NUS Datathon 2025 Report

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Introduction

In today's competitive financial landscape, optimizing the customer experience is critical for improving engagement and driving revenue growth. One of the key challenges faced by financial institutions is matching customers with the most suitable financial advisors (agents) to ensure personalized service and effective policy recommendations. The success of this matching process directly impacts customer satisfaction, conversion rates, and overall business performance. Our model will give a **Compatibility Score** for every agent given a client, based on their respective details. The top 20 candidates will proceed to the next round of ranking.

From an ethical perspective, the most pressing concern with Singapore's insurance industry by far, is illegal upselling of policies by overly profit-driven agents. Our model aims to flag potentially troublesome agents using **Cancellation Rate**, reducing their total score in the matching algorithm. From the agents' perspective, we feel it is important to ensure all agents within the team, especially new ones and those from minority races, are given equal opportunities to take on new clients. We achieve this by doing the reverse, increasing their scores if they have yet to take on their first client (**Fairness Score**), and disregarding the clients' race from the model training process altogether.

The model ranks the top 5 agents out of the 20 shortlisted for every given client based on the highest Total score as calculated below:

$$Total\ score\ =\ Compatibility\ Score\ \times\ 12 + Fairness\ score\ \times 4 - Cancellation\ rate\ \times 5$$

We also believe that ensuring unbiased advisor-client matching is crucial for trust and sustainability in the insurance industry. If given more time, we would like to use a fairness checker to evaluate economic disparities, stability, and fairness while maintaining business viability. A **sustainable economic approach** is key to long-term success — ensuring fair treatment for all clients without compromising financial stability. Thus, the fairness checker has two elements: **Agent Stability Score** and **Economic Matching Score** to ensure unbiased results for clients of different economic status.

Dataset Overview

The dataset consists of three key tables: **Agent Information, Client Information, and Policy Information.** Each table provides different types of structured data that can be integrated for feature engineering and predictive modeling.

- **Agent Information:**
  This dataset contains agent demographics, professional experience, and sales performance metrics. These features can be used to **assess an agent's sales effectiveness** and **specialization in different product categories**.
- **Client Information:**
  The client dataset provides demographic and economic details, including **age, household size, and economic status**. This information is crucial for **profiling customers, understanding their insurance needs, and predicting conversion likelihood**.
- **Policy Information:**
  This dataset captures policy-level transactions, including **product type, premium amount, and policy status (active, lapsed, or canceled)**. It helps in **identifying purchase behaviors, retention patterns, and risk indicators**.

This dataset structure allows us to **design a recommendation system** that improves client-advisor assignments, maximizing engagement and conversion rates.

Methodology

Our general approach is to build an algorithm that learns how features of the ideal agent behave with features of a client. Without access to more private data, and given Singlife's more extensive experience in the insurance industry compared to us, we think our best current assumption is to use historical matches as our. Therefore,

1. To ensure the client has an assigned agent in the event the first choice agent is unable to serve the client. By design, our model assigns more clients to better agents, so there is the possibility of excessive workload

2. To increase competition between agents, incentivising them to serve their clients better and more ethically
3. To reduce the likelihood of dominant demographics taking up all clients for themselves

Exploratory Data Analysis

Data cleaning

Method	Description	Justification
Remove Missing Values **(Categorical Columns)**	Categorical columns with missing values are removed	Median imputation cannot be applied; unethical to assume clients' race/gender
Filling Missing Values **(Numerical Columns)**	Numerical columns with missing values are replaced with the median	Less affected by outliers and maintains the integrity of data distribution

Ethical Considerations in Data Cleaning

Method	Justification
Transparency	Every step is documented clearly to maintain accountability.
Privacy	Sensitive data like `cltdob` was used responsibly and only as needed, without unnecessary exposure.
Fairness	All methods were designed to minimize bias and ensure equal representation of all data groups.
Integrity	Adjustments were made carefully to keep the dataset accurate and trustworthy.

Data preprocessing

Method	Description	Justification
Converted Data Types	Changed columns (e.g., `household_size`) to numeric.	Numbers are easier to analyze and work better with models.
Formatted Decimals	Rounded values to three decimal places.	It keeps the data clean and consistent for better readability.
Calculated Age	Derived `exact_age` from `cltdob`.	Exact age helps with more precise grouping and analysis.
Grouped Ages	Categorized clients into age groups.	Age groups make it easier to see trends and compare demographics
Encoded Expertise	Converted agent expertise into categories.	Categorical data is easier to compare and use in models.
Added Age Percentages	Created columns like `pct_young` for age group distributions.	Shows demographic insights and helps match clients with agents.
Scaled Features	Standardized numerical data.	Ensures all variables are treated fairly in the analysis
Data Splitting	Split the data into 80% training and 20% testing	Ensure there is enough data for learning patterns; prevent both underfitting and overfitting

Modeling

Feature-Weighted Euclidean Similarity (FWES)

The **Feature-Weighted Euclidean Similarity (FWES) Algorithm** is a content-based recommendation system designed to match insurance clients with the most suitable financial advisors. FWES uses a weighted Euclidean distance metric to quantify the similarity between a client's attributes and the historical profiles of agents' serviced clients. By featuring importance scores and ranking agents by its similarity, this algorithm aims to improve the precision of recommendations and optimize client-agent pairings.

First, we calculate the matching score. We split the data into **80% training** and **20% testing**. From the training set, a mapping of agents to their **past serviced clients** is created by merging the policy dataset with the client dataset. Each agent's past client attributes like economic status and family size are then averaged to create an agent profile. However, to prevent potential racial discrimination, we excluded the client's race from the algorithm to ensure ethical fairness. We are aware that not all features contribute equally to an agent's profile, so a **Feature Weighting Scheme** is included to emphasize more important attributes (i.e. economics status 40%, family size 10%). Notably, we set the weights for the client's gender and their marital status to 10%, and removed the impact of race to minimize any biases that the algorithm might possibly present.

Next, we created a feature vector for **agents who don't have prior records** in our policy_info file to **render opportunities** for them. Each client in the test set is compared with the agent profiles from the training data, both client and agent vectors are **element-wise multiplied** by their weights so that feature importance is taken into account. The smaller the Euclidean distance, the more similar the agent is to the client. Twenty agents with the lowest distance are selected and assigned a **similarity score** which is then normalized to a value between 0 and 1.

The results of the FWES (20 agents) are used as inputs in our next model.

Comprehensive Agent Scoring Model

Considering one major issue in Singapore's insurance industry is unethical upselling by agents who often have relatively high **policy cancellation rates**. To address this, we integrate agent cancellation rates into our scoring formula, thus **penalizing agents with higher cancellation rates.** This means that if an agent has a high cancellation rate, their overall score will be reduced, which decreases the likelihood for them to appear in a client's recommendation.

Lastly, we calculate the final score and recommend a final recommendation list for each client with the highest score. Summing from above, we combine the **matching score** with the **similarity score**, and take the **cancellation rate** into account using the formula we devised. This step balances **predicted agent compatibility, fairness consideration, and ethical safeguard**.

Last, to measure the effectiveness of our FWES + Comprehensive Agent Scoring Model algorithm, we computed the **True Positives (TP), False Positives (FP), False Negatives (FN) and True Negatives (TN)** in order to determine the metrics for **precision, recall** and **F1-score** which have the following formula:

$$Precision = \frac{TP}{(TP+FP)} \qquad Recall = \frac{TP}{(TP+FN)}$$

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \qquad F1 - score = \frac{2\times(precision\times recall)}{(precision + recall)}$$

Results

The most notable figure in our results is True Negatives (TN): 53643084. This means that the algorithm did not recommend 53643084 incorrect agent-client pairings and that most recommendations were correctly excluded from consideration. In addition, our algorithm achieves a 10% precision rate, which is **significantly higher than random selection**. Given there are 20000 potential agents, a random guess would only yield a precision rate of around 0.005%. Considering the complex, multi-factor matching, we consider our algorithm capable of identifying meaningful patterns, considering that our combination score concurrently considers ethical concerns, hence creating an optimized model for matching recommendation.

```
True Positives (TP): 519
False Positives (FP): 4780
False Negatives (FN): 4932
True Negatives (FN): 53643082
Precision: 0.10
Recall: 0.10
F1 Score: 0.10
Accuracy: 1.00
```

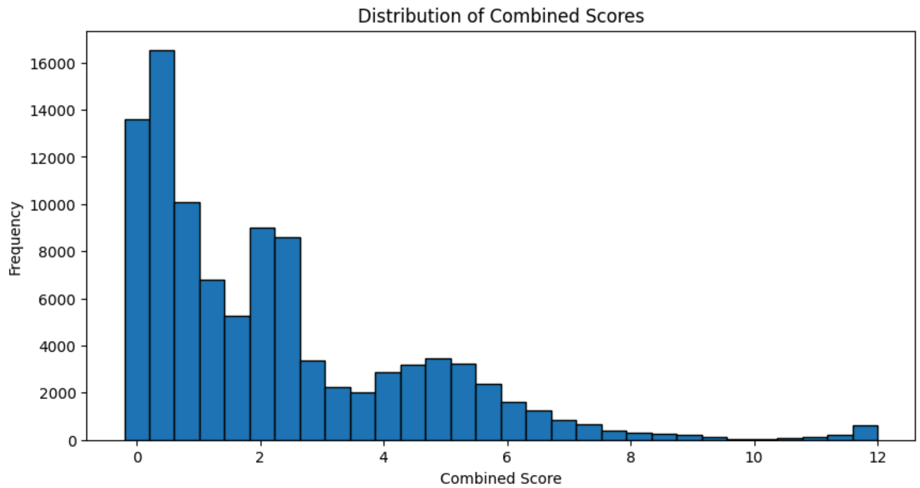

Figure 1: Distribution of Combined Scores

Figure 1 shows that the distribution of combined scores is right-skewed. There are many agents with scores that are within the range of zero to three, and below 2000 of them achieve the score of 10-12. This figure shows that our algorithm allows the combination score of the agents to be spread out, rather than being concentrated in a single bracket.

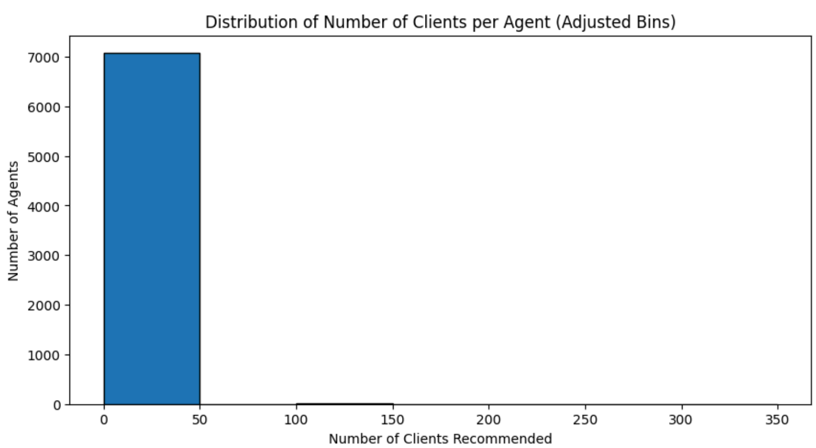

Figure 2: Distribution of Number of Clients per Agent

Figure 2 shows that an agent gets around zero to fifty clients on average which is ideal and acceptable in the workplace, while some agents are matched to about 100-150 clients. We have addressed the issue of excessive workload, as stated in our methodology, by recommending each client to five financial advisors with the highest combined score.

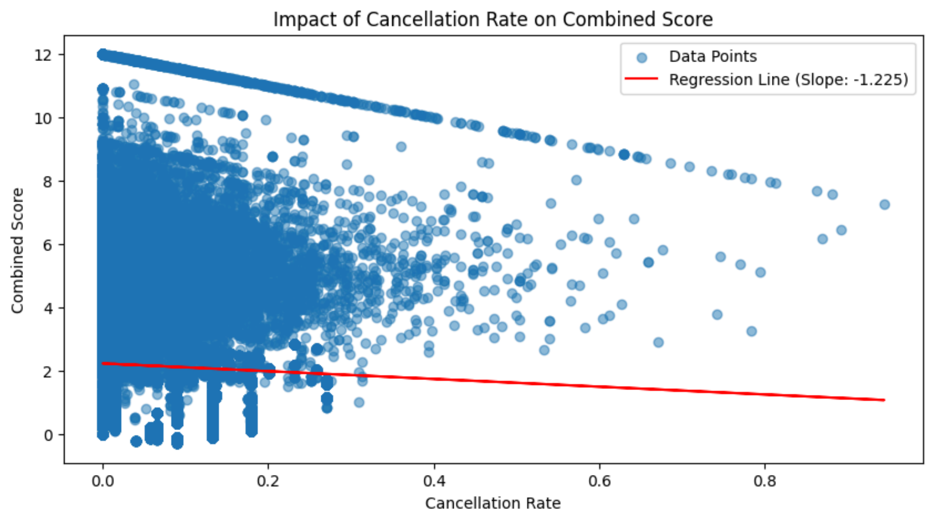

Figure 3: Impact of Cancellation Rate on Combined Score

Figure 3 shows that the Cancellation Rate and Combined Score are negatively correlated, though not to the strongest extent. The regression line has a slope of -1.225, which means that for a unit increase in cancellation rate, the combined score will fall by 1.225. This is because our Comprehensive Agent Scoring Model also considers the compatibility score and fairness score. Hence, an agent with low compatibility and ethic score will not receive a very high score even if his or her policy cancellation rate is high.

Insights

Strengths of FWES

Our recommendation system computes the average profile of clients that each agent has served, hence ensuring that recommendations align with past successful matches. The algorithm also excels at handling matching for new clients, as it relies solely on feature similarity rather than past interactions, so even first-time clients are able to receive meaningful recommendations. To prevent top-performing agents from being overwhelmed and assigned to excessive workload, our system is able to recommend multiple agents per client so that clients have alternative choices in cases of agent unavailability.

Limitations of FWES

However, the way our algorithm is built is based on the assumptions that historical matches are ideal and similarity equates to best match, given the lack of more detailed information in the dataset. But this does not always hold true. Factors beyond the dataset like communication effectiveness and policy specialization may also influence the compatibility between client and agent. Moreover, data sparsity poses the risk that agents with fewer historical matches may be misrepresented due to insufficient data, which affects recommendation reliability.

Conclusion

In conclusion, our Feature-Weighted Euclidean Similarity (FWES) algorithm presents a structured and scalable approach to matching clients with financial advisors based on feature similarity. Using a Comprehensive Agent Scoring Model, we were able to integrate ethics as a key consideration into our algorithm and ensure that both clients and agents are treated fairly.

Future Improvements

Model and our approach

The algorithm currently uses Euclidean distance as the similarity metric. For future improvements, we could use alternative similarity metrics like cosine similarity, which is used for high-dimensional data or Mahalanobis Distance which accounts for feature correlations. Also, we would like to include the Fairness-aware ML technique to ensure the model recommendations do not disproportionately exclude certain client groups. If possible, this could complement with a feedback system where clients can rate advisors to refine future recommendations.

(To further refine in the future) Fairness Checker for Ethical Advisor Matching

We build a fairness checker with two elements: **Agent Stability Score** and **Economic Matching Score** to ensure unbiased results for different economic statuses clients, enabling the company to check if their matching systems are unbiased or not.

General Scoring system

1. Agent Stability Score

Purpose: Measures advisor reliability based on policy in-force and cancellation rates.

- **Formula:**

$$AgentStabilityScore = (pct\_inforce - pct\_cancel) * \log(1 + economic\_status)$$

- **Rationale:**
    - Advisors with **high policy in-force rates** and **low cancellation rates** are more stable.
    - The log transformation prevents extreme values from skewing results while ensuring that higher economic status clients receive **more stable advisors**.

- **Normalization:**
    - The score is normalized between [0,1] to ensure consistency across different scales.

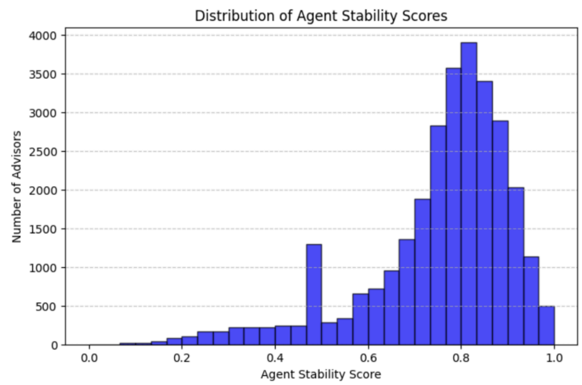

Figure 4: Distribution of Agent Stability Scores of the cleaned data

2. Economic Matching Score

Purpose: Evaluates the alignment between a client's economic conditions and their assigned advisor.

- **Formula:**

$$EconomicMatchingScore = \begin{cases} pct\_inforce * 0.7 + agent\_stability\_score * 0.3, & \text{if economic\_status} > 0.5 \\ pct\_inforce * 0.5 + agent\_stability\_score * 0.5, & \text{if economic\_status} \leq 0.5 \end{cases}$$

- **Rationale for Weighting (70/30 and 50/50):**
    - **High-income clients (70/30 weight split):** These clients already have financial stability, so the emphasis (70%) is on in-force rate (policy retention), ensuring long-term commitment from advisors. Stability matters less (30%) since they have more resources to switch advisors if needed.
    - **Low-income clients (50/50 weight split):** A balanced approach ensures that they receive stable advisors while also considering in-force rates to avoid biased distribution. Over-prioritizing stability could lead to a concentration of the most stable advisors with high-income clients, exacerbating disparities.
    - **Normalization:** Maintains comparability across different client-advisor pairings.

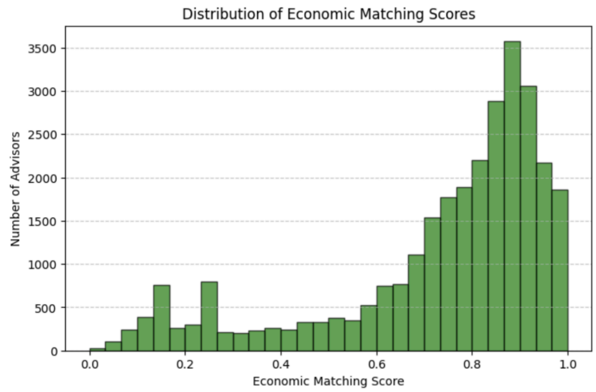

Figure 5: Distribution of Economic Matching Scores of the cleaned data

As this is a rough model, further refinements such as adaptive weightings, advanced fairness adjustments, and expanded feature integration will be necessary to make it a reliable industry standard for fair, efficient, and ethical financial advisory services. We hope this can ensure balanced **stability** and **economic matching** score distributions, identify top advisors with high stability and fairness scores, and help track how advisor-client pairings change over time to detect unintended biases.

(To further refine in the future) Fairness Checker Result:

Economic Matching Score Distribution help checks:

- **Low-income clients:** Assigned moderate-stability advisors to prevent all top advisors from clustering with high-income clients.
- **High-income clients:** Paired with stable advisors due to lower financial risk and business viability considerations.

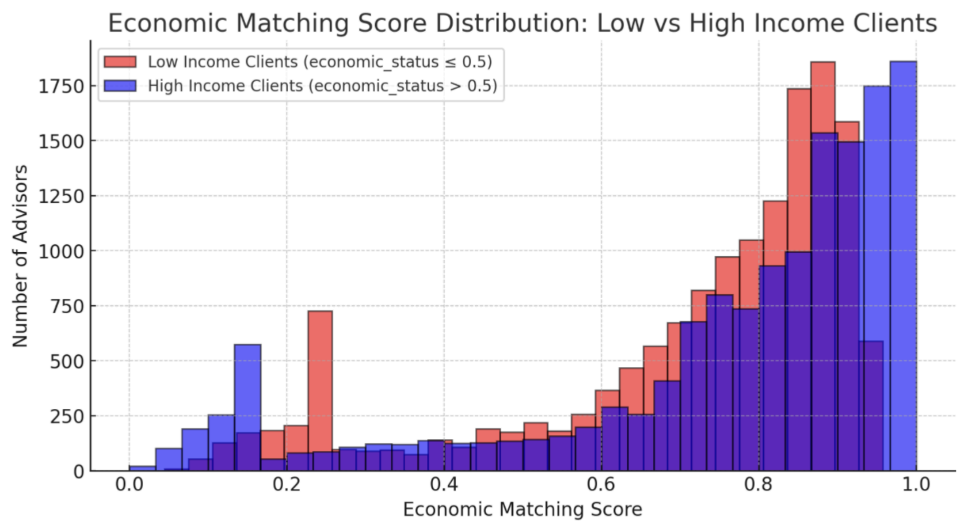

Figure 6: Distribution of Economic Matching Score of Low and HIgh Income Clients

Agent Stability Score Distribution help checks:

- **Low-income clients:** Matched with moderate-stability advisors to balance fairness and retention.
- **High-income clients:** Receive more stable advisors who prioritize long-term policy retention.

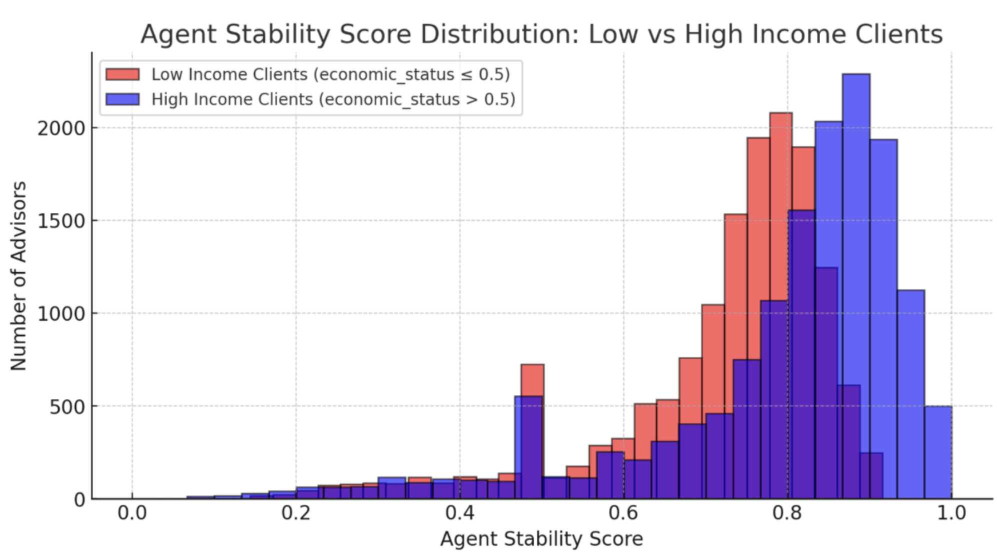

Figure 7: Distribution of Agent Stability Score of Low and High-Income Clients

Refinement of Fairness Checker and Future Improvement

Since this is an early-stage model, improvements are necessary to ensure ethical fairness and business viability**.** If we have more time, we hope to keep developing further models. The reason we want to develop this checker is that we believe ethics and sustainable economics model is the Key to Long-Term Success. We hope to balance Business and Ethics: While high-income clients generate more revenue, fair access to stable advisors ensures that low-income clients receive equitable treatment.

Several refinements are necessary to enhance accuracy, fairness, and business sustainability. The following improvements will help establish this system as a reliable industry standard for fair, efficient, and ethical financial advisory services.

There are also several things we hope to improve if we got more time:

1. Adaptive Weighting for Fairer Economic Matching

- Currently, the model uses fixed weight distributions (70/30 for high-income and 50/50 for low-income clients).
- Future iterations should develop dynamic weight adjustments based on:
    - Client engagement patterns (e.g., financial literacy, policy lapse history).
    - Economic mobility (e.g., clients who recently improved their financial status should not be stuck with advisors intended for lower-income clients).

2. Advanced Fairness Adjustments & Bias Correction

- Introduce real-time fairness monitoring to track unintended biases in advisor-client assignments.
- Implement fairness-aware machine learning techniques (e.g., demographic parity constraints, equalized odds, or adversarial debiasing) to proactively reduce economic discrimination.

- Develop a bias-correction framework to identify and mitigate potential disparities in assignments without sacrificing business sustainability.