_criteria ← normalized_criteria × weights
    ideal_solution ← max(weighted_normalized_criteria for each column)
    negative_ideal_solution ← min(weighted_normalized_criteria for each column)
    distance_to_ideal ← √(Σ((weighted_normalized_criteria - ideal_solution)² for each row))
    distance_to_negative_ideal ← √(Σ((weighted_normalized_criteria - negative_ideal_solution)² for each row))
    closeness_coefficient ← distance_to_negative_ideal ÷ (distance_to_ideal + distance_to_negative_ideal)
    if length(closeness_coefficient) = nrow(subset_data) then
      results ← dataframe(Employee.No., Employee.Name., closeness_coefficient, distance_to_ideal, distance_to_negative_ideal)
      results ← sort(results by closeness_coefficient descending)
      results_list[function_id] ← results
    else
      log("Mismatch in row numbers for Function_ID =", function_id)
    end if
  end for
  return results_list
end procedure
```

Figure 4.1 Pseudo-Code of TOPSIS Algorithm in RStudio

The pseudo-code above explains the algorithm of the TOPSIS method. The code iteratively repeats after 8 functions, so we expect to get 8 results lists. As an example, the results from the algorithm for each function are as follows , shown in Table 4.10**.** The table shows an example of the weighted normalized matrix of 5 employees for each function using the formula stated above. The weighted normalized matrix is derived from each normalized employee data point from the decision matrix, which are attributed to the specific weightings of each criterion based on each function.

Table 4.10

Weighted Normalized Matrix Potential Criterias for Each Function

Function	ID	Train	Assess	Edu	PDP	Function	ID	Train	Assess	Edu	PDP
1	258	0.072	0.004	0.002	0.016	5	1700	0.005	0.032	0.039	0.106
	385	0.072	0.003	0.005	0.016		1712	0.005	0.028	0.039	0.106
	388	0.072	0.005	0.002	0.016		1725	0.005	0.033	0.039	0.106
	471	0.114	0.004	0.004	0.016		1748	0.005	0.033	0.039	0.106
	527	0.072	0.004	0.004	0.016		1752	0.005	0.032	0.043	0.106
2	672	0.004	0.009	0.018	0.050	6	1844	0.030	0.005	0.005	0.079
	730	0.004	0.009	0.018	0.050		1963	0.030	0.006	0.005	0.079
	749	0.004	0.010	0.018	0.050		1985	0.048	0.005	0.005	0.059
	768	0.045	0.008	0.018	0.050		2026	0.030	0.005	0.005	0.079
	918	0.045	0.007	0.018	0.013		2078	0.028	0.005	0.004	0.079
3	1139	0.082	0.006	0.003	0.016	7	2117	0.001	0.014	0.018	0.095
	1151	0.082	0.007	0.003	0.016		2161	0.001	0.015	0.018	0.095
	1224	0.082	0.007	0.005	0.016		2200	0.002	0.016	0.018	0.095
	1460	0.082	0.006	0.007	0.048		2226	0.002	0.013	0.018	0.095
	1511	0.082	0.005	0.003	0.016		2299	0.001	0.015	0.018	0.095
4	1639	0.012	0.016	0.015	0.046	8	2318	0.005	0.013	0.030	0.123
	1644	0.145	0.016	0.015	0.046		2333	0.005	0.013	0.030	0.123
	1650	0.145	0.014	0.015	0.046		2355	0.005	0.013	0.030	0.123
	1672	0.229	0.011	0.015	0.046		2397	0.005	0.017	0.030	0.093
	1683	0.012	0.016	0.015	0.046		2399	0.005	0.014	0.030	0.123

Table 4.11

PIS and NIS of Each Potential Criteria for Each Function

Function	Training		Assessment		Education		PDP	
	V+	V-	V+	V-	V+	V-	V+	V-
1	0.1195	0.0000	0.0069	0.0003	0.0056	0.0006	0.0626	0.0157
2	0.0753	0.0000	0.0143	0.0007	0.0202	0.0022	0.0501	0.0125
3	0.1373	0.0000	0.0117	0.0006	0.0080	0.0009	0.0640	0.0160
4	0.2415	0.0000	0.0249	0.0010	0.0172	0.0018	0.1860	0.0370
5	0.0931	0.0000	0.0468	0.0023	0.0434	0.0048	0.1062	0.0266
6	0.0502	0.0000	0.0091	0.0005	0.0056	0.0006	0.0786	0.0196
7	0.0150	0.0000	0.0237	0.0012	0.0200	0.0022	0.0948	0.0237
8	0.0931	0.0000	0.0236	0.0012	0.0338	0.0038	0.1234	0.0308

Table 4.12

Closeness Coefficient of Employees for Each Function

Function	ID	Pi	Si+	Si-	Rank	Function	ID	Pi	Si+	Si-	Rank
1	471	0.7052	0.0475	0.1136	1	5	1752	0.5102	0.0897	0.0934	1
	527	0.5170	0.0671	0.0718	2		1725	0.5060	0.0897	0.0919	2
	385	0.5170	0.0671	0.0719	3		1748	0.5060	0.0897	0.0919	3
	388	0.5168	0.0672	0.0718	4		1700	0.5048	0.0898	0.0916	4
	258	0.5167	0.0672	0.0718	5		1712	0.4997	0.0905	0.0904	5
2	768	0.6653	0.0308	0.0613	1	6	1963	0.7661	0.0203	0.0666	1
	918	0.4978	0.0487	0.0483	2		2026	0.7651	0.0204	0.0665	2
	749	0.3683	0.0717	0.0418	3		1844	0.7637	0.0206	0.0665	3
	672	0.3681	0.0717	0.0418	4		1985	0.7533	0.0203	0.0621	4
	730	0.3681	0.0717	0.0418	5		2078	0.7395	0.0230	0.0653	5
3	1460	0.6068	0.0575	0.0888	1	7	2200	0.8237	0.0159	0.0742	1
	1224	0.5309	0.0731	0.0828	2		2161	0.8155	0.0168	0.0741	2
	1151	0.5300	0.0733	0.0827	3		2299	0.8132	0.0170	0.0740	3
	1139	0.5295	0.0734	0.0826	4		2226	0.8109	0.0172	0.0738	4
	1511	0.5293	0.0734	0.0826	5		2117	0.8107	0.0173	0.0739	5
4	1672	0.6205	0.1407	0.2301	1	8	2399	0.5216	0.0891	0.0971	1

	1644	0.4626	0.1699	0.1463	2		2333	0.5213	0.0891	0.0971	2
	1650	0.4621	0.1701	0.1461	3		2318	0.5210	0.0892	0.0970	3
	1639	0.0796	0.2687	0.0232	4		2355	0.5210	0.0892	0.0970	4
	1683	0.0796	0.2687	0.0232	5		2397	0.4236	0.0940	0.0691	5

Since weights are distributed differently across functions, the positive ideal solution and the negative ideal solution will also be different and are computed for each function shown in Table 4.11.

Using the calculated weights above from AHP and the positive and negative solutions for each function, the next step involves finding each employee's distances from the positive ideal and the distance to the negative ideal solution. The purpose is to find each employee's closeness coefficient. Through these two numbers, the closeness coefficient is inputted. The employees within each function with the highest closeness coefficient are ranked first, as the closer it is to 1, the more ideal a person is to the ideal solution. The results are shown in Table 4.12.

The TOPSIS analysis for each function displays patterns in employee rankings based on their proximity to the ideal solution and distance from the negative ideal solution. In Function 1, EMPID 471 stands out with a Closeness Coefficient (CC) of 0.7052. This indicates quite a significant gap between this employee and the other employees, as they have the smallest distance to the ideal solution and the largest distance to the negative ideal solution. While other employees, such as EMPID 527, have respectable scores, they quite lag behind due to slightly higher distances from the ideal solution. In Function 2, EMPID 768 leads with a CC of 0.6653. However, the remaining employees in this function show relatively lower CCs, with a value ranging from 0.4 and below.

For Function 3, EMPID 1460 emerges as the top-ranked employee with a CC of 0.6068. However, the difference in closeness coefficients among the top five employees is less pronounced, suggesting that it has a more competitive environment within this function. Similarly, in Function 4, EMPID 1672 is the clear leader with a CC of 0.6690. The close proximity in CCs between the second and third-ranked employees highlights a narrower performance gap. However, we can see here that the most significant employees are only EMP1672, EMP1644, and EMP1650. The fourth listed employee possesses a closeness coefficient with a very significant gap from the third one and a value of CC that is very low. This suggests that only a few employees are performing close to the ideal solution in Function 4, while the majority are not. This is also a reflection to the company that their programs implemented have not been proven effective, given the relatively low scores of closeness coefficient in several employees.

In Function 5, EMPID 1752 takes the lead with a moderate CC of 0.5104, though the scores in this function are generally lower, indicating potential room for improvement across the board. Conversely, Function 6 has EMPID 1963, who achieves a CC of 0.7661. Lastly, in Function 7, EMPID 2200 is a clear top performer with the highest CC across all functions at 0.8237. This indicates that the employee is closest to what is seen as ideal in that specific function. On the other hand, Function 8 is more competitive, with EMPID 2399 leading with a CC of 0.5216. However, the close clustering of CC values indicates a less distinct gap between employees in this function.

The TOPSIS results highlight some discrepancies and useful insights for the company. For example, as we already see in Function 2, the difference between the top performer (EMP768, CC = 0.6653) and the fifth-ranked employee (EMP730, CC = 0.3680) is vast. Such variations CC = reflect their varying potentials by identifying high-potential employees who deserve to get employee rewards and those employees who are in the lower potential region who require careful attention for their development. This also signals further investigation into whether systemic ceilings are hindering top talent from excelling. Function 4, as an example, only detects 2 employees with reasonable scoring related to the coefficient, and other employees within the same function have really low scores. This itself is a warning to the company that for some programs that are crucial, such as PDP, as a criterion, it might be inherently skewed due to unequal access. In some functions, PDP participation is limited to high-profile or recommended employees, inadvertently disadvantaging others who may have strong potential but remain under the radar. The calculator of the top 20-ranked employees by the TOPSIS algorithm can be seen in Appendix A (See Appendix).

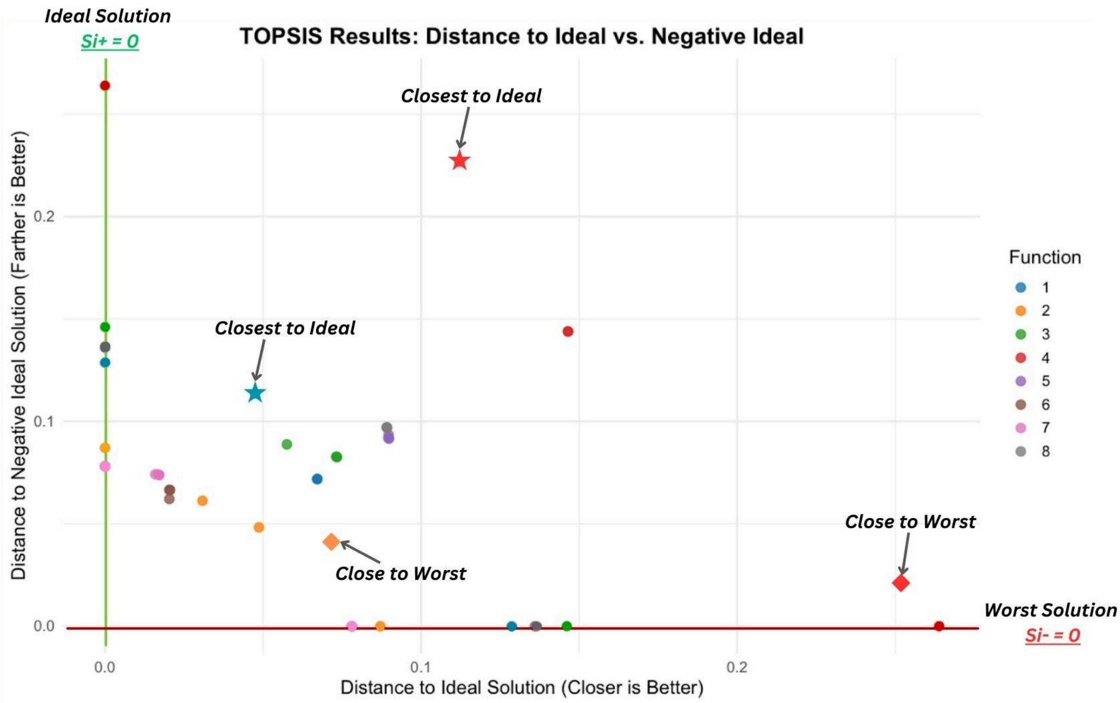

Figure 4.2 Distance to Negative Ideal Solution vs Distance to Ideal Solution Scatter Plots

The TOPSIS results are plotted to provide a visual representation of alternatives in relation to their ideal and worst solutions in terms of distance. The green vertical axis represents the ideal solution (*Si+=0*), while the red horizontal axis marks the worst solution (*Si−=0*). Alternatives are plotted based on their relative distances and their positions in terms of distance to negative solutions and distance to positive ideals , revealing their alignment with optimal or suboptimal outcomes. For visualization purposes, we represent the top 4 employees by closeness coefficient for each function. The alternatives closest to the green axis, labelled "Closest to Ideal," demonstrate employees whose potential is best in their function. These points are farthest from the red axis, compared to the other employees.

Conversely, alternatives near the red axis, identified as "Close to Worst," show significant distance from the green axis, such as the one that is diamond-shaped, meaning that they are not quite close to what is defined as the ideal solution. Ideally, these are the employees with low potential areas where improvements are necessary.

The majority of points are distributed between these extremes, clustering in the mid-range of performance. This spread indicates that while some alternatives perform moderately well, many do not fully meet ideal expectations. We should note that the chart above is representative of the top 4 employees. It is notable that in several functions, such as

Function 2 and Function 4, the fourth-ranked employee is positioned very close to the negative ideal solution. This suggests that employees ranked below them are likely even closer to the negative ideal. This serves as a critical alert for the company, and decision-makers should focus on this cluster to identify opportunities for improvement and bring these alternatives closer to the ideal.

4.3 AHP-VIKOR Results

The weight results from AHP for each function are also then implemented in the VIKOR methods, where each employee receives varying weights depending on his/her function. For each function, we iterate and do the following VIKOR algorithm in RStudio:

Algorithm 2 VIKOR Algorithm

```
procedure VIKOR(Function_IDs, merged_data, v)
  results_list ← ∅
  for function_id ∈ Function_IDs do
    subset_data ← merged_data[merged_data$Function_ID = function_id]
    criteria ← subset_data[Training.Full.Score, Assessment.x, Education.Level.Score, PDP.Score]
    weights ← subset_data[Training, Assessment.y, Education, PDP]
    best_values ← max(criteria for each column)
    worst_values ← min(criteria for each column)
    normalized_criteria ← (best_values - criteria) ÷ (best_values - worst_values)
    weighted_normalized_criteria ← normalized_criteria × weights
    S ← row-wise sum(weighted_normalized_criteria)
    R ← row-wise max(weighted_normalized_criteria)
    S_normalized ← (S - min(S)) ÷ (max(S) - min(S))
    R_normalized ← (R - min(R)) ÷ (max(R) - min(R))
    Q ← v × S_normalized + (1 - v) × R_normalized
    results ← dataframe(Employee.No., Employee.Name., S, R, Q)
    results ← sort(results by Q ascending)
    acceptable_advantage ← 1 ÷ (nrow(subset_data) - 1)
      if (Q[2] - Q[1] ≥ acceptable_advantage) and (Q[1] ranks highest in S or R) then
        results$message ← "Compromise solution: Q[1]"
     else
        results$message ← "Alternative solutions may exist"
     end if
        results_list[function_id] ← results
  end for
  return results_list
end procedure
```

Figure 4.3 Pseudo-Code of VIKOR Algorithm in RStudio

Table 4.13

Compromise Q Index of Employees for Each Function

Function	ID	Qi	Si	Ri	Function	ID	Qi	Si	Ri
1	22	0.2708	0.2272	0.1694	5	1752	0.1963	0.1633	0.0932
	118	0.3676	0.4019	0.1796		1725	0.2121	0.1948	0.0932
	197	0.4051	0.3123	0.2683		1748	0.2121	0.1948	0.0932
	404	0.4061	0.3143	0.2683		1700	0.2143	0.1992	0.0932
	165	0.4080	0.3182	0.2683		1712	0.2230	0.2167	0.0932
2	768	0.1782	0.1638	0.0720	6	1963	0.1741	0.1516	0.1074
	749	0.2616	0.2140	0.1155		2026	0.1776	0.1586	0.1074
	672	0.2624	0.2156	0.1155		1844	0.1816	0.1666	0.1074
	730	0.2624	0.2156	0.1155		2078	0.2093	0.1976	0.1208
	857	0.2624	0.2156	0.1155		1950	0.2600	0.2253	0.1611
3	1460	0.3456	0.3579	0.1433	7	2200	0.1709	0.1773	0.0803
	1179	0.3460	0.2535	0.1885		2116	0.1762	0.1726	0.0878
	1465	0.5273	0.3605	0.2985		2161	0.1797	0.1858	0.0848
	1169	0.5408	0.3874	0.2985		2299	0.1817	0.1897	0.0848
	1530	0.5452	0.3963	0.2985		2117	0.1837	0.1937	0.0848
4	1672	0.7457	0.4914	0.4000	8	2399	0.2041	0.1969	0.0971
	1644	0.8052	0.6104	0.4000		2333	0.2056	0.1999	0.0971
	1650	0.8094	0.6188	0.4000		2318	0.2071	0.2029	0.0971
	1639	0.9152	0.8304	0.4000		2355	0.2071	0.2029	0.0971
	1683	0.9152	0.8304	0.4000		2397	0.3312	0.3291	0.1532

The table above provides an illustration of 5 top-ranked employees explained through the VIKOR algorithm. Here, there exists the compromise Q ranking index, group utility measures (S), and the maximum regret (R). An interesting highlight reveals that most of the employees who are ranked first in TOPSIS *are also ranked first in VIKOR,* except for a notable difference of rankings in Function 1. This may as well highlight the discrepancies that exist between the first-ranked employee and the other employees, evidenced by the notable gap of compromise ranking Q indexes between the first-ranked employees and the rest of the employees within that function, specifically in Functions 1, 3, and 4, highlighting the best employees within the function explained by the VIKOR algorithm. The rest of the functions show similar results compared to TOPSIS's results, showing compatibility.

4.4 Reliability measurement of the models

The reliability measurement of the models has been done through correlation analysis and sensitivity analysis of the models.

4.4.1. Correlation analysis: Comparison of TOPSIS and VIKOR

The correlation method has been performed between the two models of TOPSIS and VIKOR to detect the actual interrelationship among the models and their similarity. This is also a measure of consistency between the two methods. A high correlation indicates agreement between the two methods, while a low correlation suggests significant differences. The correlation method adopts the Spearman Rank's Correlation, and it has been done through observing the rank by TOPSIS through the closeness coefficient and rank by VIKOR through the compromise Q index per function. Correlation analysis has been widely applied to test and verify various MCDM methods and their intra-relationships. (Sari, 2021; Bera et al., 2022)

The correlation analysis was performed by using employee rank data points to determine whether the models are statistically consistent or not. As shown on Figure 4.4, the Spearman's rank association between the TOPSIS and VIKOR models has a high positive correlation for each function, showing similarity. The highest correlation lies within Function 5, with correlation between the two methods equal to 0.995. We see a lower correlation in Function 1, with a correlation coefficient of 0.910. Despite it, a high correlation can be identified across all functions. It reflects that the normalization procedure and aggregation procedure of both methods are similar and also make the models more reliable. This highlights the high similarity of results produced from both models.

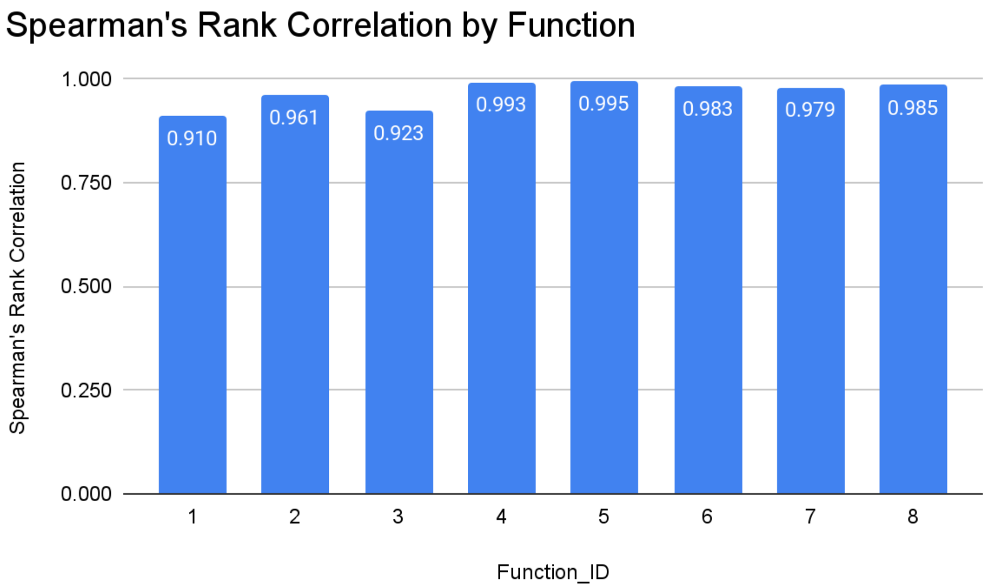

Figure 4.4 Spearman's Rank Correlation Across All Functions

This visualization compares the rank orders of two ranked variables across eight different functions (Function IDs 1–8), with the Spearman correlation coefficient quantifying their monotonic relationship. The Spearman correlation values range from 0.91 to 0.99 , indicating a strong relationship between the two rank measures for all functions. Minor deviations are observed for some functions, with the greatest ones in Functions 1 and 3, with some points spread further from the trendline, which indicates that some employees within this function indeed are ranked differently between TOPSIS and VIKOR. Through this correlation analysis, it implies that results from the VIKOR rankings through the compromise index and results from the TOPSIS rankings through the closeness coefficient indicate that the methods used to compute both rankings are similar to each other. Consistent rankings suggest that both models interpret the input data similarly and highlight the same priorities.

4.5 Nine Box Implementation and Comparison Analysis - Embedding with KPI Metrics

4.5.1 Defining Potential and Performance Standards

The results from TOPSIS and VIKOR will be implemented in the Nine Box talent management framework. Based on company standards, high performers are those with KPIs greater than 79. Medium performers are employees with a KPI score between 35 and 79, while low performers are those with a KPI score below 35. We used this as a benchmark standard for business rules that are a reflection of real-world companies.

A company has also created a standard for calculating one's potential. A person is deemed high potential when, out of a 0-5 scale scoring, their potential score is greater than 4. A person's potential is medium when they are between 3-4, and low potential when employee scores are less than 3 out of 5. To convert this into 0-1, in the case of TOPSIS, we therefore define a high-potential person when his/her closeness coefficient exceeds 0.8 and a person of low potential with a closeness coefficient below 0.4. A comprehensive classification can be seen in the figure below. In the case of VIKOR, we will utilize the compromise Q index, and since the lower the values indicate a better preference, we define that a person with a compromise Q index of less than 0.2, inverse of 0.8 in TOPSIS, is a high-potential person. The results of the Nine Box are explained in the section below.

4.5.2 Comparative Analysis - Employee Placement Distribution

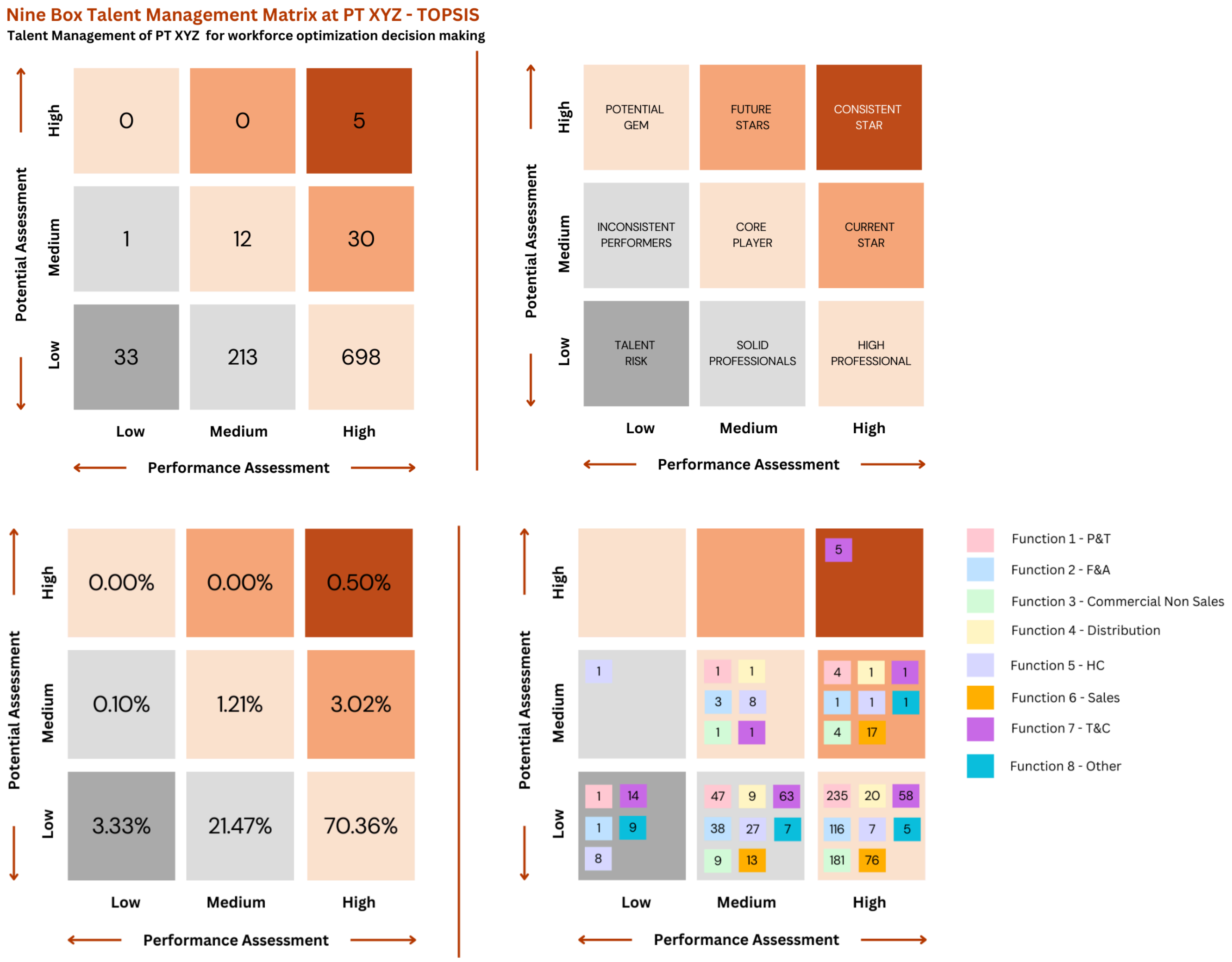

Figure 4.5 Nine Box Employee Placements by TOPSIS

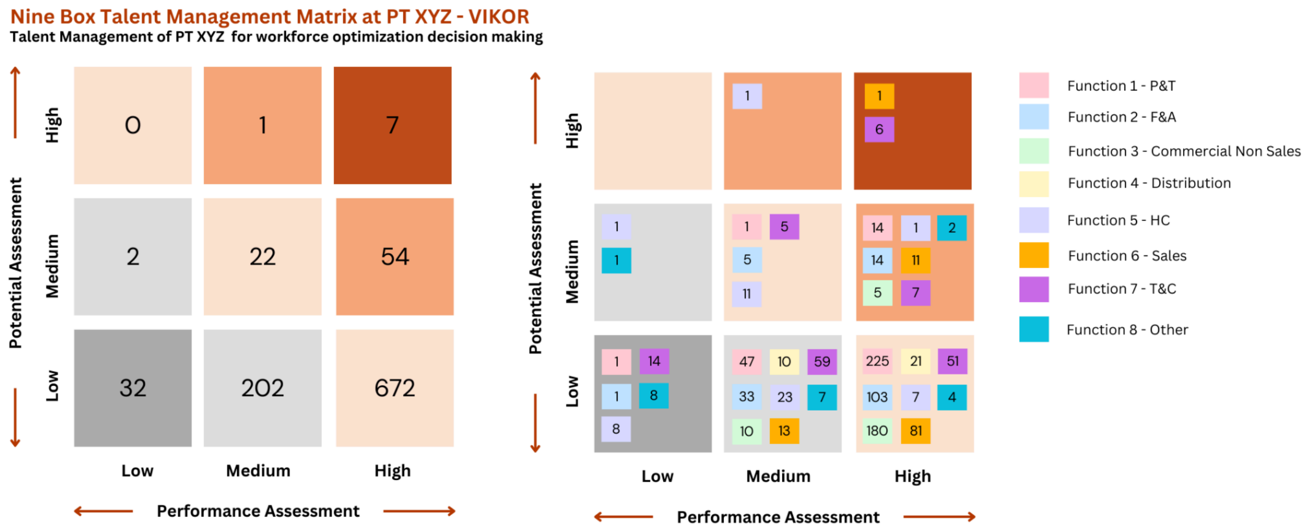

Figure 4.6 Nine Box Employee Placements by VIKOR

The Nine Box constructed upon PT XYZ's data reveals distinctive results from both algorithms. The comparison of employee placements distribution across the TOPSIS and VIKOR follows a pattern indicating the essential nature of how each method evaluates each employee. While both methods adopted the same input data, their algorithms have resulted in several discrepancies in employee categorizations within the Nine Box.

One significant point of contrast between both algorithms lies within the placements of employees within high-potential areas. Within the 'Consistent Star' category (High Performance, High Potential), TOPSIS identified 5 employees (representative of 0.5% of total employees), of which all originated from the Technology & Compliance Function. Contrasting to these results, VIKOR placed 7 employees (representative of 0.71% of employees) in the same category, with six coming from the Technology & Compliance Function and one coming from the Sales function. The five Consistent Stars rated by TOPSIS are also rated Consistent stars in VIKOR, indicating alignment in both methods. Of these five, four of them hold key and critical employees, 3 being supervisors and 1 manager. Interestingly, there remains one staff rated as Consistent Stars that is explained by both algorithms. In addition to this, the Future Stars, or those with Medium Performance and High Potential exhibit some differences with TOPSIS placing absolutely zero employees within this box. In spite of it, the VIKOR algorithm has revealed 1 employee coming from the Human Capital function within this segment. No employees were detected as Potential Gems from both methods (Low Performance and High Potential). This might be indicative that employees in PT XYZ, from this sample data, cannot be indicated as high potential but low performers at the same time.

The next significant finding we found from both algorithms is that both put very few people in the Medium performance, Medium Potential segments, or ideally often referred to as the ‘Core Player’ zone, despite higher counts in VIKOR. In an ideal situation, people within this box serve as the backbone or the foundation of the company, signifying those employees who perform well enough in their current job to meet company goals but do not necessarily have the highest growth potential and therefore have some room for improvements. The Nine Box from the TOPSIS algorithm reveals that only 12 employees, mostly coming from Human Capital functions, are put into this category. VIKOR , as a comparison, puts 22 employees, of which 11 employees come from Human Capital as well. Despite it, this signals an indication that the company may have underestimated the significance of the employees in this box—the importance of having reliable individuals who play a crucial role in the day-to-day business operations at PT XYZ. The ‘Current Star’ section, representing the High Performance and Medium Potential employees, is more clearly defined by VIKOR, as 54 employees are placed in this box. An interesting finding has shown that while VIKOR shows that most employees in this category come from the P&T and F&A functions, TOPSIS, however, holding 30 employees, primarily identifies those from the Sales function. Similar results were presented, however, within the Low Performance and Medium Potential, or commonly known as Inconsistent Performers, where only 1 employee exists in TOPSIS and 2 in VIKOR.

Observing under different lights, we see comparable results from both models, where most of the employees in our sample data are classified as ‘High Professionals’ or as High Performers but Low Potential. With 698 employees (70.36% of total employees) in TOPSIS versus 672 (67.70% of total employees) in VIKOR, this reveals an important alarm to the company. The results signify that the company views a significant number of employees as strong performers but do not possess the necessary skills to become future potential leaders, hindering and posing threats to the company’s talent succession pipeline. From a strategic perspective, PT XYZ may inadvertently be over-relying on these employees by assigning them excessive workloads and responsibilities that heavily require their current expertise and capability but fail to develop as the company’s future leaders. This calls into question the company’s future-oriented talent management strategies. The results have also raised the urgency to investigate further into the effectiveness of PT XYZ’s talent growth initiatives or capability enhancement programs existing within the company.

In light of these findings, an interesting outcome comes from the similar classification explained by both TOPSIS and VIKOR, where relatively few employees are classified as Talent

Risk, with 32 employees in VIKOR and 33 employees in TOPSIS, indicating comparable results for those employees who not only underperform but also lack growth potential. While this is a critical category for interventions like performance improvement plans or employee exit plans, the small gaps between both models suggest that to a certain degree the methods agree on identifying bad hired employees, which strengthens the outcomes of both models.

The functional breakdown provides additional layers of insight at PT XYZ. Explained by both methods, Function 1 (P&T) and Function 3 (Commercial Non-Sales) are most concentrated in the low potential, high-performance quadrant, signaling a significant challenge in nurturing potentials despite high performance within these functions. While this can be a great sign that the most workforce-dominated functions perform exceptionally well in their current job, integral to the company's core , it also signals a trigger to the company that these employees are not well-equipped to become future leaders, which poses a threat in the future. The TOPSIS algorithm reveals better distribution, especially within the medium and high potential sections of the Nine Box. The spread of employees within the low potential sections from both algorithms is quite similar to each other.

Table 4.14

Mismatch Analysis of AHP-TOPSIS vs AHP-VIKOR

Measure	# of Employees	% of Employees
Number of Matches	921	92.84%
Number of Mismatches	71	7.16%
Employee classified as Higher Potential in VIKOR from Mismatch	55	5.54%
Employee classified as Higher Potential in TOPSIS from Mismatch	16	1.61%

While the results align closely, there remain existing gaps that occur within the employee placements in the Nine Box. We further analyze the compatibility results from both the TOPSIS and VIKOR algorithms and to what degree they have a strong alignment and agreement with each other. Table 4.14 shows that , out of 992 employees present in the data, about 921 matched employees were explained by both algorithms, leading to a compatibility rate of 92.84%. This leaves 71 employees, or the equivalent of 7.16% of mismatched employees. From these mismatched employees, 55 employees (5.54% of total employees) were classified as higher potential from the VIKOR algorithm than the TOPSIS algorithm. Around 16 employees were classified as having higher potential in TOPSIS.

The results from the table emphasize VIKOR's compromising solutions since it considers both group utility and individual regret, particularly favoring employees who perform well across multiple criteria but are not necessarily top performers in any single category. This may as well explain that TOPSIS treats criteria and alternatives more linearly, whilst VIKOR amplifies its compromise-oriented approach by finding a balanced result. Another layer of analysis reveals that the vulnerabilities of employee mismatches in cases where TOPSIS explained employees as higher potential than VIKOR are mostly in P&T , Commercial Non Sales, and Sales functions. These small instances might be explained by some alternatives posing higher sensitivity to the criteria weightings specific to the functions. Though uncommon, when investigated further, a similar pattern from the 12 mismatched employees where TOPSIS explains higher potential reveals that the difference between distance to ideal solutions and distance to negative ideal solutions is small, meaning that these employees' performance is almost equally close to the best and worst. However, in this case, all employees have a distance to the ideal solution slightly closer than it is to the distance to the negative ideal solutions, leading to them being classified higher in the TOPSIS algorithm.

4.6 Sensitivity Analysis by Threshold Adjustments in Nine Box Placements

Sensitivity analysis is conducted to understand volatility in the nine box placements when we change the threshold of each box (what classifies as low, medium and high potential). The purpose of doing this is to understand the stability of both models and which one fits more with the organizational goals and needs at PT XYZ. Therefore, a simple sensitivity analysis regarding threshold adjustments of the potential side in the nine-box was executed. For each threshold adjustment, we calculate the transition rates and the category stability index. The *transition rates* refer to how many employees have moved their positions to a different box after the threshold adjustment out of the total employees. The *category stability index*, on the other hand, refers to how many employees remain in the same box despite threshold changes.

Table 4.15

Sensitivity Analysis of Nine Box Placements

Threshold Adjustments	Transition Rate (%)		Category Stability Index (%)	
	AHP-VIKOR	AHP-TOPSIS	AHP-VIKOR	AHP-TOPSIS
-20%	4.4%	5.8%	95.6%	94.2%
-15%	4.1%	3.7%	95.9%	98.4%
-10%	3.7%	3.4%	96.3%	95.9%
-5%	2.9%	1.2%	97.1%	98.8%
0%	0.0%	0.0%	100.0%	100.0%
5%	1.0%	0.5%	99.0%	99.5%
10%	1.4%	1.1%	98.6%	98.9%
15%	4.1%	1.6%	95.9%	98.4%
20%	5.0%	1.7%	95.0%	98.3%

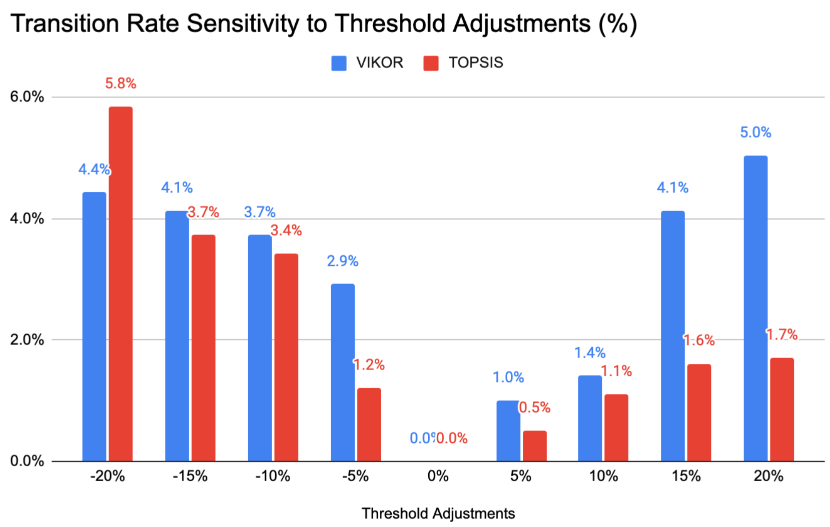

Figure 4.7 Transition Rate Sensitivity to Threshold Adjustments

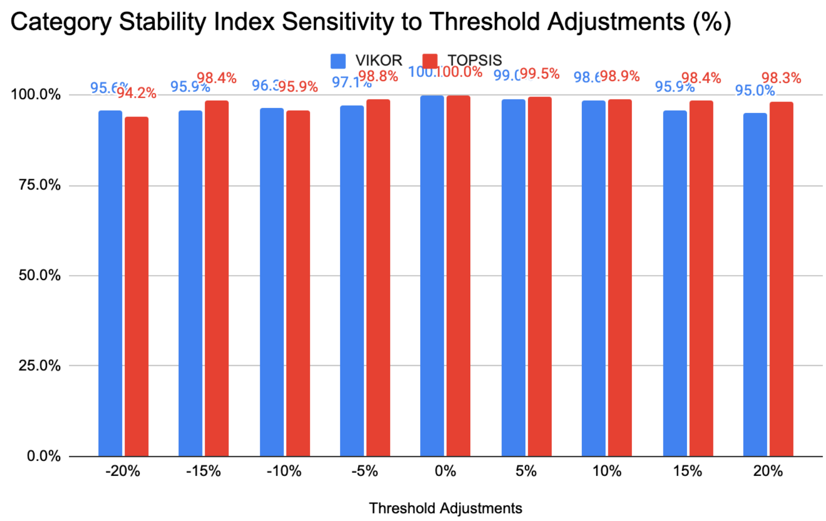

Figure 4.8 Category Stability Index Sensitivity to Threshold Adjustments

The results shown in the visualizations above exhibit a notable trend of transition rates as we modify the threshold of the Nine Box potential side. As we decrease/increase the threshold adjustments from -20% to 20% from the reference point at 0% change (or equivalent to company standard cutoffs), the transition rates increase. TOPSIS , in general, exhibits a relatively lower sensitivity to threshold adjustments compared to VIKOR. Across all threshold adjustments , the transition rates for TOPSIS remain consistently lower, except at the lower end when thresholds were lowered by 20%, leading to a transition rate of 5.8%. The transition rates decline steadily as adjustments approach the baseline at 0% or move upward when threshold adjustments are increased. An interesting finding has shown that when we increase the threshold adjustments by 5%, the transition rate by VIKOR increases twice as much as the transition rate by TOPSIS. A notable comparison happens when we increase the threshold extremely by 15% and 20%. A 15% increase in threshold adjustment leads to a significant jump in transition rates by VIKOR to 4.1% and to 5.0% at a 20% increase, the highest recorded transition rates across all adjustments for both methods. In contrast, TOPSIS at the same 15% adjustment illustrates a transition rate of 1.6%, which is significantly lower. This reflects the narrower distribution of TOPSIS scores and its inherent stability, with fewer employees falling near the shifting threshold boundaries. An increasing transition rate results in a lower category stability index. Transition rates increase in the TOPSIS when thresholds are increased, but gradually, leading to a relatively stable category stability index.

Sensitivity analysis examines the point at which changes in input values begin to produce noticeable changes in output results. In general, VIKOR's sensitivity becomes apparent at the initial stages of threshold adjustment, where 5% adjustments have led to a transition rate of 2.9%. When compared to TOPSIS, this is more than two times the amount of transition rates (TOPSIS = 1.2%). In addition to this, high vulnerability also occurs when the threshold adjustments increase by 15% in VIKOR. TOPSIS, however, shows its peak volatility when threshold adjustment decreases by 10%, with transition rates at 3.4% (at -10% adjustments) and when transition rates heighten at 5.8% when thresholds are adjusted by -20%. In spite of it, TOPSIS shows a consistent increase in transition rates when all threshold points are increased positively from 5% to 20%.

While TOPSIS poses a more stabilized model at the cost of fewer employee transitions, this might hinder its ability to reflect changes in employee behaviors and positions within the Nine Box grid. The use of TOPSIS, therefore, is suitable for environments where consistency is prioritized, typically on a yearly employee evaluation basis. VIKOR, promoting a dynamic environment, can be more suitable in situations where flexibility and greater responsiveness are preferred, preferably in a fast-paced environment when tracking of developmental trends is desired.

4.7 Overall Observations and Recommendations

Alignment with PT XYZ's objectives and feedback from expert judgments are crucial measures of which models are desired in the company to ensure actionable insights are data-driven from the preferred model. In general, the TOPSIS algorithm seeks to find the best alternatives in terms of the absolute distance from the ideal solution and distance from the negative ideal solution. VIKOR, however, seeks to find a compromise solution by balancing between the group utility-based and minimizing regret. The results from both algorithms explain such high similarity for the Nine Box. Whether PT XYZ has a preference towards one method over the other depends heavily on the objectives and the goals of the company. Preference towards higher flexibility and widely distributed employee placements might suggest that VIKOR is a preferable option for PT XYZ, as shown through the sample data we have obtained from the company. However, TOPSIS can be preferred if they want a more rigorous and strict approach.

A series of recommended action plans are constructed for PT XYZ based on the results from the Nine Box. To do this, a data-driven approach and summary analysis are built upon the results explained similarly from both models to increase the robustness and accuracy of the results.

Talent risks are hazards to the company as they are classified as bad hires. The company must exercise caution and put careful attention to dealing with these employees, as they serve as the company's possible investment misuse. As many as 32 employees have been identified as problematic hires in the company from sample data of 992 from both algorithms. Of the 32 employees in the talent risks area, 59% are between the ages of 20 and 20, with 2 to nearly 6 years of experience working in the company. The company must conduct further investigation as to reasons behind this finding, as they should have been working at their peak during their prime years, yet their development progress to the company falls short. This may warrant an investigation into the quality of onboarding processes and the effectiveness of recruitment selections. *Talent hoarding* may be another cause of such situations, where superiors may feel reluctant to develop their top employees by limiting or withholding their development opportunities to maintain control or avoid competition.

Furthermore, we discovered 6 veteran employees—those who had worked for the company for more than 15 years. Among them, two remain in staff-level positions, indicating those who had not advanced in their careers for more than 15 years. Despite their long tenure, they have not recently made meaningful contributions to the organization and have failed to develop over the years, given the low career progression levels for some. Notably, most of these veteran employees are between the ages of 40 and 50. The indication of minimal employee progression even after 15 years may indicate employees being too comfortable working in the company and not motivated to improve any better. Psychologically, they might also feel that their skills may be obsolete after being replaced with the influx of newer employees who often bring fresh, innovative ideas to the company.

The approach the company can adopt can be based on two things: constructing an employee exit plan or dealing with them promptly by providing immediate feedback to such employees and expecting short-term improvements. If not getting improvement quickly, the company might need to find ways, ethically, to remove them. They also might consider alternative roles that may better suit the person. If not dealt with , the company is taking away more than the necessary resources from more promising employees, which may as well add more value to the company.

To ensure that these employees categorized as low performers can be handled sufficiently, people within these boxes may receive *performance improvement plans (PIP).*

Performance improvement plans are immediate, short-term corrective actions/formal approaches for a company to remedy employees performance gaps. This includes those who fail to fulfill their responsibilities in their job. Before being placed in an exit plan, some employees can be offered opportunities to enhance their performance by giving immediate results through PIPs tailored to each specific job. With that being said, the company must also carefully select employees that are worth putting into the PIP program to ensure that they are not wasting any more unnecessary investments on employees whose paths to improvements are unclear. A suggestion is given to PT XYZ so that the PIP schemes are given in the third quarter. This is because the implementation of PIP during the third quarter will allow the company ample time to track and analyze employee performance over the course of 3 quarters, which, by that time, should have performed reasonably near to the end-of-year targets. Employees who are not meeting the company standards or are far from realizing their targets should be flagged by the company and given consideration for PIP. By the end of the year, the company can decide whether to hire the employees or place them in an outplacement program based on the findings of PIP. However, for this to be realized, PT XYZ must ensure that submissions of KPI are on schedule. If KPI submissions are late, and therefore it takes some time to analyze the performance of employees, then a suggestion for PIP to start earlier in quarter 3 is proposed.

In terms of developing employee potential, PT XYZ must clearly and efficiently streamline their employee development initiatives. For any low potentials identified, the company might want to also develop them through several tailored trainings for the employees fit to their role. Once improvements are seen, evidenced through their movement upward in the Nine Box , the company might consider them to undergo personalized development plans. The rate of PDP successors compared to the total number of key and critical positions shows significant discrepancies, primarily notable within the sales function (see Appendix). This is quite concerning given that this indicates some KnCs in the company currently lack future successors, hindering the succession planning initiatives. To develop and nurture employees, a suggestion is made for companies to implement some talent development initiatives. If employees are currently located in the medium potential section, the company may also want to construct clear career paths for them and decide whether employees are well-suited for managerial/specialist roles. If managerial, PT XYZ may invest in them, such as undergoing managerial training and PDP, if not yet. If they are well-suited for specialist roles, consider offering them to take academic training such as certifications or courses that help leverage their skills further. If employees are currently located in the low-potential section, the company might want to offer them basic training fit for their role first and see if they can leverage their potential out of the training. However, a suggestion is made that PT XYZ might not want to excessively invest in people categorized as talent risks, as investing too much in them may result in a waste of resources if it becomes apparent that employees lack motivation to improve.

The people who are located on other extremes, within the consistent star category, should be the main focus of the company and should focus on the employees within this box to be their future leaders, as they are critical to the company's long-term goals of succession planning. Among the consistent stars, whose both algorithms are able to explain only 5 existing employees, 60% are male (3 employees) and 40% female (2 employees). While two of these employees have received promotions, one has not, which can be a notice to the company to ensure that talent management efforts are sufficiently proactive. The company must also put great efforts into refining retention strategies, given an alarming situation that only 2 out of 5 employees have actually been given retention, to retain high-potential individuals. The situation worsens as they may be at risk of attrition, especially if they become attractive talents to other companies. 3 of the consistent stars are supervisors, with 1 staff-level employee and only 1 manager. This imbalance may indicate a bottleneck in career progression, especially within managerial roles, as it indicates that only a few are ready to become future leaders in the company. Another slice of analysis reveals that both methods have agreed to the fact that only people coming from Function Sales and T&C are qualified to become consistent players. This in itself serves as a highlight that there are inefficient and mismanaged strategies of potential development performance issues within other functions, possibly due to inequalities of opportunities between functions that hinder some employees from developing during their careers in the company.

A proactive retention strategy and company performance-based incentives/rewards at PT XYZ must be planned thoroughly, which also includes personalized growth plans tied to long-term career trajectories. These actions will help those at risk of attrition to feel more appreciated and motivated to retain and work longer in the company. There are various ways in which PT XYZ could leverage their strategies, whether it be monetary or non-monetary benefits. Rather than also relying on retention or promotions, PT XYZ could offer non-monetary rewards such as executive international/advanced certifications. Non-financial incentive programs are structured to motivate positive behavior change, which can increase job satisfaction. In addition, defining clear career pathways can provide employees within this segment clear career progression pathways, emphasizing possibilities for employees like further skill development and leadership roles.

Engagement is another key factor to drive the productivity of employees. According to research held at MIT, engaged employees are productive employees (Somers, 2023). Keeping employees within this box engaged is therefore a crucial step for PT XYZ to ensure they aren’t at risk of leaving the company. When analyzed further, the average engagement score within this box is lowered due to some reasons behind the low engagement score in the recruitment process. PT XYZ might want to delve deeper into analyzing reasons behind this dissatisfaction in the recruitment process, as addressing these concerns would foster overall employee experience, enhancing overall satisfaction. PT XYZ also needs to look for early signs of demotivation/dissatisfaction within these employees, if any, and keep them engaged by giving external monitoring and internal project tasks that the company believes they could excel on. This will create a sense of belonging for the employees. As part of engagement, it is also important that superiors check in with the employees regularly and assess if they are satisfied with their current role. These employees play a pivotal part in contributing the most to PT XYZ, so the company should compensate for their efforts accordingly.