Final Project

Estimating needs and Product reccomendation

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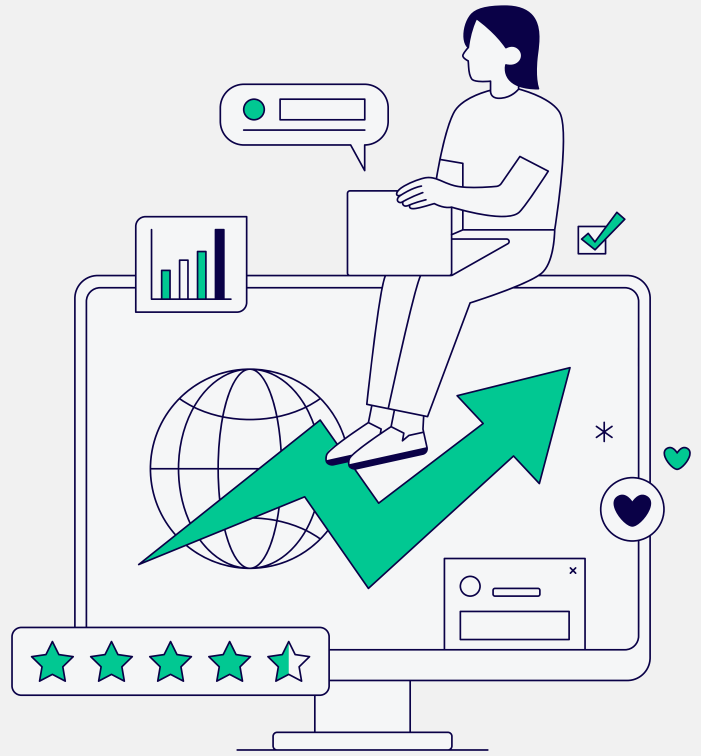
Our goal



- **Build a Data-Driven Needs & Recommendation Engine**

Develop a scalable pipeline that identifies each client's Income and Accumulation needs using tailored features and an optimized, recall-constrained stacking classifier.

- **Deliver Personalized, MiFID-based-Compliant Advice**

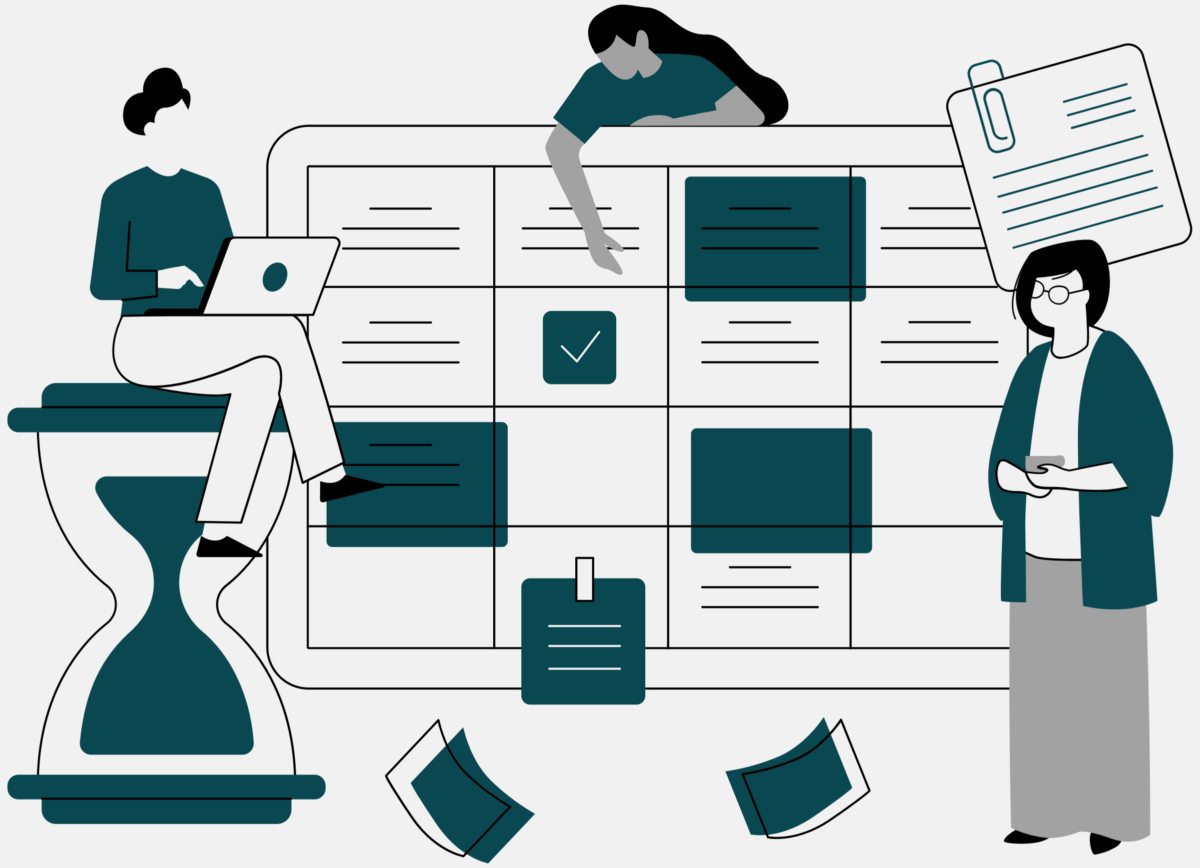
Integrate a bespoke ipywidgets MiFID II-based questionnaire with ML-derived financial-literacy and risk-propensity scores to create a weighted composite profile.

- **Maximize Client Fit & Commission Revenue**

Leverage an expanded product universe and next-best-action logic (ε-based risk filtering) to match every client with the most suitable offering—driving higher conversion rates and fee income.

Work Flow

Step-by-step outline of our project phases



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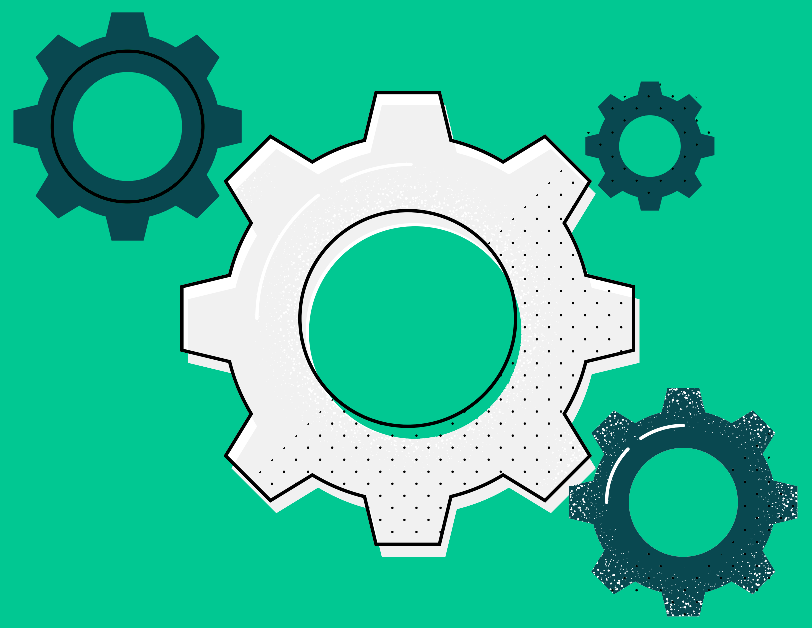
Features Engineering



- We applied **logarithmic transformations to Wealth and Income** to normalize their skewed distributions and reflect the principle of diminishing marginal utility in client assessments.

- We derived the **Income-to-Wealth ratio** (and its log) to gauge clients’ liquidity and spending capacity relative to their total assets.

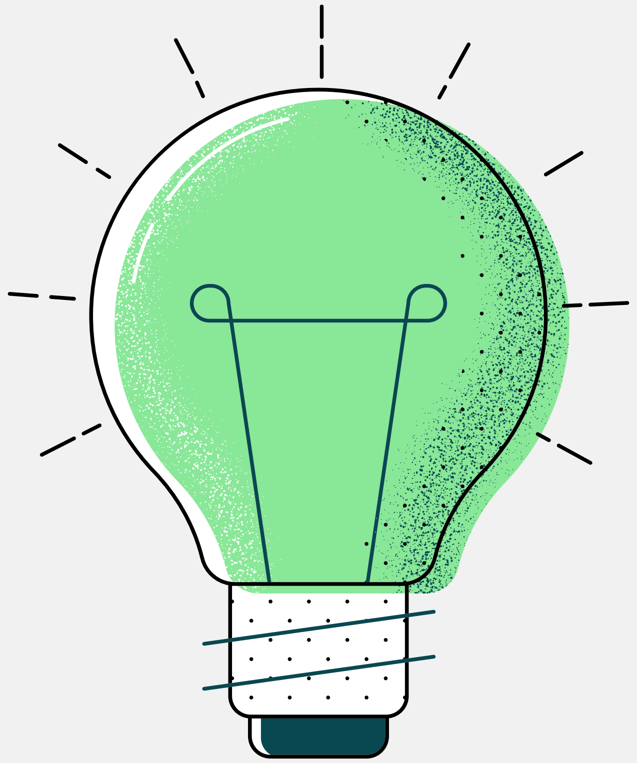
- **Binary flags** like Is_Single, Is_Senior, and Has_Education segment clients by household structure, life-stage, and financial literacy—key drivers of product suitability.

- The **Risk_Age_Interaction** feature captures how a client’s risk appetite changes with age, aligning product risk profiles to life-cycle preferences.

- By combining **core demographics** with these **engineered metrics**, we enrich our model’s ability to tailor investment recommendations to each client’s financial context.

Metric Index

Why we chose to maximize recall



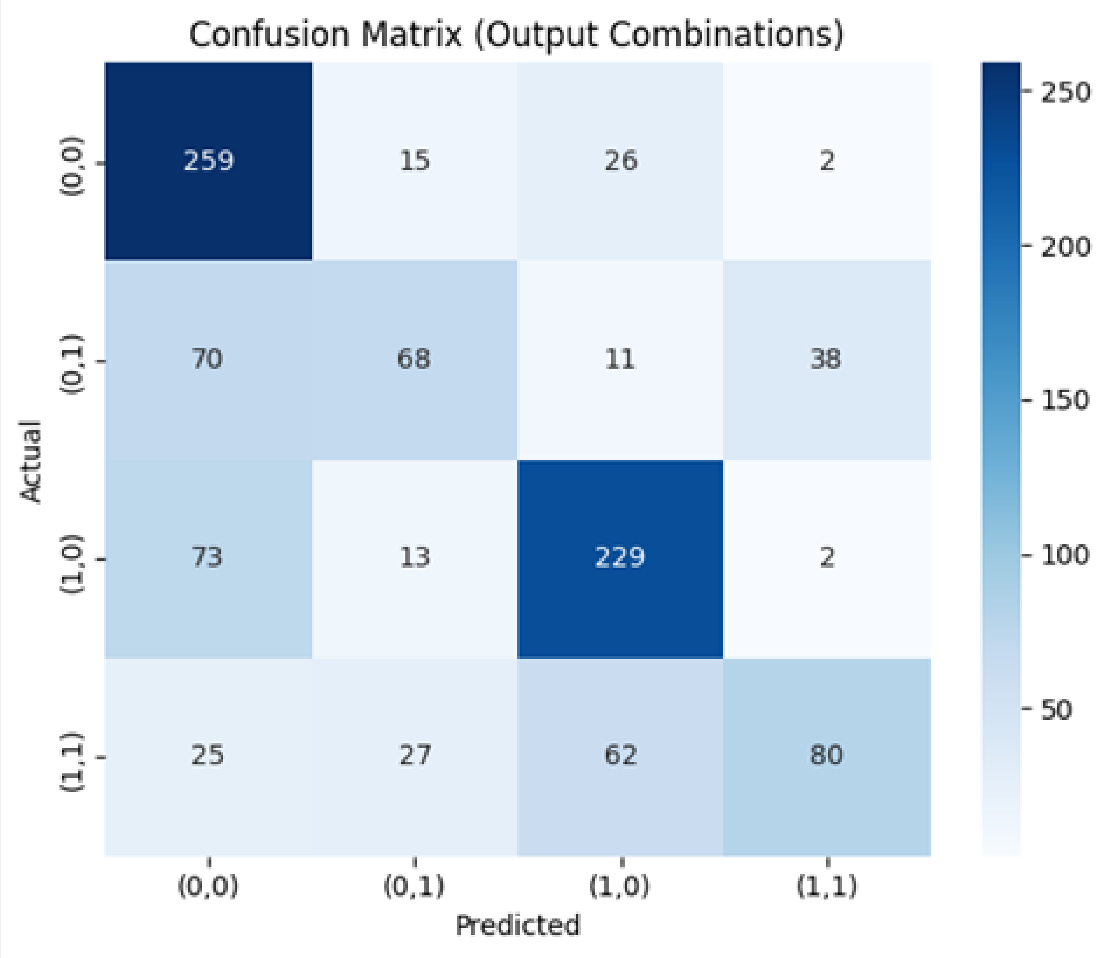
- **Maximize Commission Opportunities**
We prefer to reach out to one extra prospect—even if they don't convert—rather than risk missing a genuine buyer and losing fee income.

- **High-Recall Coverage for At-Risk & Underserved Segments**
A high-recall model ensures we catch as many "at-risk" or "underserved" clients as possible, even if it means reviewing a few extra candidates.

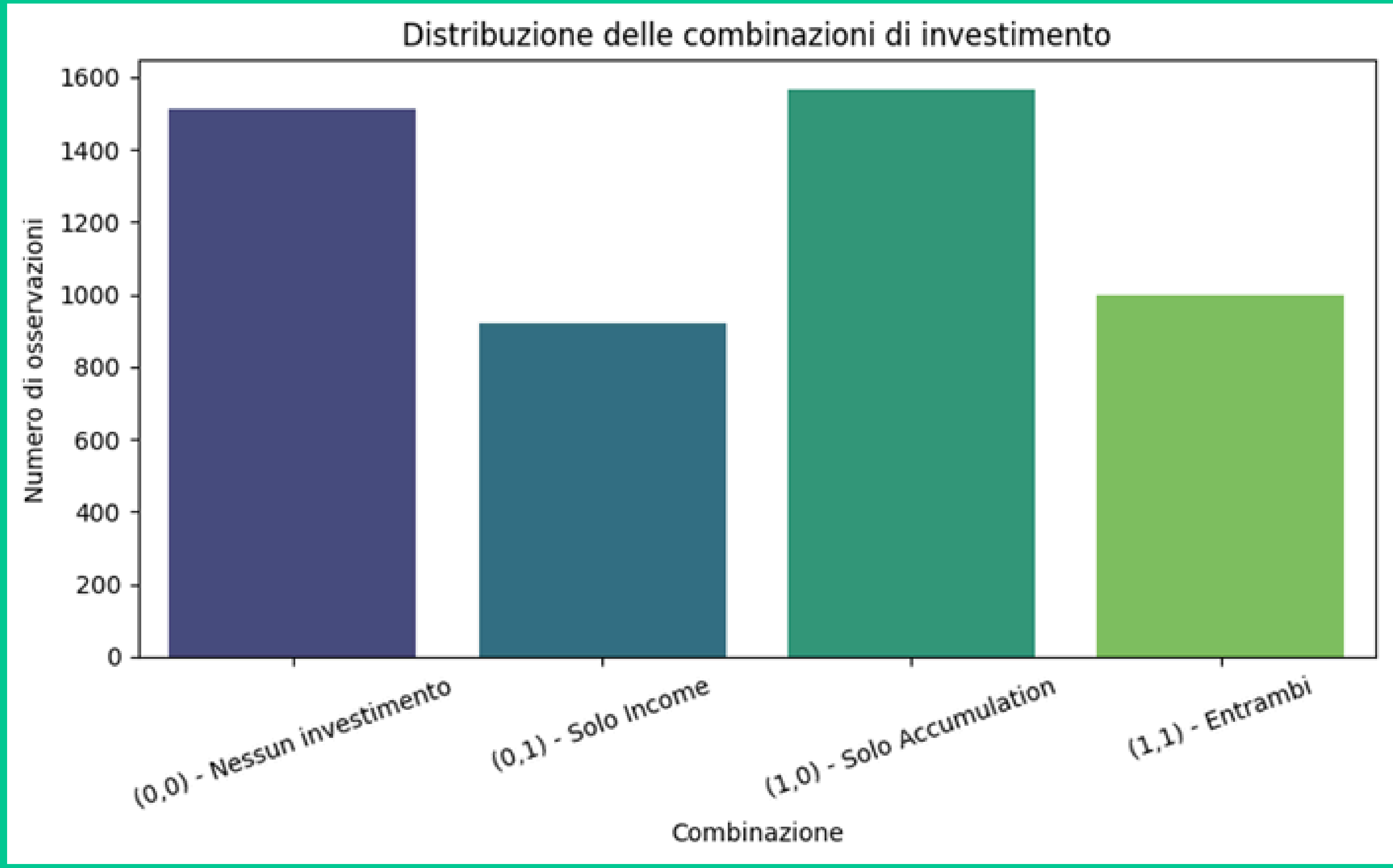
- **Balanced Optimization (Recall Threshold + F1)**
We enforce a minimum recall threshold to guarantee broad reach, then tune the model to maximize F1—ensuring we maintain efficiency (precision) within that recall boundary.

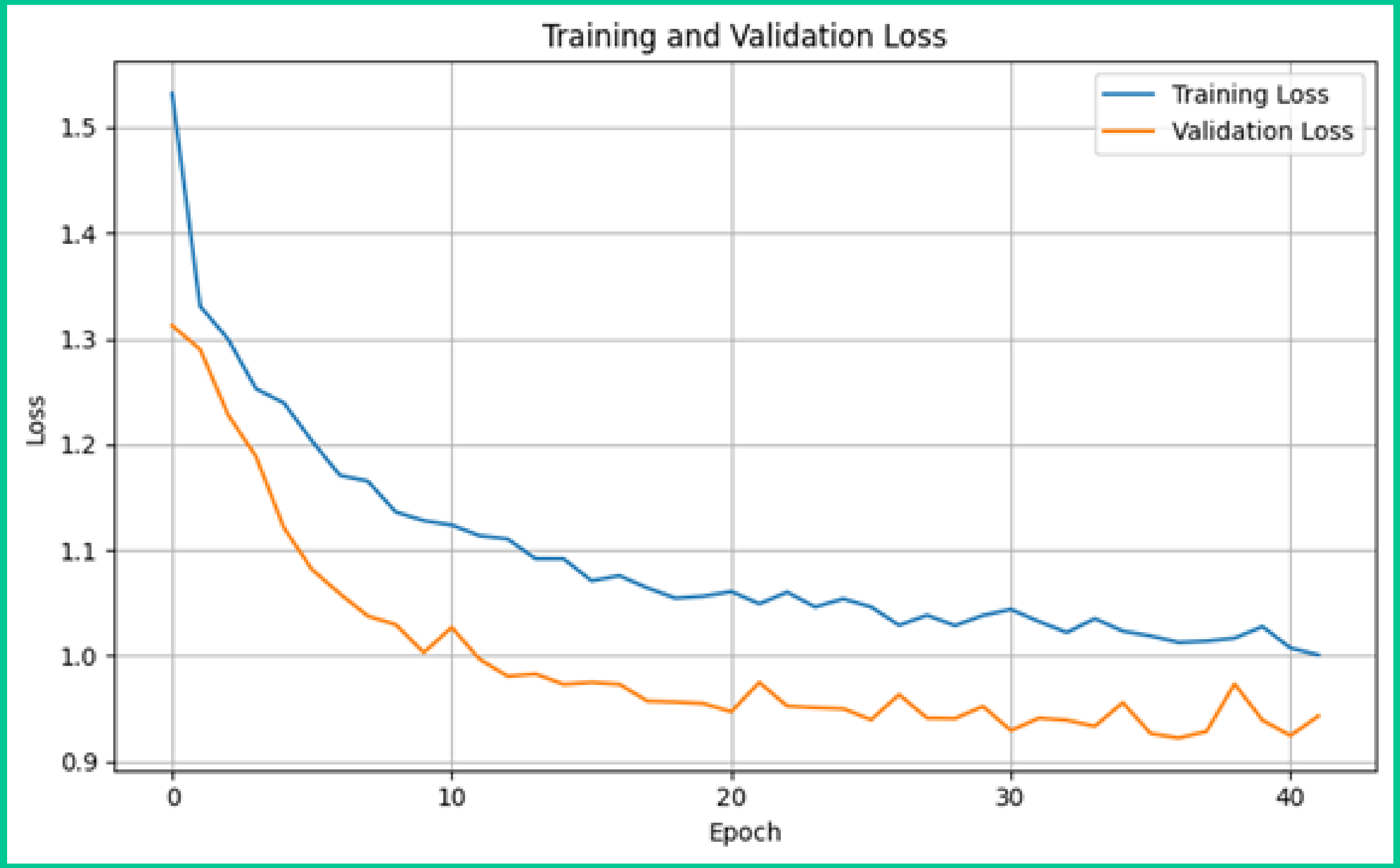
Multioutput Classifier

Neural Network



	precision	recall	f1-score	support
(0,0)	0.61	0.86	0.71	302
(0,1)	0.55	0.36	0.44	187
(1,0)	0.70	0.72	0.71	317
(1,1)	0.66	0.41	0.51	194





We initially framed the task as a **multi-output classification** problem—encoding the joint (AccumulationInvestment, IncomeInvestment) outcome into four categories—and trained a **deep neural network** (dense layers with batch normalization and dropout) to predict all combinations at once.

However, the network's training and validation losses stagnated, and the resulting classification report revealed particularly poor recall for critical classes, indicating the joint model was unable to disentangle the two targets effectively. These results may also be explained by the fact that the two targets are only weakly correlated, making it inherently difficult for a single model to capture both signal patterns simultaneously.

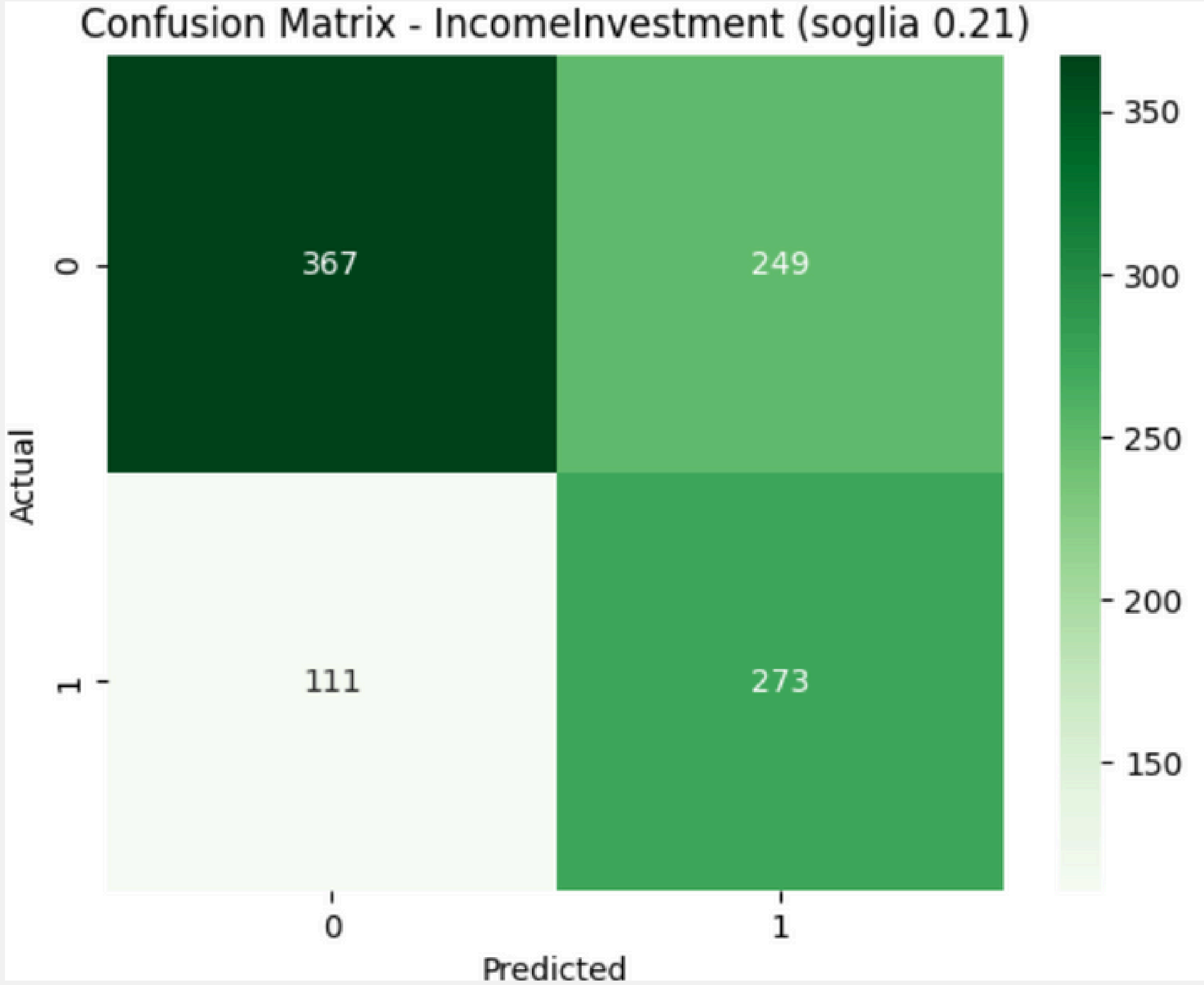
To address this, we **decoupled** the targets into two separate binary problems—one for IncomeInvestment and one for AccumulationInvestment—and evaluated a suite of algorithms (Random Forest, XGBoost, SVM, MLP) on each.

We then built a **stacking ensemble** combining RandomForest, XGBoost (with scale_pos_weight to handle imbalance) and SVM as base learners, with a Logistic Regression meta-learner, and tuned decision thresholds to enforce a recall ≥ 0.70 on each task.

This **stacking classifier** consistently delivered the highest recall-constrained F1 scores across both investment needs, so we adopted it for our final recommendation system.

Stacking Classifier

Random Forest, XGBoost, SVM, MLP



Classification Report - IncomeInvestment

	precision	recall	f1-score	support
0	0.768	0.596	0.671	616
1	0.523	0.711	0.603	384
accuracy			0.640	1000
macro avg	0.645	0.653	0.637	1000
weighted avg	0.674	0.640	0.645	1000

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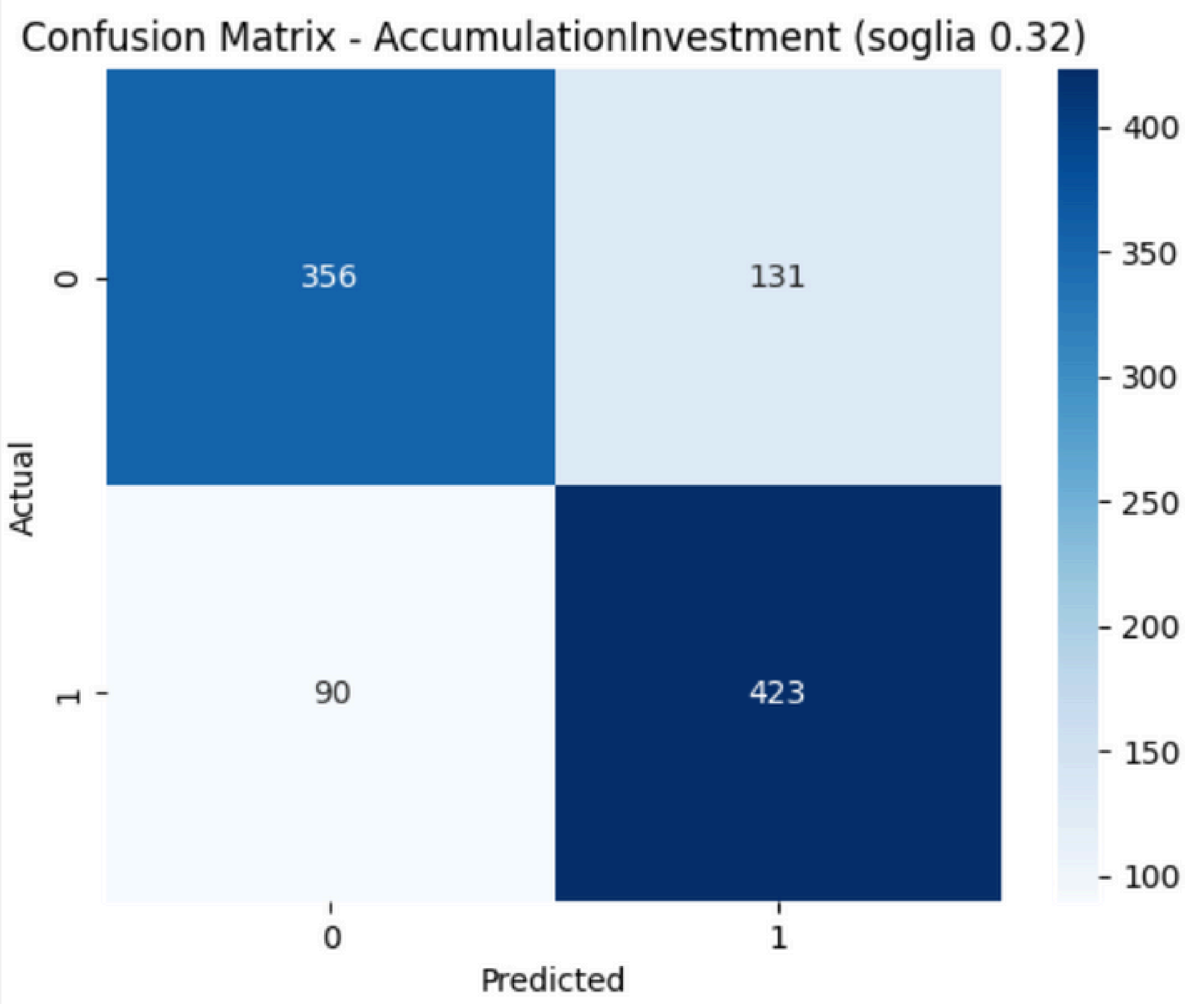
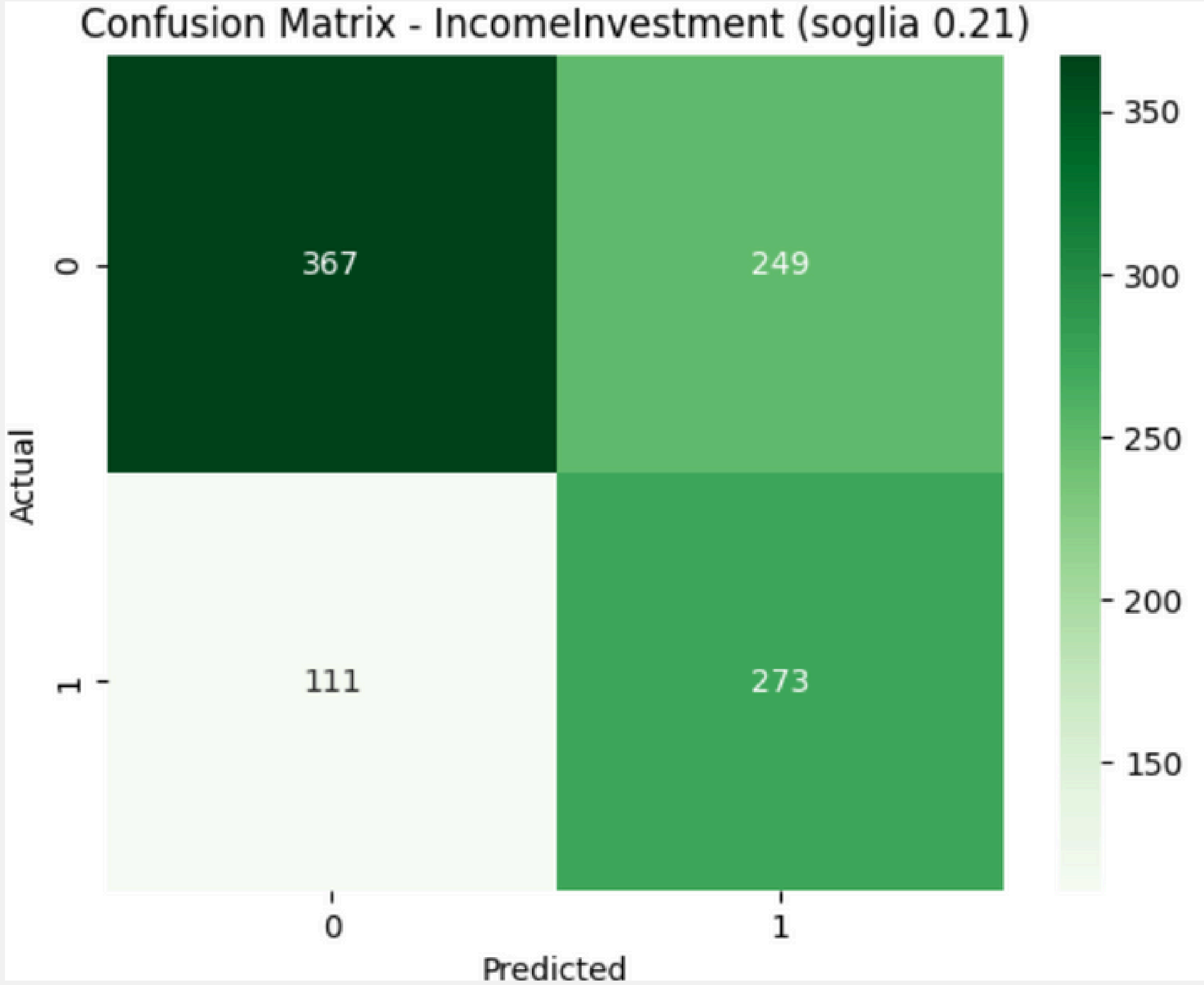


Classification Report - AccumulationInvestment

	precision	recall	f1-score	support
0	0.798	0.731	0.763	487
1	0.764	0.825	0.793	513
accuracy			0.779	1000
macro avg	0.781	0.778	0.778	1000
weighted avg	0.780	0.779	0.778	1000

Unbalanced dataset

BORDERLINE-SMOTE + ENN



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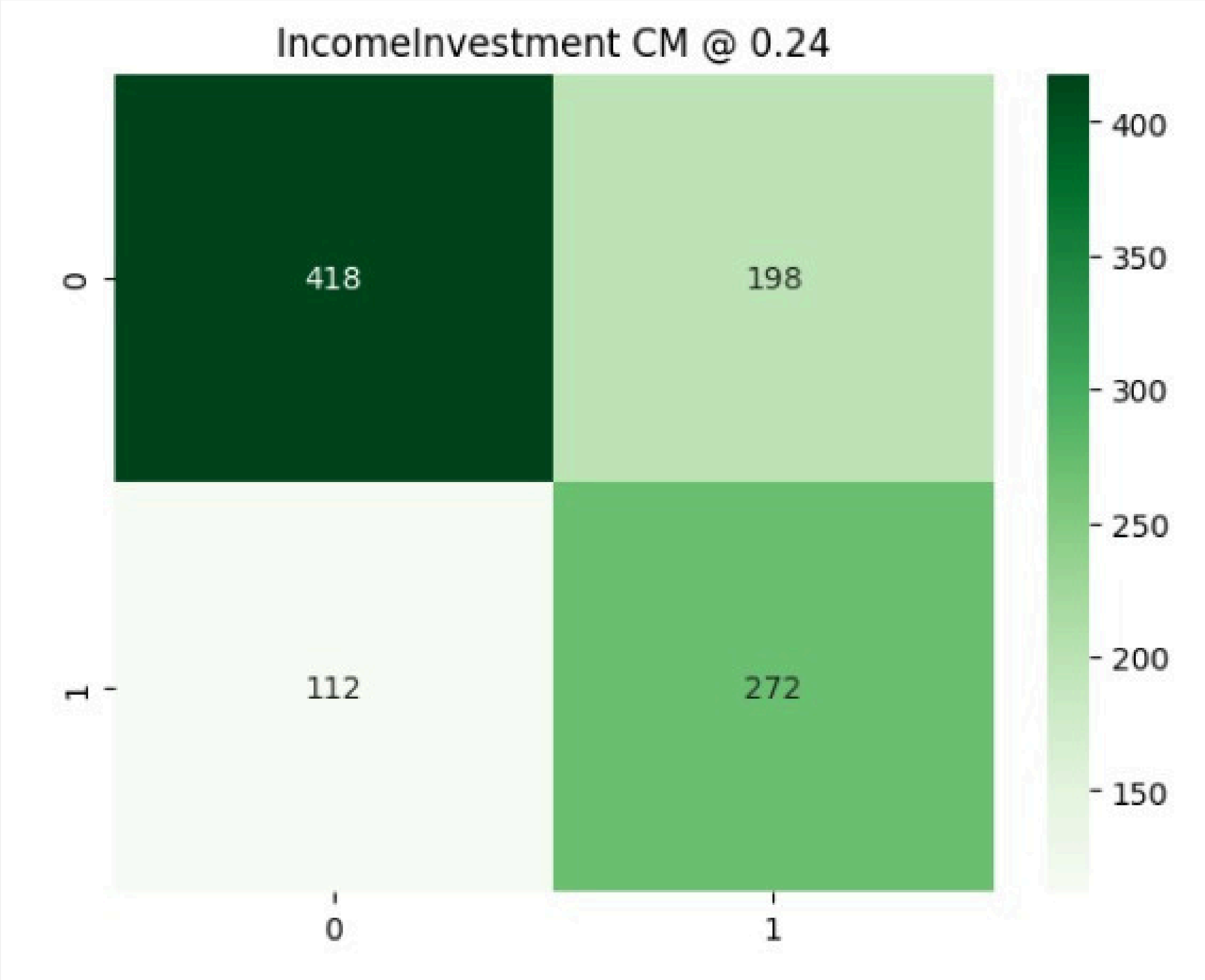


IncomeInvestment (recall ≥ 0.70)

✓ Threshold ≥ recall 0.70: 0.235 → F1 = 0.637

	precision	recall	f1-score	support
0	0.789	0.679	0.729	616
1	0.579	0.708	0.637	384
accuracy			0.690	1000
macro avg	0.684	0.693	0.683	1000
weighted avg	0.708	0.690	0.694	1000

Models comparison: base models

Income Investment

SVM - Engineered Features

	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.742	0.013	0.724
1	Precision	0.826	0.011	0.781
2	Recall	0.416	0.029	0.391
3	F1	0.553	0.025	0.521

NaiveBayes - Engineered Features

	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.747	0.009	0.717
1	Precision	0.702	0.009	0.668
2	Recall	0.591	0.03	0.523
3	F1	0.641	0.016	0.587

DecisionTree - Engineered Features

	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.714	0.018	0.694
1	Precision	0.625	0.019	0.609
2	Recall	0.641	0.035	0.568
3	F1	0.632	0.024	0.588

Accumulation Investment

SVM - Engineered Features

	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.72	0.019	0.727
1	Precision	0.724	0.029	0.725
2	Recall	0.736	0.016	0.754
3	F1	0.73	0.019	0.739

NaiveBayes - Engineered Features

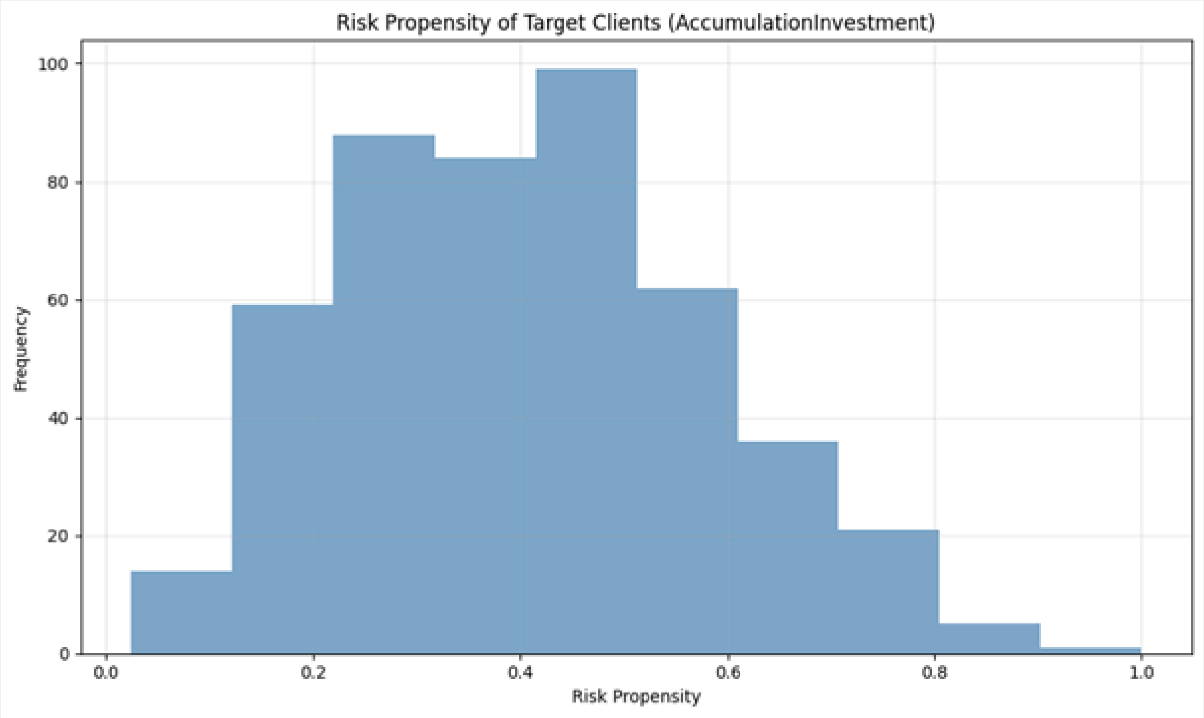
	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.634	0.019	0.616
1	Precision	0.622	0.023	0.603
2	Recall	0.734	0.03	0.737
3	F1	0.673	0.023	0.663

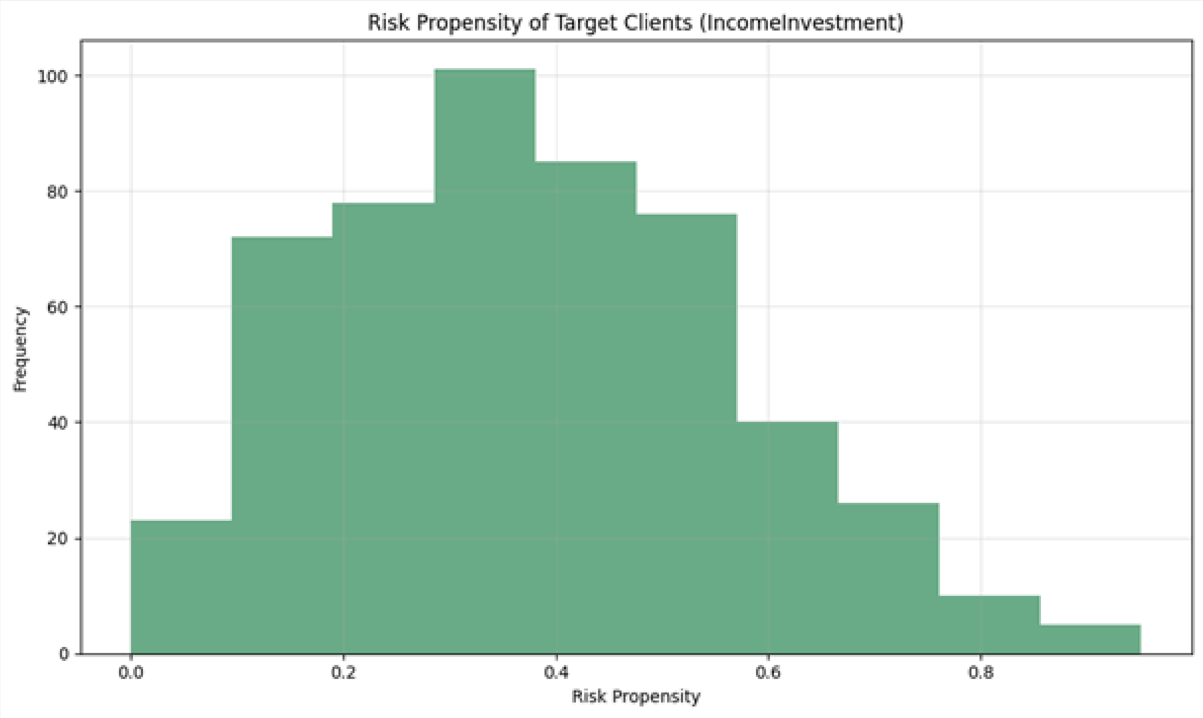
DecisionTree - Engineered Features

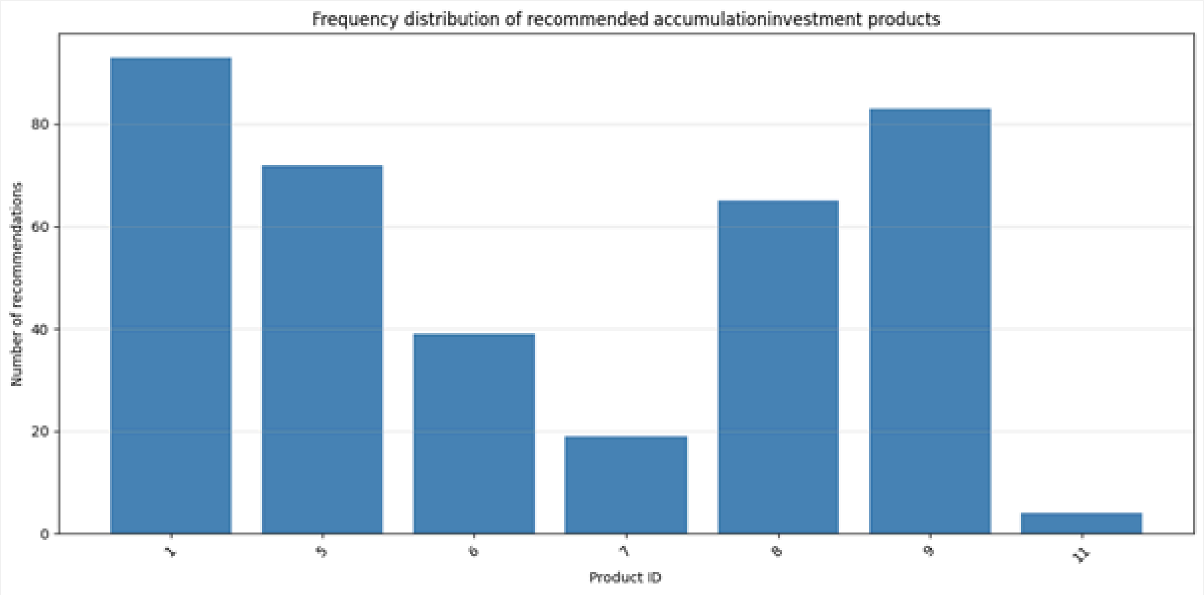
	Metric	CV Mean	CV Std	Test Set
0	Accuracy	0.747	0.006	0.735
1	Precision	0.748	0.004	0.73
2	Recall	0.765	0.009	0.768
3	F1	0.756	0.003	0.748

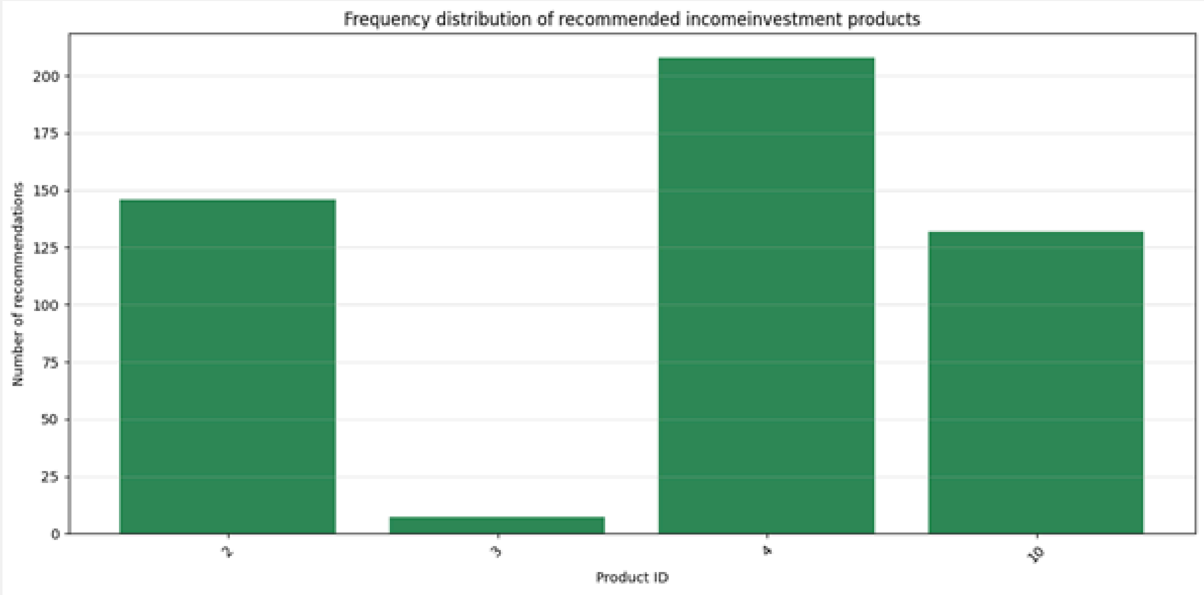
Compared to relying on individual base models like Naïve Bayes, SVM, or Decision Trees alone, our Stacking Classifier delivered a significant boost in overall performance. While it is true that this more complex ensemble approach comes with higher computational and maintenance costs, the substantial gains in key metrics, particularly recall and F1 score, more than justify the investment.

Risk propensity of our clients







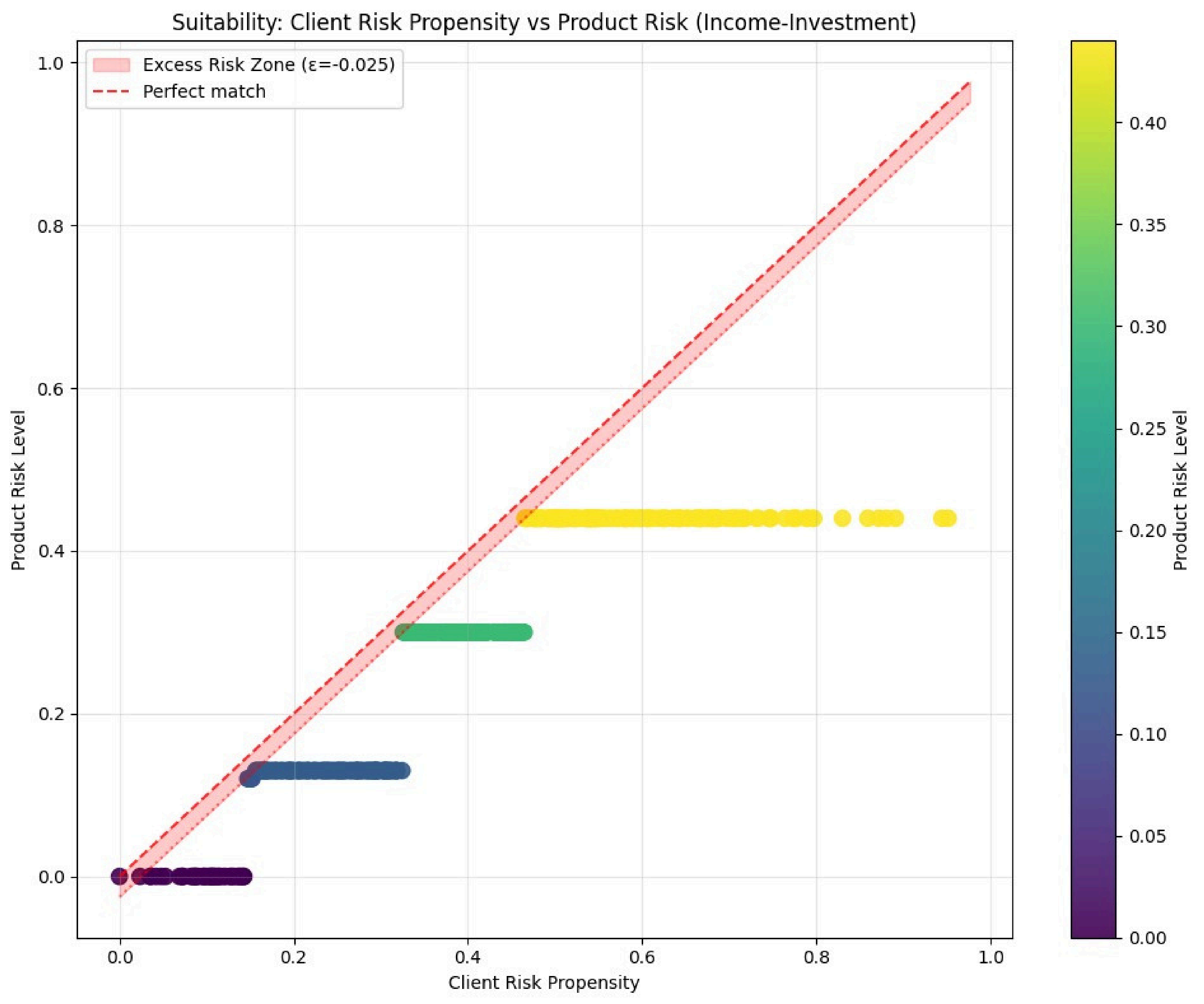


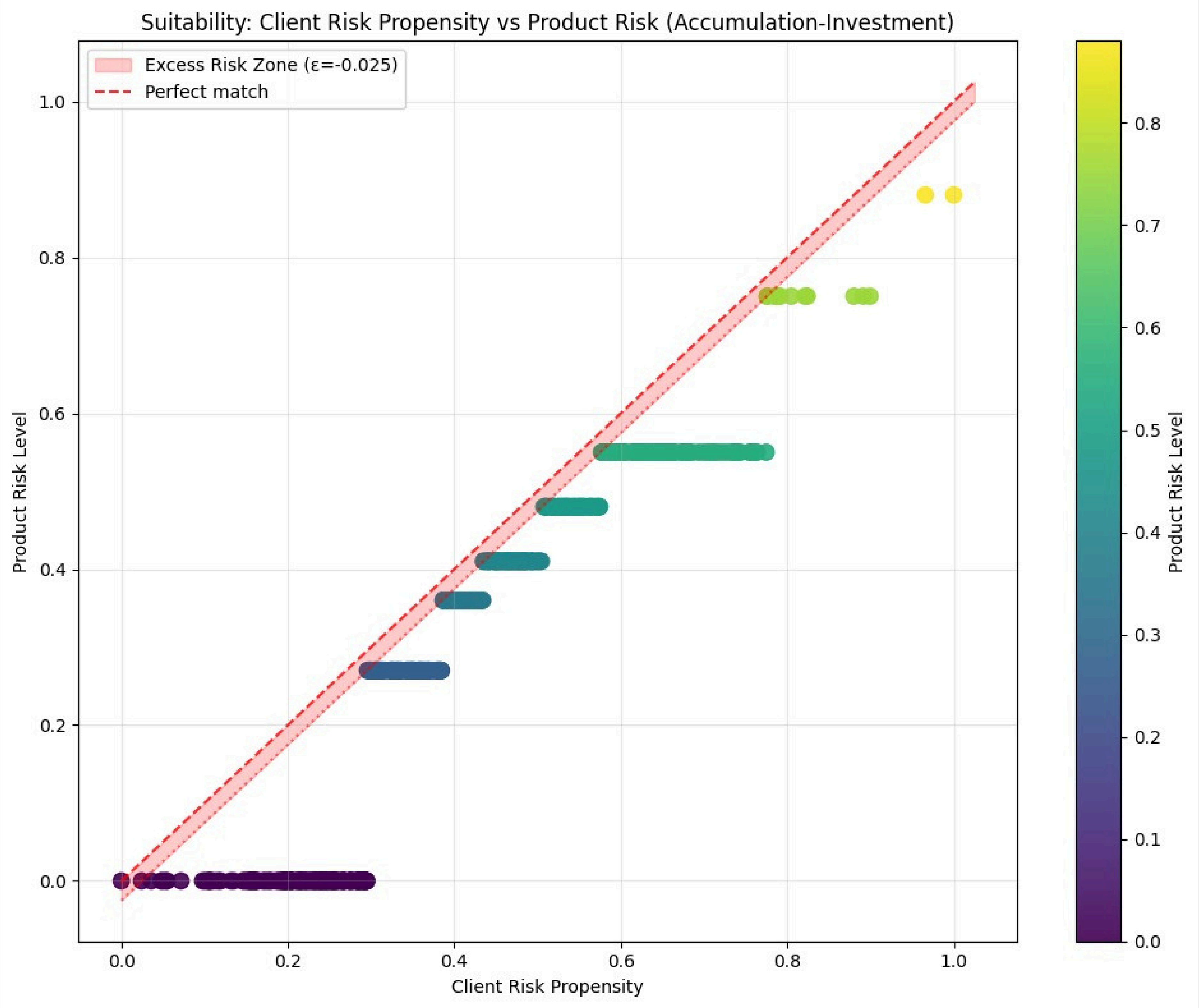
FOR EACH CLIENT FLAGGED FOR INCOME OR ACCUMULATION NEEDS, WE BUILT A "NEXT-BEST-ACTION" DATAFRAME THAT PAIRS THEIR **PREDICTED NEED, RISK PROPENSITY**, AND THE **APPROPRIATE PRODUCT POOL** (BY NEED TYPE).

WITHIN EACH POOL, WE **FILTERED PRODUCTS WHOSE RISK LEVELS DON'T EXCEED THE CLIENT'S RISK PROPENSITY MINUS EPSILON,** THEN SELECTED THE HIGHEST-RISK PRODUCT STILL WITHIN THAT TOLERANCE—ENSURING WE PUSH CLIENTS TOWARD THE MOST REWARDING YET SUITABLE OPTION.

CLIENTS WITHOUT ANY PRODUCT IN THEIR RISK WINDOW ARE STILL RECORDED, ALLOWING US TO IDENTIFY GAPS IN OUR OFFERINGS OR CLIENTS NEEDING BESPOKE SOLUTIONS.

FINALLY, WE RAN **DIAGNOSTIC ANALYSES**—HISTOGRAMS OF CLIENT RISK, RECOMMENDATION-RATE STATISTICS, TOP-RECOMMENDED PRODUCTS, AND A SCATTER PLOT OF CLIENT VS. PRODUCT RISK—VALIDATING THAT OUR RECOMMENDATIONS ALIGN WITH EACH CLIENT'S COMFORT WITH RISK.





Product Reccomendation

New products, new results

We extended our product mapping to include five new offerings namely:

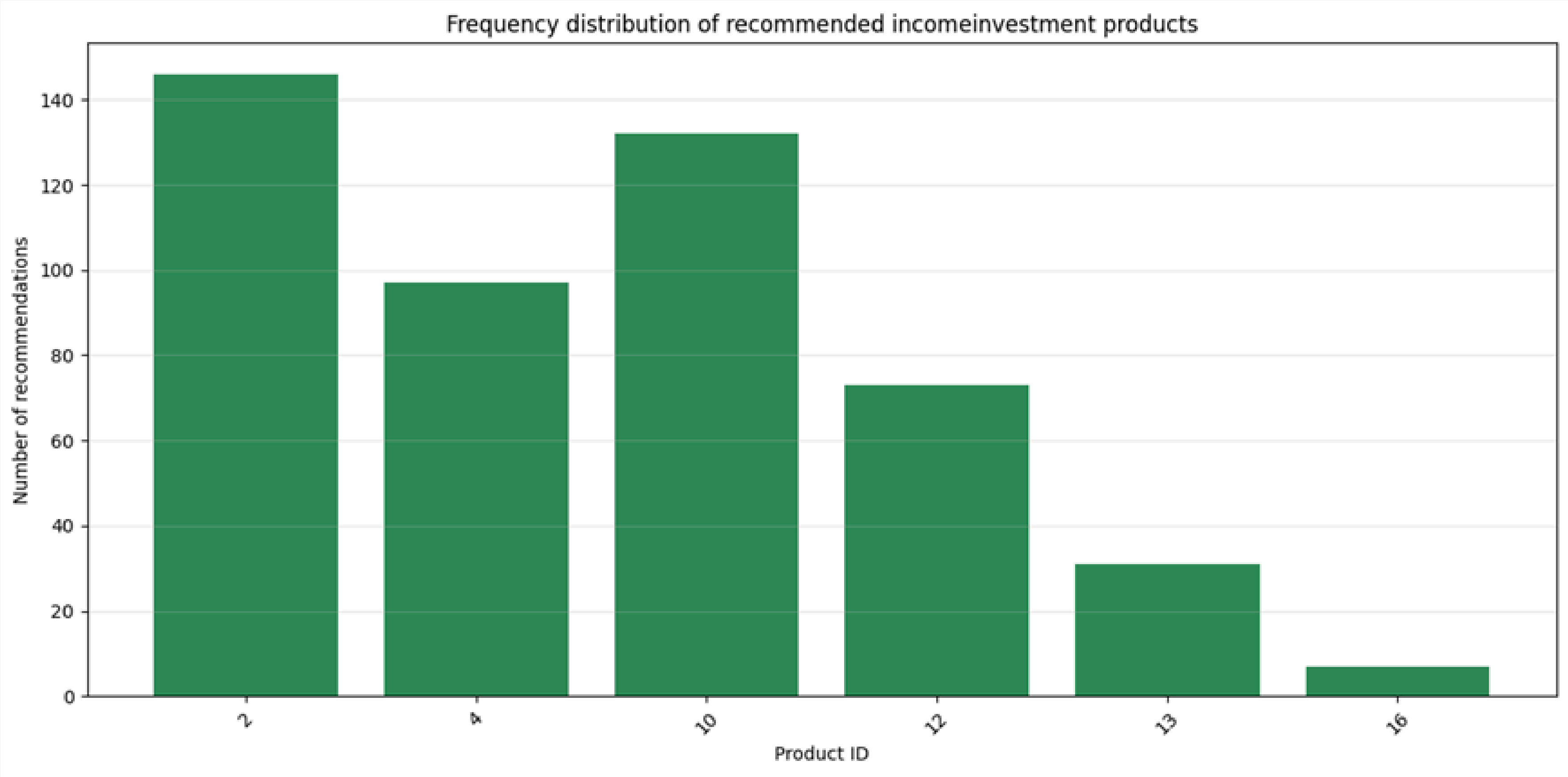
- Global Diversified Income Fund
- Emerging Markets High Yield Bond Fund
- Sustainable Growth Equity Portfolio
- Short-Term Government Bond Accumulation Fund
- Tranche Equity CDO

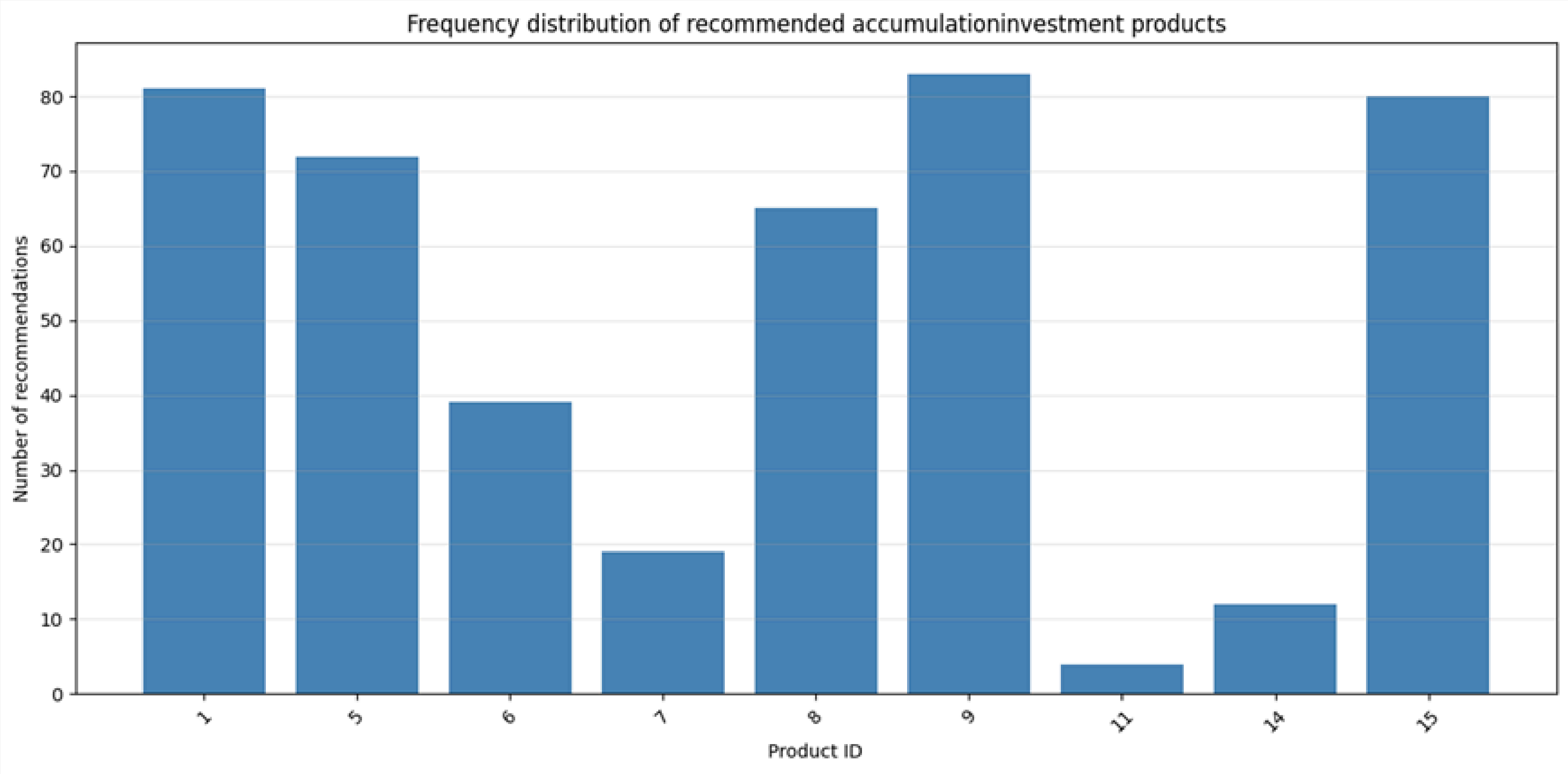
We selected those specific products because they strategically address gaps in our offering and align with both client needs and market dynamics: each new product maps to an uncovered risk bucket, ensuring every client profile has a precise match.

These additions widen our risk–return spectrum, from very conservative (Short-Term Government Bond) up to higher-risk/high-return instruments (Emerging Markets High Yield).

The ε-based suitability filter seamlessly evaluates each client's risk tolerance against this expanded universe, ensuring they're steered toward the most ambitious yet acceptable choice within their comfort zone.

Finally, all downstream analytics and visualizations will reflect these new products, giving us deeper insight into how clients distribute across our enriched lineup.


Frequency distribution of recommended incomeinvestment products
Number of recommendations
Product ID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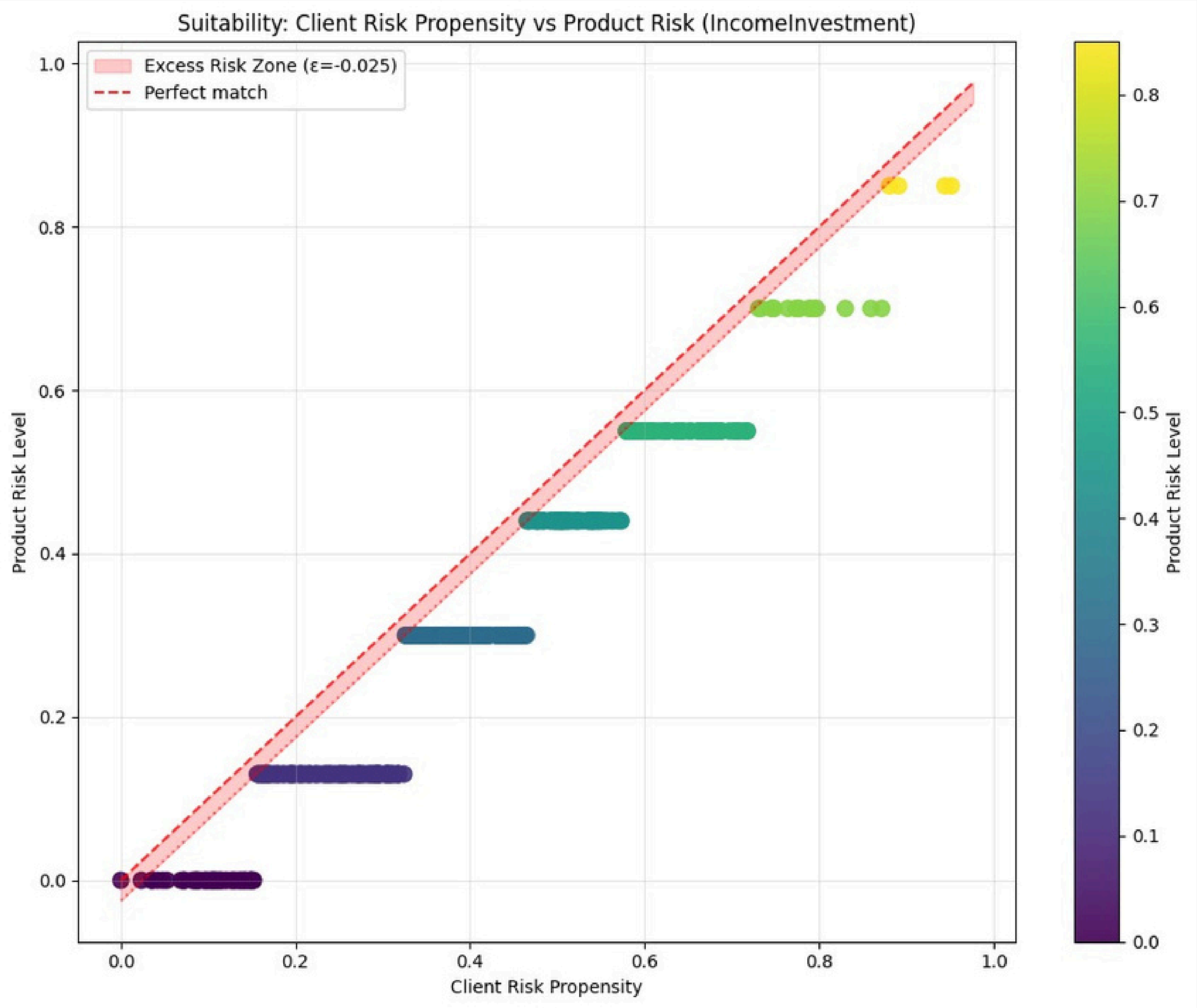
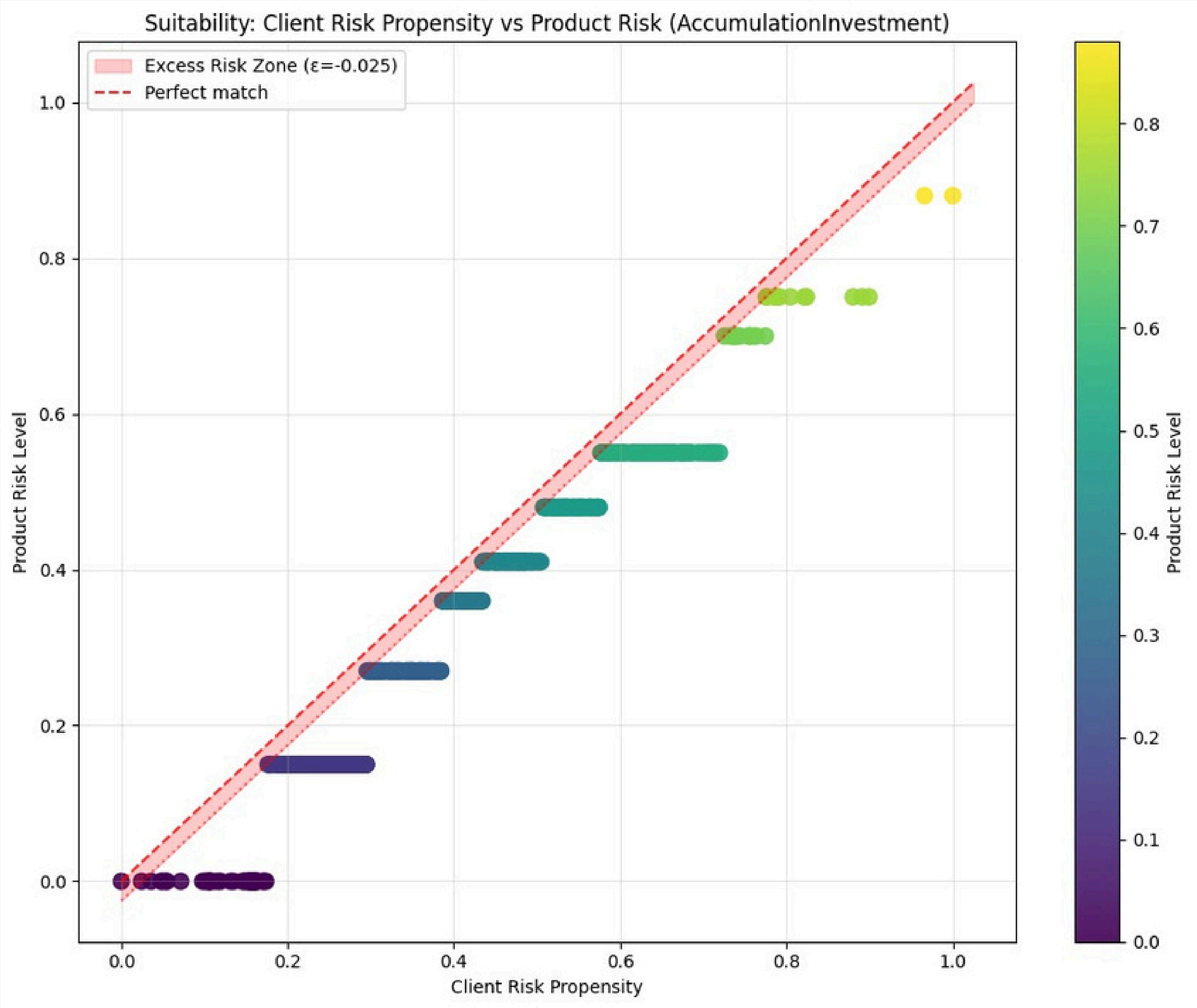
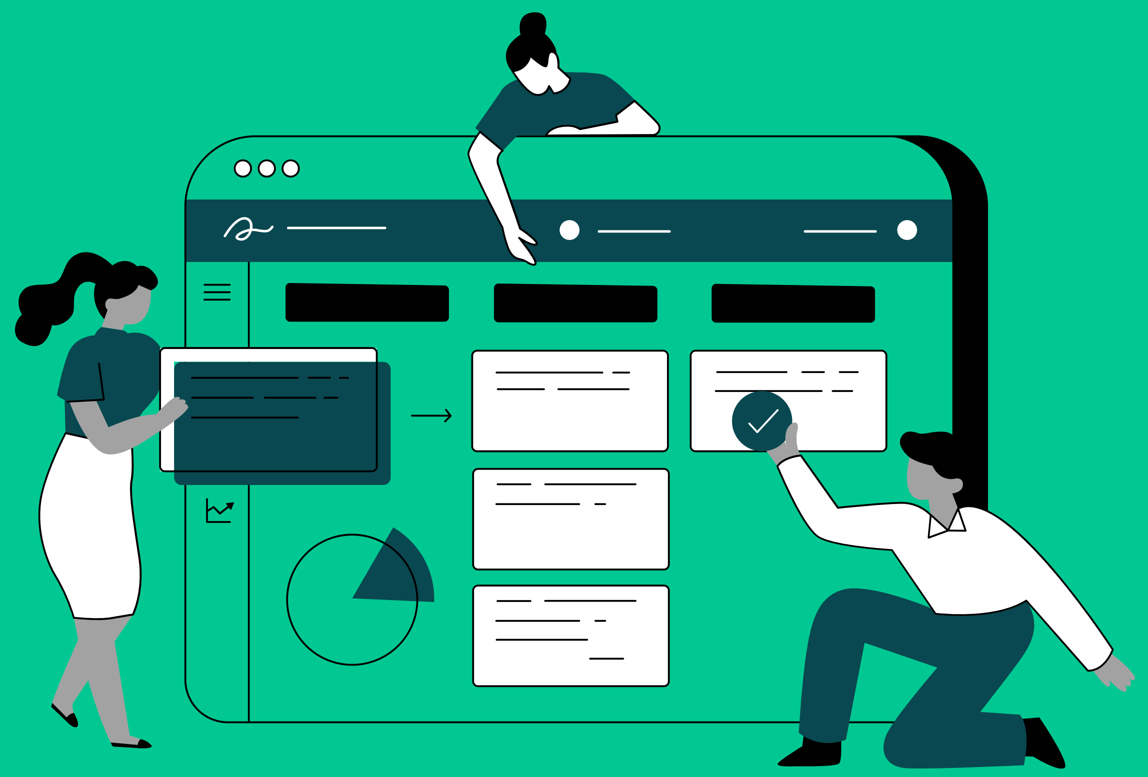

Suitability: Client Risk Propensity vs Product Risk (IncomeInvestment)
Excess Risk Zone (ε=-0.025)
Perfect match
Product Risk Level
Client Risk Propensity


Suitability: Client Risk Propensity vs Product Risk (AccumulationInvestment)
Excess Risk Zone (ε=-0.025)
Perfect match
Product Risk Level
Client Risk Propensity

Our own financial questionnaire



In our final step, we implemented a fully bespoke questionnaire, built as an interactive ipywidgets interface that:

•Dynamically captures clients' demographics (age, gender, family size), wealth and income data

•Guides them through tailored financial-literacy and risk-propensity questions

•Computes both a MiFID-based literacy/risk score and an XGBoost-predicted risk propensity

•Blends those into a composite risk profile

•Instantly delivers personalized product recommendations based on that profile

This end-to-end solution transforms raw questionnaire responses into real-time, compliant advice, all within a seamless Jupyter-notebook widget.

Would you like to know what is the most suitable product for you?

Click here to try now!