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Model Evaluation and Implementation Strategy Planning Based on Attrition Predictive Model in Perseroan Luar Negeri Ltd

Gland Wialldi[1], Hary Febriansyah[2]
[1]Bandung Institute of Technology, Bandung, West Java, Indonesia, gland_wialldi@sbm-itb.ac.id
[2]Bandung Institute of Technology, Bandung, West Java, Indonesia, hary@sbm-itb.ac.id

Corresponding Author: gland_wialldi@sbm-itb.ac.id[1]

Abstract: Over the past three years, Perseroan Luar Negeri Ltd.'s five Singapore-based subsidiaries have experienced a consistent increase in attrition rates above annual average benchmarks, raising concerns about service continuity, increased rehiring and onboarding costs, and weakened customer relationships. To address this, the Group implemented machine-learning models designed to potential leavers six months in advance. This research evaluates the first full year of the model's deployment and proposes integrating predictive insights into HR decision-making. The evaluation includes both offline assessments (precision-recall screening of six algorithms during production) and an online evaluation using Wilson-scored recall/precision, Popular-Stability-Index for covariate drift, Linear Four Rate for concept drift, and two business KPIs: voluntary turnover delta and retention yields. Findings shows that only recall-focused models met business targets. Covariate drift, likely triggered by performance-rating freezes and mandated training, caused significant recall deterioration, whereas concept-drift tests remained negative, validating algorithm logic. To address these issues, the study proposes short-term solutions through model retraining. Mid-term actions include conducting exit-interview analyses, redefining attrition baselines, developing quality-control dashboards, establishing comparative benchmarks, and adjusting voluntary turnover calculations to highlight hidden successes during market volatility using industry attrition projections and sector-engagement indices. For long-term sustainability, the study recommends comprehensive training and documentation programs to establish robust talent-risk governance.

Keywords: Employee Attrition, Machine Learning, Online Model Evaluation, Retention Strategy, HR Analytics

INTRODUCTION

Headquartered in Singapore and operating in over 20 countries, Perseroan Luar Negeri Ltd. is a state-owned Singaporean conglomerate. Though starting as one single company, over the years, Perseoran Luar Negeri Ltd. has undergone significant transformation to position itself as a leading asset manager and operator with a focus on sustainable urbanization and technological advancement. The company operates through a network of subsidiaries strategically segmented into key sectors, namely Perseroan Korporasi, Perseroan Kapital, Perseroan Infrastruktur, Perseroan Real Estat, and Perseroan Telekomunikasi & Transportasi.

Over the last three years, Perseroan Luar Negeri Ltd. found difficulties in recruiting people for the subsidiaries. With long chain of command, miscommunication often happens, resulting in multiple recruitments of entry-level job in the same positions. The holding also experienced difficulty in hiring managerial positions, as no one seem to match the whole company and its subsidiary requirement. Apart from recruitment problem, the holding HR department saw a rise in attrition or number of people leaving the company in the past 3 years.

Table 1. Attrition Rate (%) of Perseroan Luar Negeri Ltd.

Subsidiary	Annual Attrition Rate (%)		
	2021	2022	2023
Perseroan Kapital	15.19%	20.55%	20.78%
Perseroan Infrastruktur	7.72%	9.75%	12.62%
Perseroan Real Estat	19.06%	23.00%	26.88%
Perseroan Telekomunikasi & Transportasi	5.14%	7.70%	9.98%
Perseroan Korporasi	16.88%	19.42%	19.65%

For comparison, according to reports from the Ministry of Manpower in Singapore, in 2023, the average monthly attrition rate is in 1.4%. With a simple approximation to the annual rate will be somewhere around 15.56%, using compound approximation, up to 16.8%, using the 12 times multiplication. The following table are the details of average monthly attrition rate for each industry in comparison with the annual attrition of Perseroan Luar Negeri Ltd. in 2023:

Table 2. Attrition Rate (%) of Perseroan Luar Negeri Ltd. in Comparison with Average Annual Attrition Rate in Singapore (2023)

Subsidiary	Annual Attrition Rate (%)		
	2023	Average (Lower Bound)	Average (Upper Bound)
Perseroan Kapital	20.78%	12.42%	13.2%
Perseroan Infrastruktur	12.62%	15.56%	16.8%
Perseroan Real Estat	26.88%	14.53%	15.6%
Perseroan Telekomunikasi & Transportasi	9.98%	14.53%	15.6%
Perseroan Korporasi	19.65%	15.56%	16.8%

Some subsidiary companies are already above the average upper bound of annual attrition rate; such as Perseroan Kapital, Perseroan Real Estat, and Perseroan Korporasi. When turnover exceeds the average, it has only negative effects such as increased costs, productivity loss, disruption, knowledge loss, and damage to reputation (Shenoy, 2016, p. 98). When this happens, it triggers as a warning indicator for the HR Team to initiate employment retention program with the goals of achieving organizational stability and long-term success.

To tackle both attrition and recruitment problems, particularly for managerial positions, Perseroan Luar Negeri Ltd. implemented a strategic initiative by applying analytics in its HR practices. The use of analytics in organization reflects the capability of the organization in using data, analytics, and evidence-based management extensively to drive strategy, decisions, and actions (Rigamonti et al., 2023). The management initiated a development of Attrition Dashboard to monitor reasons behind employee attrition, initially by reviewing exit surveys from the past five years. This approach responded to concerns from the recruitment team regarding the frequent reopening of positions and difficulty in sourcing suitable candidates. However, the exit surveys showed very low response rates (less than 10%), with superficial answers like “family problems” or “personal decisions,” thus limiting their usefulness. The HR department found these insights inadequate and considered them “too late” for timely interventions.

In light of these challenges, management decided to explore a more quantitative approach by developing a predictive attrition model. This model identifies key parameters significantly influencing employees’ decisions to leave, enabling objective and data-driven insights into attrition. By leveraging this model, Perseroan Luar Negeri Ltd. aims to pinpoint specific attrition drivers, implement effective retention strategies, and improve overall HR quality. Although the predictive model's development was completed within this paper's timeline, the primary focus will be establishing a rigid evaluation method to assess the model's effectiveness upon initial full implementation in the company's business processes.

METHOD

To make the model evaluation, there are two types of evaluation that needs to be considered with each has different objective (Zheng, 2015, pp. 2-4). The first evaluation is called "offline evaluation" which measures model performance based on historical data. This will then be used as the way to choose which model is the most suitable to deployed. The other evaluation is "online evaluation" measures the performance of the chosen model using live data after the model has been deployed. The reason behind the separation is that online evaluation process evaluates the performance of chosen model after it's been deployed. Due to that, the evaluation is more complex than the offline evaluation process.

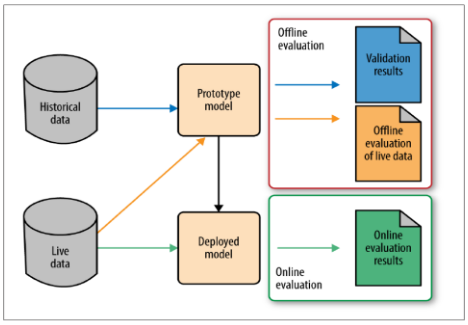

Figure 1. Machine Learning Model Development and Evaluation Workflow

The goal purpose is to assess how well the model performs after being implemented and used in a live setting for the first time. This evaluation helps determine whether the model continues to give useful and reliable results when applied to real employee data over a six-month period. On method approach part talks more about the process of the evaluation itself, which is decomposed into three layers:

1) Live-model metric score: Here we recompute the model's key discrimination metric together with its Wilson confidence interval.
2) Covariate & conceptual drift: Next, we test whether the data or the underlying resignation mechanism has changed, using PSI_{max} for covariate drift and the two-proportion Z-test (univariate LFR) for concept drift.
3) Business metrics: Finally, we translate technical health into organisational value via the six-month voluntary turnover rate delta and Retention-Yield indicators.

Each layer acts as a "filter": if all three are satisfactory, the model is deemed fit for purpose; if any layer fails, the evaluation funnels a clear escalation signal to management. Lastly, all evidence on model evaluation interpretation & results will be used to answers whether the model is able maintained statistical validity and also still generating business benefit. This final part helps managers and HR teams decide what action to take next based on clear and structured findings from the evaluation.

RESULTS AND DISCUSSION

Before we evaluate the model, we need to understand the initial design of the model itself. The framework used to build Perseroan Luar Negeri Ltd.'s attrition model is based on the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework. This framework is considered as a must standard procedure for applying data analysis (Schröer et al., 2021). According to this framework, there are three key important points: the first mile, the middle mile, and the last mile.

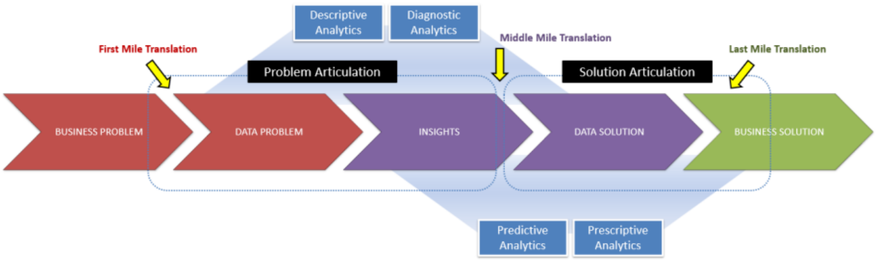

Figure 2. CRISP Framework

The first mile focuses on accurately describing the business challenge, ensuring that the objectives are well-defined and in line with the company's strategic goals. This requires a deep understanding of the elements that contribute to employee attrition, as well as the prediction model's desired outcomes. The middle mile focuses on diagnosing the problem and transforming it from a business problem to a data problem.

This step entails analysing current data, finding relevant variables, and refining the prediction model to increase its accuracy. The last mile ensures that the solution is adoptable by stakeholders. This step involves translating insights into actionable strategies, effectively communicating the results to decision-makers, and implementing the necessary changes to achieve the intended business outcomes.

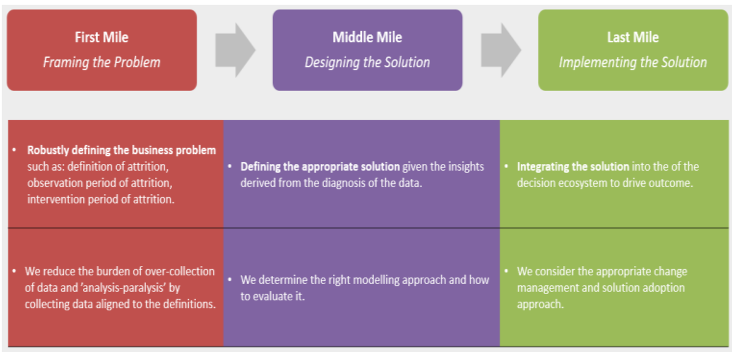

Figure 3. First-Mile, Middle-Mile, and Last-Mile Framework

After discussions with Perseroan Luar Negeri Ltd., it was clarified that the primary intention behind building the attrition model was to reduce the rate of voluntary employee departures by specifically predicting resignation likelihood. Perseroan Luar Negeri Ltd. decided to focus initially on a pilot project targeting its Singapore-based employees, aiming to refine the model and retention strategies before potential regional expansion. The data used for the attrition model will come from their comprehensive employee database, collected since 2017. Specific variables will be identified during the first-mile friction process, where the business problem is clearly defined and relevant data points are selected. For robust analysis, multiple models will be comparatively evaluated, designed specifically to predict binary outcomes (true or false) of employee attrition.

During the first-mile analysis, three main components must be defined: the definition of attrition, the observation period, and the performance period. Attrition is specifically defined as the submission of a resignation tagged as 'regrettable'—non-forced resignations, whether withdrawn later or not. Importantly, regretted attrition differs from voluntary attrition, as some voluntary resignations are considered 'coerced.' Currently, Perseroan Luar Negeri Ltd. lacks resignation submission data. Based on descriptive analysis, the predictive model targets a maximum of 20% of the employee population as potential attrite, reflecting average annual attrition rates. From a total of 3,305 employees, the model focuses solely on 2,680 employees at the executive level or above, and retention strategies will exclusively target High Potential employees, typically 10-30% of actual attrite employees.

In the middle-mile analysis, various existing methodologies, such as those proposed by Hossein et al. (2023) and Nandal et al. (2024), inform the structured multi-phase approach to predictive modeling. This structured process, including data selection, feature engineering, feature selection, data preprocessing, model building, training, performance comparison, and implementation, ensures the model accurately identifies employees likely to attrite within the next six months performance period.

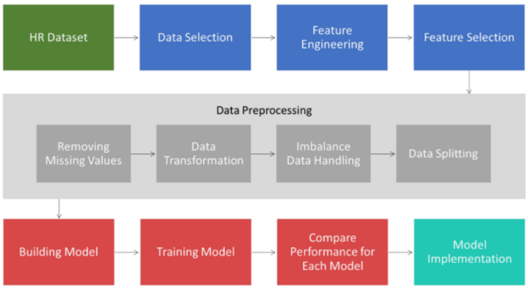

Figure 4. Model Framework

The first step involved collecting data from certain datasets, which contained comprehensive information on employee performance, satisfaction, and demographics. From these data, we have to identify which information that we need to choose in hopes of recognizing early indicators that an individual may be contemplating resignation. While exact predictions can be challenging, based on the theory discussed before and discussion with the managerial team, we focus on six major categories of information, each highlighting patterns that could suggest a higher risk of attrition. Those six categories are Engagement Data, Internal Pressure Data, External Pressure Data, Cultural Fit Data, Behaviour Data, Internal Environment Data.

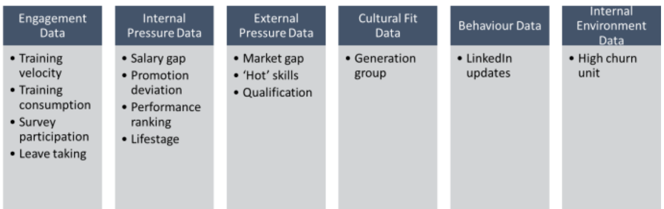

Figure 5. Six Categories Data Indicating Employee Attrition

The methodology involved constructing predictive models using a variety of machine learning algorithms, including XGBoost, Random Forest, Logistic Regression, k-Nearest Neighbour (KNN), Support Vector Machine (SVM), and Adaptive Boosting (AdaBoost). These models were chosen to explore different approaches to classification and to identify the most effective algorithm for predicting employee turnover. Each model was trained on the preprocessed dataset, and its performance was calculated using appropriate metrics.

After the discussion with the Boarding team as well as HR Heads, the main focus of the model will be to reduce the employee for leaving as much as possible to reduce the attrition rate itself. Thus, the focus of the model will be to maximise the recall performance. But, even if we want to get the recall performance as big as possible, there are other considerations that are still needs to be reviewed.

One of the example cases for this is when the model considers every employee to have the likelihood to give the resignation letter, resulting the model to have 100% recall score. This is happened because it can capture every person that has the actual intention to give the resignation letter, with sacrificing everyone else to be considered to give the resignation letter as well. When this happens, it can lead to negative consequences such as increased distrust among employees, unnecessary stress, and potential disruption in team dynamics.

In order to reduce such a possibility, the management team personally requested to limit the total populations that will be predicted to have probability to give resignation letter to be below 25%. This number comes from the risk appetite of the HR Management team willing to take for using the model and also referring from the average attrition rate occurred in Perseroan Luar Negeri LTD. Based on that scenario, it was then proposed that the model that we are looking for is a model that may results at least 50% of recall score with the addition of percentage total of employees predicted as having likelihood to give a resignation letter below 25%.

Another question raised for this proposed metrics is the alternative solutions when none of the proposed model meets with the proposed criteria. It is then decided that the alternative solutions for this is to gain performance of precision score at least above 50% while still also maintaining the percentage total of employees predicted as having likelihood to give a resignation letter below 25% as well. Lastly, when we are facing a case of no models that meets those criteria, we will choose any models can produce the highest recall score ignoring the percentage populations. For this specific case, the management team will only gather information of why the employee decided to leave without giving any prevention strategy beforehand.

Table 3. Offline Evaluation Model Metrics and Actions

Evaluation	Metrics	Actions
First Priority	• Reaching Recall above 50% • Total Population to Prevent below 25%	• Doing Prevention Strategy • Gather data across all leavers from exit survey
Second Priority	• Reaching Recall above 50% • Total Population to Prevent below 25%	• Doing Prevention Strategy • Gather data across all leavers from exit survey
Last Priority	• Reaching Highest Recall across all models	• Gather data across all leavers from exit survey

After several process of training and optimizations, we found 3 models that is suitable for first priority evaluation metrics and 1 model each for both second and last priority evaluation metrics. Those 3 models that meets with the first priority evaluation metrics are models for Perseroan Kapital, Perseroan Real Estat, and Perseroan Telekomunikasi & Transportasi. While the model that fits second and last evaluation metrics are for Perseroan Korporasi and Perseroan Infrastruktur respectively. The following table represents the details of the results:

Table 4. Offline Evaluation Model Metrics Results

Subsidiary	Evaluation Metrics	Machine Learning Model	Recall Score	Precision Score	% Population
Perseroan Kapital	First Priority	Logistic Regression	60.00%	22.22%	12.16%
Perseroan Real Estat	First Priority	Logistic Regression	62.50%	15.63%	20.87%
Perseroan Telekomunikasi & Transportasi	First Priority	Logistic Regression	50.00%	5.56%	22.01%
Perseroan Korporasi	Second Priority	Random Forest	18.75%	50.00%	17.06%
Perseroan Infrastruktur	Last Priority	k-Nearest Neighbours (KNN)	55.56%	6.33%	46.31%

Offline metrics, by design, capture performance only within the fixed distribution and temporal scope of training-validation data. In contrast, real-world workforces continuously evolve due to hiring initiatives, policy shifts, or macroeconomic factors, causing changes in feature distributions and resignation probabilities. Online Evaluation Process is specifically designed to address these dynamics, providing a method to monitor and evaluate model performance post-deployment. However, as real-world scenarios differ greatly, detailed literature on online evaluation processes is limited compared to offline evaluation.

Classical literature, such as Caruana and Niculescu-Mizil (2006), extensively discusses offline evaluation metrics like accuracy, precision, recall, or ROC curves, yet rarely explores model behavior after leaving the prototype stage. Similarly, HR analytics literature typically concludes with offline precision-recall evaluations on historical data, without discussing subsequent monitoring strategies. Although Widner & Kubat (1996) and later Gama et al. (2014) introduced concept drift monitoring, the operationalization of ongoing model evaluation remains largely unexplored.

Sculley et al. (2015) argue that technical metrics alone become meaningless if misaligned with actual business outcomes, advocating a "business-fitness function" to ensure model alignment with business goals. Yet, despite this business-centric view, recalibration of traditional metrics such as precision and recall using live data remains crucial. These metrics not only quantify performance but also act as early-warning indicators—such as sudden recall drops signaling potential covariate drift (Gama et al., 2013).

For Perseroan Luar Negeri Ltd.'s attrition model, which predicts resignations within a six-month horizon, performance evaluations require waiting for the first cohort to complete the full observation period. This structural latency is critical, as premature evaluation systematically inflates precision and underestimates recall (Zheng, 2015). Given subsidiaries have different offline success criteria, online metrics are specifically chosen—recall for Perseroan Kapital, Real Estate, Telekomunikasi & Transportasi, and Infrastruktur, and precision for Perseroan Korporasi.

Once predictions mature, precision and recall are recalculated using actual resignations, accompanied by Wilson score intervals to quantify uncertainty. Orawo (2021), Kott (2017), and Brown et al. (2001) consistently validate Wilson intervals for accurate error-band estimation, enabling executives to distinguish genuine performance drops from random fluctuations. If recall or precision fall outside these intervals or drop below 50%, the event triggers an alarm for further action.

Monitoring covariate drift utilizes the Population-Stability Index (PSI) calculated on the top ten variables ranked by mean absolute SHAP importance. SHAP values, estimated via TreeSHAP (for Random Forest) and KernelSHAP (for logistic regression and k-NN), capture over 90% of feature attribution mass (Lundberg & Lee, 2020). A PSI value exceeding 0.5 signals significant drift and necessitates model retraining (Siddiqi, 2006; Yurdakul & Naranjo, 2020).

Concept drift monitoring is addressed through the Linear Four Rate (LFR) detector (Lu et al., 2019), employing a Z-test comparing live and offline recall or precision rates. A Z-value above 2 (or 1.96 for stricter Wilson interval compliance) indicates meaningful drift, prompting deeper analysis or intervention. Finally, business-level metrics, including voluntary turnover rate delta (Cascio, 2014) and retention yield (Allen, Bryant & Vardaman, 2010), provide strategic insights into the effectiveness of retention strategies, guiding decisions on updating or redesigning the attrition model framework.

Evaluation Results

Over the first year of live deployment of each subsidiary company's employee attrition model, with the help of two-times online evaluation each conducted in six-month cohort period, it can be concluded that only the model that follows the first priority principle achieves the actual business target. For second priority model used in Perseroan Korporasi, as it focusses more towards precisions unlike any other subsidiary companies, saw a significant plunge in precision from 50 to only just 14 percent despite a rise in the recall result, contradictory with the business users' initial expectation. Lastly, in third priority model case in Perseroan Telekomunikasi & Transformasi, its performance mirroring their offline model results not only the recall but also the behaviour of labelling almost half of its workforce as "high-risk," making the model impossible to be implemented for retention strategy.

Despite this, all models experience covariate drift and making the model might perform worse especially Perseroan Kapital and Perseroan Real Estat, which are two subsidiaries that has very high annual attrition rate, experienced a recall collapse from about 60 percent in training to 28 percent and 43 percent respectively. Across all five subsidiary companies, the root cause diagnostics converged into similar hypothesis. The existence of mandatory training, mass recruitment, promotions & resignment scheme, as well as jobs rotations might be the root cause of both model performance drop as well as the making the covariate drift itself. This existence not only affects each of their own variable to shift, but also variables that correlates with that such as performance and peer ratings, years since last promotions, and employee age distributions. However, this existence itself still needs to be confirmed whether such cases are actually happened and in which subsidiaries it occurred.

Some variables might also have a possibility to shift due to one period anomaly such as the possibility of mass pandemic event that affects absenteeism or short courses that needs to be taken for certain staff only. Once this happens, it slightly reduces the model performance as well but not as big as the previous variables mentioned. And also, when these variables realigned in the next cohort, the recall rebounded to its expected performance outcome. Combined with the fact that all models found no concept drift when being tested using Linear Four-Rate test, it confirms that the algorithms remain structurally sound while their input distributions have shifted.

On the other hand, during business metrics monitoring, it got enlighten of why pure model metrics can be misleading. Voluntary-turnover delta fluctuated across subsidiaries, but judging success against last year's company rate often punished teams that were in fact outperforming a heated labour market. The proposed solution for this specific case is to benchmarking delta against a projected industry mean annual attrition rate. This can be derived from the historical industry mean, macro job-demand indices, and sector-level engagement composites. This adjustment can reframe apparently "negative" deltas as genuine wins when industry churn spikes.

The reasons for macro job-demand indices and sector-level engagement composites are chosen is due to the existence of external factor that drops the initial voluntary rate before reduced by retention strategy and also half leave spike and peer rating drops respectively. This also backed up by Guerry and De Feyter (2009) when they create a Markov-chain techniques for forecasting stocks and flows of workers across job states for each industry using macro job-demand indices and sector-level engagement composites from longitudinal labour-force files. This then can be used to measure how the voluntary rate will become in the next 12 months, then use the previous industry annual attrition rate as the base of where it initially lies.

Macro job-demand indices can actually be proxied by time series statistics using ratio of vacancies to unemployment demonstrated initially by Clark & Hyson (2000) then optimized by Davis et al. (2012). Alternatively, it can use the methods proposed by Adrjan & Lydon (2019) where they use real-time vacancy data from millions of Indeed postings with wage offers can proxy for sector-specific job demand. This alternative can possibly be done by Perseroan Luar Negeri LTD as recently it got data sharing agreements with LinkedIn at the end of training period.

As for the sector-level, Hakanen et al. (2019) propose a method to proxy engagement index using standardized score of Best Linear Unbiased Predictor (BLUP) from multilevel regression model of two-layered Utrecht Work Engagement Scale – 3-item version (UWES-3) data. Those two layers will cluster the data by individual employee demographics as a first layer and the second layer is company sectors. UWES-3 survey itself was proposed by Schaufeli et al. (2019) as a short-form psychometric scale designed to measure employee work engagement.

Each of the three items in UWES-3 captures one of the core dimensions of work engagement as defined by the Job Demands–Resources (JD-R) model in Schaufeli & Bakker (2004), which are vigour, dedication, and absorption. JD-R model itself was fundamentally framed using Khan's (1990) concept of meaningfulness–safety–availability triad of engagement theory. Further research may still be required to validate or refine the variables used in projecting the industry's mean annual attrition rate for practical implementation. These variables can also be triangulated and strengthened by analysing patterns from exit interview data.

The roadmap below translates the engagement-centred business solutions into an eighteen-month action sequence. It begins with a technical stabilisation sprint; retraining all subsidiary models on the latest data; then moves into a knowledge-building cycle that mines exit interviews and external labour statistics to enrich the predictive pipeline and readjust business metrics evaluation process. Once upgraded, the plan shifts to full operationalisation with an autonomous monitoring dashboard, while a group-wide engagement-literacy programme secures long-term, self-sustaining capability. Each task is timed so that outputs from one stream (e.g., the projected industry attrition baseline) feed directly into the next one (e.g., the dashboard's drift alert), ensuring tight feedback loops and minimising idle time between phase.

Table 5. Implementation Plan

Task	Who	What	When	Where	Why (Justification)	How
Model retraining & champion selection	HR Data Science Team, HR Lead	Retrain all five subsidiary models on the most recent six-month dataset; select the model that tops the first-priority offline metric for each subsidiary	Month 1	Corporate Analytics Cluster; local data marts	Restores technical fitness after the drift episodes detected in the previous cohorts	Refresh feature stores, rebuild modelling process, conduct offline evaluation, then sign-off by CDO
Exit-interview evidence reviews	HRBP, People Analytics CoE	Code exit-interview transcripts; confirm or reject hypotheses on mandatory training surges, mass recruitment, and promotion–resignation schemes	Month 2–4	Corporate HRIS & subsidiary HR offices	Converts anecdotal drift explanations into quantified variables for model enrichment	Do thematic analysis across all subsidiary companies' exit interviews and do FGD for hypothesis confirmation with each HR subsidiary team separately
Design method to project industry attrition baseline	Labour-Market Intelligence Unit, External Econ Advisers	Assemble five-year sector quits data, vacancy pressure indices, UWES-3 sector engagement scores; publish semi-annual projection spec	Month 1–5	HQ Strategy Office	Provides the external benchmark required to normalise business-metric deltas across subsidiaries	Literature review, methods comparison analysis, stakeholder review
Build enriched comparison model & XAI study	HR Data Science Team	Add confirmed exit-interview variables and projected attrition baseline; compare against current champion plus deep-learning and RL variants; run SHAP/XAI to prioritise retention levers	Month 4–7	Corporate Analytics Cluster	Tests whether richer features or advanced algorithms yield materially better recall and clearer actionable drivers	Conduct parallel model training pipelines, then do A/U-statistic offline evaluation test before moving to executive demo
Pilot deployment of winning model	DevOps, Subsidiary IT Team	Roll out comparison winner to a shadow slot for one cohort; monitor live metrics	Month 8–9	Subsidiary production servers	Ensures real-world robustness before full switch-over	Model Production process
Autonomous monitoring & QC dashboard	People Analytics CoE, BI Engineering	Integrate online evaluation metrics workflow into a single dashboard	Month 6–9	Group BI platform	Automates governance and raises early warnings of macro or covariate drift	Build ETL process for data pipeline used in dashboard, decides the SLA-based alerting process, then build the dashboards
Engagement-literacy programme & documentation	L&D, HRBP, Line Managers	Create playbooks, run workshops, certify HR and managers on engagement theory, dashboard use, and retention tactics	Month 10–18	Hybrid: Corporate Academy & virtual classrooms	Embeds knowledge so that ongoing improvements do not depend on the core analytics team	Develop holistic training plan, documents all necessary materials, deliver the learning program, evaluate the learning program

CONCLUSION

In conclusion for the analysis results, business solutions that can be suggested for this case will be divided into 3 parts: immediate solutions, mid-term solutions, and long-term solutions. In the immediate term, Perseroan Luar Negeri Ltd should retrain all five subsidiary models on the newest six-month dataset and select, for each entity, the version that maximises its first-priority offline metric (recall with maintaining below 25% of total targeted "high-risk" in live period). Rapidly refreshing the weight vectors in this way restores the technical baseline and reducing chance for further covariate drift.

Over the next one-to-two cycles the focus shifts from technical to analytic and insight. Exit-interview transcripts must be mined to confirm or debunk the hypotheses surfaced during the online evaluations; such as the existence of mandatory training, mass recruitment waves, or accelerated promotion-and-resignation schemes; while a parallel work-stream builds and validates a method for projecting the industry's mean annual attrition rate. Once those two evidence sets are in hand, the team should enrich the prediction pipeline, analyse between the upgraded model and the current champion, and benchmark both against more advanced architectures such as deep neural network, reinforcement-learning agents, etc. or prolong training period model. Additionally, using explainable-AI techniques to pinpoint the features with the greatest impact on retention can boost retention strategy. The winning approach then feeds an autonomous monitoring dashboard that reports technical health, business-metric deltas, and deviations from the projected industry baseline in near real time.

For longer term solutions, sustainability depends on people rather than algorithms. Codifying these practices into playbooks, training modules, and decision rights; and rolling them out across HR business partners, line managers, and analytics staff; will embed engagement literacy and continuous-improvement routines into day-to-day operations, ensuring that the system remains resilient as markets, data streams, and organisational priorities evolve.

REFERENCES

Abd Alia, Z. N., & Alhamad, A. M. (2022). Behavior financial theory and analysis of investor behavior in the capital markets in Lebanon. *Journal of Management and Economic Studies, 4*(2), 82–90. https://doi.org/10.26677/TR1010.2022.1014

Adrjan, P., & Lydon, R. (2019, October). *Labour market tightness and wages: Evidence from online job postings*. Paper presented at the IZA Conference on Big Data in Labor Economics, Bonn, Germany.

Al Mamun, C. A., & Hasan, M. N. (2017). Factors affecting employee turnover and sound retention strategies in business organization: A conceptual view. *Problems and Perspectives in Management, 15*(1), 63–71. https://doi.org/10.21511/ppm.15(1).2017.06

Al-Suraihi, W. A., Samikon, S. A., Al-Suraihi, A.-H. A., & Ibrahim, I. (2021). Employee turnover: Causes, importance and retention strategies. *European Journal of Business and Management Research, 6*(3), 1–10. https://doi.org/10.24018/ejbmr.2021.6.3.893

Ambrosat, S., & Grünwald, C. (2023). Towards a future-proof organisation: Using foresight in HR and organisational development. *Strategic HR Review, 22*(5), 169–173. https://doi.org/10.1108/SHR-07-2023-0040

Baylor, D., Brecht, L., Casagrande, N., et al. (2017). TFX: A TensorFlow-based production-scale machine learning platform. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1387-1395).

Belete, A. K. (2018). Turnover intention influencing factors of employees: An empirical work review. *Journal of Entrepreneurship & Organization Management, 7*(3), 253–267. https://doi.org/10.4172/2169-026X.1000253

Branham, L. (2005). *The 7 hidden reasons employees leave: How to recognize the subtle signs and act before it's too late*. AMACOM.

Brown, L. D., Cai, T. T., & DasGupta, A. (2001). Interval estimation for a binomial proportion. *Statistical Science, 16*(2), 101–117. https://doi.org/10.1214/ss/1009213286

Carter, S. P., Dudley, W., Lyle, D. S., & Smith, J. Z. (2019). Who's the boss? The effect of strong leadership on employee turnover. *Journal of Economic Behavior & Organization, 159*, 323–343. https://doi.org/10.1016/j.jebo.2018.12.028

Caruana, R., & Niculescu-Mizil, A. (2006). An empirical comparison of supervised learning algorithms. In *Proceedings of the 23rd International Conference on Machine Learning* (pp. 161-168). https://doi.org/10.1145/1143844.1143865

Cascio, W. F. (2014). Leveraging employer branding, performance management, and human resource development to enhance employee retention. *Human Resource Development International, 17*(2), 121–128. https://doi.org/10.1080/13678868.2014.886443

Clark, K. A., & Hyson, R. (2000). Measuring the demand for labor in the United States: The Job Openings and Labor Turnover Survey. In *Proceedings of the American Statistical Association, Survey Research Methods Section* (pp. 251–256).

Davis, S. J., Faberman, R. J., & Haltiwanger, J. C. (2012). Labor market flows in the cross section and over time. *Journal of Monetary Economics, 59*(1), 1–18.

El-Rayes, N., Fang, M., Smith, M., & Taylor, S. (2020). Predicting employee attrition using tree-based models. *International Journal of Organizational Analysis, 28*(6), 1273–1291. https://doi.org/10.1108/IJOA-10-2019-1903

Gama, J., Sebastião, R., & Rodrigues, P. P. (2013). On evaluating stream learning algorithms. *Machine Learning, 90*(3), 181–213.

Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., & Bouchachia, A. (2014). A survey on concept drift adaptation. *ACM Computing Surveys, 46*(4), Article 44. https://doi.org/10.1145/2523813

Gómez-Uribe, C. A., & Hunt, N. (2015). The Netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems, 6*(4), Article 13.

Guerry, M., & De Feyter, T. (2009). Markovian approaches in modeling workforce systems. *Journal of Current Issues in Finance, Business and Economics, 2*(4), 351–370.

Hakanen, J. J., Ropponen, A., Schaufeli, W. B., & De Witte, H. (2019). Who is engaged at work? A large-scale study in 30 European countries. *Journal of Occupational and Environmental Medicine, 61*(11), 877–886.

Holtom, B. C., Mitchell, T. R., Lee, T. W., & Eberly, M. B. (2008). Turnover and retention research: A glance at the past, a closer review of the present, and a venture into the future. *The Academy of Management Annals, 2*(1), 231–274. https://doi.org/10.1080/19416520802211552

Hossain, M. S., Hossain, M. R., Hasan, S. M. M., Akter, F., Srizon, A. Y., Farukuzzaman, M., & Islam, H. (2023). Leveraging AI-driven strategies to mitigate employee turnover in commercial industries. In *Proceedings of the 2023 26th International Conference on Computer and Information Technology (ICCIT)*, Cox's Bazar, Bangladesh. https://doi.org/10.1109/ICCIT60459.2023.10441379

Hur, H., & Hawley, J. (2019). Turnover behavior among US government employees. *International Review of Administrative Sciences, 86*(4), 641–656. https://doi.org/10.1177/0020852318823913

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Academy of Management Journal, 33*(4), 692–724.

Kaplan, R.S. and Norton, D.P. (1996) Strategic Learning: The Balanced Scorecard. Strategy & Leadership, 24, 18-24. https://doi.org/10.1108/eb054566

Kaur, P., Malhotra, K., & Sharma, S. K. (2020). Moderation-mediation framework connecting internal branding, affective commitment, employee engagement and job satisfaction: An empirical study of BPO employees in Indian context. *Asia-Pacific Journal of Business Administration, 12*(3/4), 327–348. https://doi.org/10.1108/apjba-10-2019-0217

Kearns, P. (2003). *HR strategy: Business focused, individually centred*. Butterworth-Heinemann.

Kott, P. S. (2017). A note on Wilson coverage intervals for proportions estimated from complex samples. *Survey Methodology, Statistics Canada, 43*(2). http://www.statcan.gc.ca/pub/12-001-x/2017002/article/54872-eng.htm

Lai-Bennejean, C., & Beitelspacher, L. (2021). Impacts of salespeople's biased and unbiased performance attributions on job satisfaction: The concept of misattributed satisfaction. *European Journal of Marketing, 55*(2), 468–496. https://doi.org/10.1108/ejm-11-2018-0816

Lu, J., Liu, A., Dong, F., Gu, F., Gama, J., & Zhang, G. (2019). Learning under concept drift: A review. *IEEE Transactions on Knowledge and Data Engineering, 31*(12), 2346–2363.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems* (Vol. 30).

March, J. G., & Simon, H. A. (1958). *Organizations*. John Wiley & Sons.

Mohammad, I., & Jahangir, A. (2014). Factors influencing intention to quit or stay in jobs: An empirical study on selected sectors in Bangladesh. *Stamford Journal of Business Studies, 6*(1), 142–164. https://www.researchgate.net/publication/292963289

Nandal, M., Grover, V., Sahu, D., & Dogra, M. (2024). Employee attrition: Analysis of data-driven models. *EAI Endorsed Transactions on Internet of Things, 10*(1). https://doi.org/10.4108/eai.28-1-2024.172902

Orawo, L. A. (2021). Confidence intervals for the binomial proportion: A comparison of four methods. *Open Journal of Statistics, 11*(5), 806–816.

Park, T. Y., & Shaw, J. D. (2013). Turnover rates and organizational performance: A meta-analysis. *Journal of Applied Psychology, 98*(2), 268–309. https://doi.org/10.1037/a0030723

Pukelsheim, F. (1994). The Three Sigma Rule. *The American Statistician*, 48(2), 88–91. https://doi.org/10.2307/2684253

Rigamonti, E., Gastaldi, L., & Corso, M. (2023). Measuring HR analytics maturity: Supporting the development of a roadmap for data-driven human resources management. *Management Decision, 62*(13), 243–282. https://doi.org/10.1108/MD-11-2023-2087

Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior, 25*(3), 293–315.

Schaufeli, W. B., Shimazu, A., Hakanen, J. J., Salanova, M., & De Witte, H. (2019). An ultra-short measure for work engagement: The UWES-3 validation across five countries. *European Journal of Psychological Assessment, 35*(4), 577–591.

Schlechter, A. F., Syce, C., & Bussin, M. (2016). Predicting voluntary turnover in employees using demographic characteristics: A South African case study. *Acta Commercii, 16*(1), Article 274. https://doi.org/10.4102/ac.v16i1.274

Schröer, C., Kruse, F., & Gómez, J. M. (2021). A systematic literature review on applying CRISP-DM process model. *Procedia Computer Science, 181*, 526–534. https://doi.org/10.1016/j.procs.2021.01.199

Sculley, D., Phillips, T., Ebner, D., Chaudhary, V., Young, M., Crespo, J.-F., & Dennison, D. (2015). Hidden technical debt in machine learning systems. *Advances in Neural Information Processing Systems, 28*, 2503–2511.

Sharma, A. (2018). Confusion matrix in machine learning. *GeeksforGeeks.* https://www.geeksforgeeks.org/confusion-matrix-in-machine-learning/

Shenoy, N. (2016). Employee turnover – impact on organizations and reasons. *International Journal of Advanced Research in Management, 7*(1), 96–104.

Siddiqi, N. (2006). *Credit risk scorecards: Developing and implementing intelligent credit scoring*. Wiley.

Singh, K., & Singh, R. (2019). A study on employee attrition: Effects and causes. *Journal of Research in Engineering, Science and Management, 2*(8), 174–178.

Thakur, P. (2020). A chronological review of human resource management. *Journal of Emerging Technologies and Innovative Research, 7*(2), 537–541.

Widmer, G., & Kubat, M. (1996). Learning in the presence of concept drift and hidden contexts. *Machine Learning, 23*(1), 69–101. https://doi.org/10.1007/BF00116900

Xu, H., Ho, Q., & Kumar, A. (2020). Model performance management at LinkedIn. *IEEE Data Engineering Bulletin, 43*(2), 40–51.

Yurdakul, B., & Naranjo, B. (2020). Statistical properties of the population stability index. *Journal of Risk Model Validation.* https://doi.org/10.21314/JRMV.2020.227

Zheng, A. (2015). *Evaluating machine learning models: A beginner's guide to key concepts and pitfalls.* O'Reilly Media.